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An investigation of the dividend-signalling theory from the perspective of behavioural finance: evidence from the UK

by

FAKHRUL HASAN

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ABSTRACT

The main focus of the research reported in this thesis is the dividend signalling theory. More specifically, I investigate the dividend signalling theory from the perspective of orthodox finance and from the perspectives of two unorthodox areas of finance (behavioural finance and the calendar anomalies literature) using a sample of firms from the FTSE 350 index observed between 1990 and 2015.

The thesis revolves around four research questions. First, do dividend changes contain any information about future earnings? Second, do dividend-increase (decrease) announcements have a positive (negative) effect on stock returns? Third, does investor sentiment play any role in the reaction of the stock market to dividend announcements? And fourth, do calendar anomalies play any role in the relationship between dividend announcements and stock returns? My thesis employs an empirical approach and makes original contributions to the behavioural finance literature, the corporate finance literature and the literature on calendar anomalies.

According to my analysis, there is no evidence that dividend-increase (decrease) announcements are followed by increases (decreases) in firm earnings. However, at the same time, I document that dividend-increase (decrease) announcements are accompanied by abnormal increases (decreases) in stock market returns. These conflicting findings represent a puzzle that I would hope to investigate in my future research. From a behavioural finance point of view, I also find some evidence that investor sentiment influences the response of stock prices to dividend announcements. More specifically, I document that dividend-decrease announcements have a smaller than usual negative effect on stock returns when temperature in London is high and, as a result, investor sentiment is likely positive. Similarly, I find that the negative impact of dividend-decrease announcements on returns is bigger than usual when the

air pollution level in London is high and, as a result, investor sentiment is negative. With regards to calendar effects, consistent with the "sell in May and go away" anomaly, I document that the stock market reacts more positively to dividend-increase announcements during the November-April period than during the rest of the year, and the stock market reacts less negatively to dividend-decrease announcements during the November-April period than during the rest of the year. Regarding the turn-of-the-month anomaly, I find that that the stock market reacts less negatively (actually positively) to dividend-decrease announcements if they occur at the turn of the month than if they occur during the rest of the month. Counter-intuitively, the stock market seems to react less positively (more negatively) to dividend-increase (decrease) announcements if they occur in January than if they occur during the rest of the year. Previous investigations of the dividend-signalling theory have relied exclusively on an orthodox approach; the findings documented in this thesis suggest that future investigations about this theory could benefit from the insights produced by the behavioural finance literature and the literature on calendar anomalies.

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DEDICATION

I would like to dedicate this thesis to my loving Father and Mother.

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1 INTRODUCTION

1.1. AIM OF THE STUDY

This study develops and estimates a number of econometrics models specified to investigate the dividend-signalling theory using UK data. Dividends act as an important conveyor of information. Dividend changes may trigger changes in stock prices because they may convey new information about the firm's future earnings and profitability. Why do companies pay dividends (or analogously why are stockholders interested in receiving dividends), given that it is well known that dividends are often taxed heavily? This question is of special interest in the UK, where the dividend tax is higher than the capital gain tax. Previous research has used a number of dividend policy theories to explain the dividend policy puzzle. In this thesis I analyse the dividend-signalling theory both from the perspective of orthodox finance and from the perspectives of two unorthodox areas of finance (behavioural finance and calendar anomalies literature) and, by doing so, I hope I can make a contribution to the debate on the dividend-signalling theory and the dividend policy puzzle.

1.2. STRUCTURE OF THE STUDY

Chapter 2 presents the first part of the literature review. In this section I discuss the relationship between orthodox (corporate) finance and dividend policy. More specifically, I examine the relationship between different dividend policy theories and dividend policy. I also examine here the relationship between different corporate finance elements and dividend policy.

Chapter 3 contains the second part of the literature review. In this section I discuss the relationship between behavioural finance and dividend policy. More specifically, I analyse the relationship between different behavioural finance theories and dividend policy and I compare behavioural finance and orthodox finance approaches to dividend policy. I also examine here the effect of various behavioural anomalies and calendar anomalies on stock market returns.

Chapter 4 discusses the research approach and research philosophy used in this thesis. This chapter presents the choice of research methodology. In this chapter I also discuss the data collection method of data analysis.

Chapter 5 is the first empirical chapter in this thesis. Chapter 5 is based on a very well known dividend policy theory called dividend signalling theory or "the information content of dividend hypothesis". According to this theory, dividend changes cause changes in stock prices because they convey new information about the firm's future earnings and profitability. The main aim of this chapter is to test empirically whether dividend changes contain information about future earnings

The impact of dividend changes on stock returns is discussed in chapter 6. More specifically, in chapter 6 I test whether dividend-increase (decrease) announcements have a positive (negative) effect on stock market returns. In this chapter I use a very well known event study methodology. Like in chapter 5, in this chapter I use two different model specifications, and one of them is a partially new model specification that I call "binary model". Chapter 6 also investigates whether stock market returns react differently to dividend announcements during the Great Recession (2008-2009) than during regular periods.

Clinical and psychological surveys have uncovered that weather has significant effects on human mood and behaviour. It is also well established in the psychological literature that mood and feelings have a huge effect on the human decision-making process and particularly on economic decision making. For this reason, chapter 7 employs weather factors (temperature, air pollution and rain, all measured in the city of London) as investor sentiment proxies. In this chapter I extend my chapter 6's findings by examining the role that these three investor sentiment proxies play in the relationship between dividend announcements and stock returns.

Chapter 8 extends the analysis to calendar anomalies. In this chapter I employ four very well known calendar anomalies, which are the Halloween effect (Sell in May and go away), turn-of-the-month effect, Monday effect and January effect to address the novel question of whether calendar anomalies play any role in the relationship between dividend announcements and stock returns.

Chapter 9 presents a general discussion of the empirical findings and discusses the strengths and weaknesses of the thesis.

Lastly, chapter 10 summarises the main results of the thesis and offers potential directions for future studies.

2 THE RELATIONSHIP BETWEEN ORTHODOX FINANCE AND DIVIDEND POLICY

2.1. INTRODUCTION

Corporate Dividend policy is one of the important components of firm policies. For companies dividends act as an important conveyor of information; however, it is not clear why companies pay dividends or analogously why stockholders are interested in receiving dividends, given that it is well known that dividends are often taxed heavily, especially in the UK where the dividend tax is higher than the capital gain tax (Bozos, Nikolopoulos and Ramgandhi, 2011). In this chapter I will explain details about the relationship between orthodox finance and dividend policy. More specifically I will explain details about the relationship between dividend policy and dividend policy theories, and also the relationship between dividend policy and orthodox or corporate finance elements. This will help the reader to understand how dividend policy theories and corporate finance key factors have an influence on the dividend announcements or dividend policy of any given company. In my four empirical chapters I will concentrate on the dividend-signalling theory. And on the other hand key factors such as earnings, dividend yield, corporate governance and capital structure helped me to choose my control variables.

Lintner's (1956) in his path breaking work on dividends said that the payment of regular cash dividends to shareholders is a chronological tradition in developed capital markets. Lintner's (1956) argument was that company managers should understand that shareholders are entitled to get firm's profits in the form of dividends. There are numerous issues that are considered at the time of paying dividends, permanent earnings or earnings being one of them. Firms that pay dividends consider the relation between the decision to pay dividends and earnings; studies have found that dividends vary according to profitability, growth, firm size, total equity, cash balance, and dividend history, a relation that also holds for dividend initiations and omissions.

Dividend changes are positively associated with stock returns in the days surrounding the dividend change announcement (Aharony and Swary (1980, Asquitg and Mullins (1983), Kalay and Loewenstein (1985), and Petti (1972)). Nissim and Ziv (2001) argue that, there is a relationship between dividend changes and future permanent earning changes, and dividend increases are positively related to unexpected earnings but, on the other hand, dividend decreases are not significantly related to earning changes. According to Lintner (1956), dividend changes are more related to changes in permanent earnings. Whereas Watts (1973) and Gonedes (1978) showed there is no relationship between current dividends and future earnings.

Various dividend policy theories have been proposed, but in this thesis I focus on the most common and most prominent one, which is the dividend-signalling theory. The theoretical models such as those developed by Bhattacharya (1979) and Miller and Rock (1985) suggest that dividend policy changes convey news regarding future cash flows. They developed these theoretical models by using an important economic notion of asymmetric information between managers and investors. The general implications of the dividend-signaling hypothesis are (1) a positive relationship between dividend changes and the price reaction to dividend changes; (2) a positive relationship between dividend changes and the future earnings changes. This dividend hypothesis is one of the key issues of the field of corporate finance; therefore, survey and discussion on this issue by incorporating several new viewpoints are valuable for the discipline. This dividend hypothesis is valuable and new perspectives are needed because the puzzle has not been resolved yet.

Section 2.2 presents the relationship between dividend policy and dividend policy theories. In section 2.3 I examine the relationship between corporate finance and dividend policy. Section 2.4 presents the conclusion.

2.2. THE RELATIONSHIP BETWEEN DIVIDEND POLICY AND DIVIDEND POLICY THEORIES

Companies' dividend policy depends on different dividend policy theories. In this section I explain the relationship between dividend policy and dividend policy theories.

2.2.1.MILLER AND MODIGLIANI DIVIDEND THEORY

According to Miller and Modigliani (1961) in a perfect capital market, dividend payout policy is irrelevant to firm value because "(1) only investments, which generate future earnings and cash flows, affect firm value, and (2) investments are independent of dividends". Later Fama and Miller (1972) highlight an important caveat of this dividend irrelevance theorem, which is "Dividend policy should not affect investment decisions".

In imperfect markets, dividend policy may influence investment decision, because when managers have more information about firm's assets value and investment projects than outside investors, then other problems can constrain the firm's access to external funds (Jensen and Meckling 1976; Myers and Majluf 1984). Recent research finds evidence consistent with dividends having a constraining or negative effect on investments (Santhosh, Chun-San and Yong, 2013).

Investors' information set about future earnings changes when dividends change, and the earnings information itself is an essential part of the firm's underlying operations and hence should affect firm value, resulting in a potential ‘‘hopeless confounding of the real and purely informational effects’’ of dividends (Miller and Modigliani 1966). Penman (1983) finds that dividend changes carry modest information after controlling for management forecasts of earnings but their effects are statistically significant and economically relevant. And on the other hand, Kane et al. (1984) conclude that dividend changes transmit information incremental to earnings information announced in chorus. Their effects, too, are economically relevant and statistically significant. Lang and Litzenberger (1989) find that the price reaction to dividend changes is greater for firms with lower expected profitability of future investments. They argue that this result supports the free cash flow hypothesis but is inconsistent with the dividend-signalling hypothesis.

Miller and Modigliani (1961) suggest that investors decide to invest in a firm according to its dividend policy and changes in the payout policy lead to a change in the ownership structure. However, this payout change does not affect the firm’s value because a priori no class of investors (called here clientele) is better than another. Shefrin and Thaler (1988) suggests that the reason why investors (or clientele) want different dividend yield is due to the level of taxation. Firms with low dividend yields are attractive for investors whose taxation is the highest; on the other hand investors with low level of taxation are interested in firms with high dividend yields.

According to Miller and Modigliani (1961) and Shefrin and Statman (1984), whether an investor is an individual or a pension fund, the optimal level of dividend yield can be different. Elton and Gruber (1970) measure the clientele effect by studying how the values of shares behave over the ex-dividend period, they use short term and long term taxation rates as equal, an identical taxation level for all investors and a homogeneous ownership structure Elton and Gruber (1970) manage to find out the conditions in which an investor is indifferent when it comes to selling or buying a stock before or after the ex-dividend date.

In summary, investment decisions can be affected because of the dividend policy. Changes of dividend policy change investors' information set about future earnings. Dividend changes carry modest information after controlling for management forecasts of earnings, and transmit information incremental to earnings information announced in chorus. Investors decide to invest in a firm according to its dividend policy and a change in the payout policy leads to a change in the ownership structure.

2.2.2. LIFE-CYCLE THEORY AND DIVIDEND POLICY

The life-cycle theory has been advanced by Fama and French (2001), Grullon et al. (2002) and DeAngelo et al (2006). Life-cycle theory suggests that the trade-off between the advantages and disadvantages of the retention of earnings varies over the life of the firm. In the early stage of profitability all firms have the great investment opportunity and at the similar time they have the less opportunity to internally generate cash when internal financing is cheaper than external financing. The prime decision is to maintain cash to fund growth. While these benefits of retention are widely accepted and empirically important in the literature, the motivations for later stage distributions are less so, probably because factors such as the agency costs of free cash flow are less easily measured than security issuance costs, tax penalties on pay-outs, and the stock-price impact of equity offerings.

The growing firms, which have abundant investment opportunities should not return cash to shareholders in preparation for necessary investment for their future growth rather they should prioritize retained earnings (RE). On the other hand, it is preferable for the mature firms to return excess funds to shareholders in order to partly ease free cash flow problems (Jensen 1986). This idea is well known as the dividend life-cycle theory (Fama and French 2001; Grullon et al. 2002; Julio and Ikenberry 2004; DeAngelo and DeAngelo 2006; DeAngelo et al. 2006). In the US, there is evidence consistent with the theory. For example, DeAngelo et al. (2006) positions a RE ratio (= RE/book-value of equity) as a scale to express the stages of firm growth, and presents evidence that firms with high RE (mature firms) pay dividends (Ishikawa, 2011).

Mature firms are more profitable and are able to internally generate cash in excess of their investment requirements. The optimal policy will then be to retain sufficient earnings to invest in positive net present value projects and distribute excess cash to shareholders. When a firm pay dividends it means that firm is reaching sustainable profitability. The amount of free cash flows, however, depends on the capital requirements of the firm to finance its growth. Generally, growing firms with abundant investment opportunities tend to have low free cash flows and, in turn, pay lower dividends. On the other hand, mature firms with inadequate profitable projects to invest tend to have high free cash flows and be able to make high dividend payments. Therefore, the firm's dividend policy appears to be affected by its life cycle. This is known as the life-cycle theory dividends (see, e.g., DeAngelo et al., 2006; Fama and French, 2001; Grullon et al., 2002).

Grullon, Michaely, Swaminathan (2002) find that dividend-increasing firms do not increase their capital expenditures in the years after dividend increases. Around dividend increase announcements the systematic risk of dividend-increasing firms significantly declines, and for that reason those firms' cost of capital also declines significantly. Grullon et al. (2002) indicate that this decline in systematic risk is a significant determinant of the positive stock price reaction to dividend increases. Kane et al. (1984) documented the fact that announcements of changes in earnings and dividends are evaluated in conjunction with each other. According to Ishikawa (2011) dividend increases at the time of an increase in earnings are more appreciated than at the time of a decrease in earnings. Ishikawa (2011) called this "corroboration effect." However, Ishikawa (2011) suggests that "factors that additionally cause an increase in stock prices in corroboration of the announcement of dividend increases do not only include a direct performance factor such as an increase in earnings".

There is positive (negative) correlation between dividends increases (decreases) and stock prices associated with the firm's growing stages. Ishikawa (2011) use PBR (Price to book-value ratio) as GROWTH, and he found that the coefficient of a mature firm's dividend decreases is significantly negative, whereas the coefficient of a growing firm's dividend decreases is significantly positive. These results are consistent with the prediction by the dividend life-cycle theory. Free cash flow issues could further worsen if market discount a mature firm's dividend decreases, while market also discount a growing firm's dividend decreases but less than the usual decreases, since them to be preparations for future investment. On the other hand, dividend increases have a result completely opposite to that predicted by the life-cycle theory. Ishikawa (2011) find that the coefficient of a mature firm's dividend increases are significantly negative, whereas the coefficient of a growing firm's dividend increases are significantly positive. This result suggests that the positive correlation between dividend increases and stock prices is stronger in growing firms and weaker in mature firms.

Grullon, Michaely, Swaminathan (2002) find a permanent increase in the dividend pay-out ratios of dividend-increasing firms. This means that these firms can maintain higher dividends, which is consistent with Lintner's (1956) finding that managers attempt to smooth dividends. Following these findings, Grullon et al. (2002) propose the maturity hypothesis, positing that a firm tends to increase dividends when it moves to a more mature phase from a growth phase. As we know when a growth firm transforms into a mature firm, its investment opportunities decline, which, in turn, would lead to an increase in the firm free cash flows. A mature firm then pays out these free cash flows in the form of dividends or share repurchases. Therefore, a dividend increase may signal not only a change in the firm's fundamentals but also a commitment of management not to overinvest.

DeAngelo, DeAngelo, and Stulz (2006) say that the life-cycle theory offers a more plausible explanation for the massive payouts because according to life-cycle theory firms pay dividends when the agency and other costs of retaining free cash flow exceed the flotation cost and other benefits of retention. DeAngelo, DeAngelo, and Stulz (2006) also say that the agency cost-inclusive life-cycle theory most powerfully explains the dividend decisions of the largest longstanding dividend payers because of their choice to distribute substantial dividends consistently over long horizons. With flotation costs and/or asymmetric information problems as in Myers and Majluf's (1984) pecking order theory, managers will distribute the full value of the free cash flow stream over the life of the enterprise, but will distribute nothing until the probability is zero that unanticipated attractive new investments might force them to seek outside capital. In principle, such asymmetric information problems can cause firms to sacrifice dividends entirely until the final period(s) of their lives.

Life-cycle theory suggests that there is a trade-off between the advantages and disadvantages of the retention of earnings, which varies over the life of the firm. The growing firms with abundant investment opportunities should prioritize retained earnings (RE) rather than return cash to shareholders in preparation for necessary investment for their future growth. When firms mature, they become more profitable and are able to internally generate cash in excess of their investment requirements. Dividend-increasing firms do not increase their capital expenditures in the years after dividend increases. The life-cycle theory offers a more plausible explanation for the massive payouts because in that theory, firms pay dividends when the agency and other costs of retaining free cash flow exceed the flotation cost and other benefits of retention.

The main idea behind the firm life cycle theory of dividends is, mature firms has more ability to generate more cash and mature firms easily find out the profitable investment opportunities. If a firm generates free cash flow then at the end of the day it is the firm's main duty is to distribute its free cash flow to shareholders in the form of dividends (Bulan and Subramanian, 2008).

Mueller (1972) proposed the theory that a firm has a relatively well-defined life cycle, which is fundamental to the firm life cycle theory of dividends. His focus is on the agency problem, which is whether the managers work to maximise shareholder wealth or managers work for their own sake and whether managers overinvest in assets by overlooking shareholders' interests. Drawing on the work of Knight (1921) and Schumpeter (1934), Mueller (1972) posits that a firm originates in an attempt to exploit an innovation involving a new product, process, or marketing or organisational technique.

In the early stages firms usually invest all their available resources in developing the innovation and improving profitability. According to Bulan and Subramanian (2008), in these initial stages the agency problem is either absent or not significant for three reasons.

"First, the firm faces so many opportunities for profitable investment that the pursuit of growth is also consistent with the pursuit of profits. Second, unable to meet all its financing needs through internal cash generation, the firm is forced to tap external capital markets and is therefore subject to market monitoring and discipline. Third, the entrepreneur or manager still retains a sufficiently high fraction of the firm's shares for his or her interests to be well aligned with those of the other suppliers of capital" (Bulan and Subramanian, 2008).

2.2.3. CATERING THEORY OF DIVIDEND POLICY

Catering theory of dividends was developed by Baker and Wurgler (2004). Their main argument was that, managers usually modify corporate payout policies speculatively when investor sentiment favours the payment of dividends (Ferris, Jayaraman and Sabherwal, 2009). At the same time, Baker and Wurgler (2004) provide a catering explanation for the unexpected reductions in the percentage of dividend paying firms within the U.S. Li and Lie (2006) provide further confirmation of catering effects among U.S. firms through an examination of changes in corporate payout ratios and their relation to the market dividend premium.

The international presence of dividend catering theory is limited and its findings are mixed (Ferris, Jayaraman and Sabherwal, 2009). But Ferris, Sen and Yui (2006) documented that in the U.K. a shift in catering incentives most likely explains the declining inclination to pay dividends over the 1998-2002 sub-period. On the other hand Eije and Megginson (2008) have done a test over fifteen European countries over the 1989-2003 period and failed to find evidence of catering in their sample. Among all other findings, their findings are recognised best, because their regression specifications are substantially different from those estimated by Baker and Wurgler (2004b). After that Denis and Osobov (2008) ran their estimation over six countries and reported that some of their findings appear inconsistent with dividend catering. They report that the percentage of dividend payers is reduced unexpectedly in those countries where the dividend premium is largely positive and the reason behind this reduced dividend payers is lower rates of dividend initiations by newly listed firms. However, they do not formally test for the presence of dividend catering.

La Porta et al. (1997) reported that shareholders in common law countries enjoy more investor protections than in civil law countries. La Porta et al. (1999, 2000), Denis and McConnell (2003), and others detect that this legal enfeeblement of shareholders leads to an agency conflict between agents and principals.

According to the catering theory managers would opportunistically modify corporate payout policies when investor sentiment favours the payment of dividends. Some of the studies have found evidence in support of the catering theory, while some other has not.

2.2.4. FREE CASH FLOW HYPOTHESIS AND DIVIDEND POLICY

According to Jensen (1986) free cash flow hypothesis is the answer of why firms pay dividends, because it explains dividends as a means to mitigate agency cost of free cash flows. The free cash flow hypothesis is based on the persisting argument that there is a conflict of interest between managers and shareholders. Because managers allocate the firm's resources and assets for their own benefit, rather than they act for the best interest of the shareholder (Jensen and Meckling, 1976). Managers' often spend resources on luxurious office and unjustifiable mergers and acquisitions, overinvestment on negative NPV projects are most common example of managers' selfish behaviour. To mitigate the overinvestment problem, Easterbrook (1984) and Jensen (1986) suggest that firms return excess cash to shareholders by paying dividends or repurchasing shares.

An proposition of the free cash flow hypothesis is that cash-rich firms, which are mature with scarce investment opportunities tend always face overinvestment problem, a dividend increase announcement by these firms should be convoyed with a positive stock market reaction, because then shareholders will realise that management are not wasting corporate cash flows. Lang and Litzenberger (1989) test free cash flow hypothesis using Tobin's Q ratio to determine the group of overinvesting firms. They use a sample of 429 regular dividend changes firms between 1979 and 1984, and they end up with the result that, the average announcement return of large dividend change is significantly higher for firms with low Tobin's Q than for firms with high Tobin's Q. This evidence is consistent with the free cash flow hypothesis that dividend increases by overinvesting firms signal management's intention to mitigate overinvestment problem, thereby causing larger stock market reaction (Thanatawee, 2011).

On the other hand, Howe, He, and Kao (1992) find no significant association between announcement returns and Tobin's Q, when they examine 55 self-tender offers and 60 special dividend announcements between 1979 and 1989. Again they run regression between the announcement returns and the firm's cash flow before the event and an interaction term between Tobin's Q and cash flow, but their findings offer no evidence supporting the free cash flow hypothesis (Thanatawee, 2011). Yoon and Stark (1995) find that the average abnormal return of low-Q firms is significantly higher than that of high-Q firms for dividend increases when they examine a sample of 4,179 dividend changes between 1969 and 1988. But stock price reactions between these two groups after controlling for the size of dividend change, the dividend yield, and the market value of the firm was same.

Free cash flow hypothesis argues that dividends are to mitigate agency costs of free cash flows. The free cash flow hypothesis is based on the argument that there is a conflict of interest between managers and shareholders. Managers always allocate the firm's resources to benefit themselves, rather than act for the best interest of the shareholder. The average announcement return in response to large dividend change is significantly higher for firms with low Tobin's Q than for firms with high Tobin's Q.

2.2.5. PECKING ORDER THEORY AND DIVIDEND POLICY

Pecking order theory is based on the work of Myers (1984) and Myers and Majluf (1984). They argue that in the existence of asymmetric information, a firm will follow a pecking order in their financing, in which a firm would prefer internal source of financing to external source of financing alternatives, and that a firm adjusts its target dividend payout to its investment opportunities (Al-Najjar, 2011). In the Hierarchy theory (pecking order theory), the following assumptions are taken- first, entrepreneur's prefer to finance their activities with internal sources, such as net profit less dividends, depreciation allowances and revenue from sale of short-term securities and others redundant assets. And second assumption is, in cases when it is necessary to finance activities with debt capital, debt securities are issued first, followed by new shares (Duliniec,1998; Quan, 2002 and Mazur, 2007).

According to pecking order theory, entrepreneurs are usually look for the cheapest sources of activity financing in order to minimise their risk and limit the costs of equity issue or payment of interest on credits and loans they have taken. If necessary to use the debt capitals, debt securities are issued first (McManus, Gwilym and Thomas, 2006; Duliniec, 2007). Due to that reason there is a competition between decisions on reinvestment of achieved profit and payment of dividends. Al-Najjar (2011), say that if the retained earnings are insufficient, then the firm will borrow rather than issue new stocks, which causes to debt ratio to increase. Whereas Myers (1984) argues that firms prefer debt financing rather than issuing equity, as debt financing has lower information costs. That is why, the last option for the firm is to issue stock.

2.2.6. DIVIDEND-SIGNALLING THEORY AND DIVIDEND POLICY

The basis of signalling theory derives from a study by Lintner (1956), in which 28 companies managers were interviewed to find out which factors were most instrumental in firms' payout policies. Models of dividend-signalling (e.g. Bhattacharya, 1979; John and Williams, 1985; Miller and Rock, 1985) suggest that dividend changes are employed by firms to convey future earnings information. However, empirical studies based on time-series regression analysis (e.g. Watts, 1973; Gonedes 1978) suggests that dividend convey very little information about the subsequent earnings of the firms.

Path breaking paper by Miller and Modigliani (1961) suggested 'the information content of dividends', which means that if managements' future earnings expectations affect their current dividend payout decisions, then dividend changes will convey information to the market regarding future earnings (Tsuji, 2012). Allen and Michaely

(2003) formalized this notion in two ways, which are "dividends are used as an ex-ante signal of future cash flow as in Bhattacharya (1979) and dividends supply information regarding earnings as a description of the sources and uses of funds identity as in Miller and Rock (1985)". According to Allen and Michaely (2003) the difference is important for interpreting empirical results since the second alternative can be considered as stating that the fact that dividends convey information does not necessarily mean that dividends are being used as a signal by managers. Allen and Michaely (2003) also found that the dividend signalling hypotheses included three important implications that had been empirically examined, which are "(1) unexpected dividend changes should be accompanied by stock price changes in the same direction; (2) dividend change should be followed by subsequent earnings changes in the same direction and (3) unexpected changes in dividend should be followed by revisions in the market's expectations of future earnings in the same direction as the dividend change.

The signalling theory of dividends posits that firms convey their optimism for the future by initiating dividend payments (Hobbs and Schneller, 2012). Lintner was convinced by that, dividends dependent were not only upon the amount of cash needed to finance projects in the short-term, but that they also represented management's belief in the sustainability of company earnings over the long-term. Due to that reason managers usually increase or initiate payouts only when they believed that subsequent earnings would be high. John and Williams (JW) (1985) and Miller and Rock (1985) show that the level of dividends signals the level for a firm's cash flow, while Kale and Noe (1990) demonstrate that the level of dividends signals the variance of the firm's cash flow.

Previous empirical evidence suggests that investors always interested to dividend increases and initiations; the stock prices of firms that initiate dividends tend to increase around the time of the initiation announcement (Asquith and Mullins, 1983; Healy and Palepu, 1988). Similarly, the signalling theory implies that any subsequent decrease or elimination of dividends will be viewed with extreme disfavour by the financial markets (Healy and Palepu, 1988; Michaely et al., 1995; Benartzi et al., 1997).

DeAngelo et al. (2004) report that the aggregate level of real dividends increasing but dividends becoming increasingly concentrated rather than widely distributed. According to the signalling theory, using dividend payment initiatives companies are sending a positive signal to the capital markets about high future cash flows and profits, and this signal rests a massage (c.f. Lintner, 1956) that the initiation of dividends represents a commitment to sustained payments. Therefore, that firms whose expecting higher future cash flow to pay dividends are the firms that are most rewarded by investors at the time of the initiation announcement.

Hobbs and Schneller (2012) findings are extension of DeAngelo and DeAngelo (1990) findings to dividend omissions and shows that firms which operating performance declining cease dividend payments quickly after initiation. But Hobbs and Schneller (2012) do not find evidence for the signalling theory's implication that dividends signal a promising future for the firms that initiate them, which consistent with Grullon et al. (2005), who find little correlation between changes in dividends and subsequent firm profitability. This suggests that at least on the basis of ex-post performance, the initiation of dividends should actually convey negative news to the market (Hobbs and Schneller, 2012).

Hobbs and Schneller (2012) find that the firms that go on to become permanent payers perform better than those that become temporary payers, even though this findings is not true in all the case, because there are evidence that dividend sustainability is directly related to future performance. Given this result and the dominant view that dividend initiation is a positive signal in part because of the implicit suggestion that the payments will persist. The important implication is that firms will try to obtain correct market valuation through dividend signaling only when shares of equity have to be sold in the market, either by insiders to satisfy personal cash needs or by the firm to raise investment capital. Then, conditional on this decision to initiate dividends, the dividend level will signal firm quality and result in the correct valuation of the firm's shares.

Models of dividend signalling suggest that dividend changes are employed by firms to convey future earnings information. Miller and Modigliani (1961) suggested 'the information content of dividends', or so called dividend-signalling theory which means that if management's future earnings expectations affect their current dividend payout decisions, then dividend changes will convey information to the market regarding future earnings and profitability. There are some studies in favour of this hypothesis and against it.

2.3. KEY FACTORS INFLUENCE ON DIVIDEND POLICY

The literature has identified some key factors that affect dividend policy. In this part of this chapter I will discuss such key factors.

2.3.1. EARNINGS INFLUENCE ON DIVIDEND POLICY

From long time in the financial research the effect of dividends on the valuation of securities has been a controversial subject and still researchers are trying to find out the solution of this controversial subject. Since Miller and Modigliani (1961) demonstrated the irrelevance of dividend policy, from then to till now researchers attempting to explain market price reaction to firms' dividend decisions. Dividend decisions have mainly influenced by the information issues and tax effects. Information issues have been empirically investigated by examining market reactions to announcements of dividend changes. The effect of differential tax treatments of dividends and capital gains usually has been examined through cross-sectional regression testing the significance of dividend yield in explaining returns.

Arjun and Dale (1983) said that a greater dividend pay-out strategy has an impact on an increase in the dividend pay-out ratio and should be complemented by decrease in price if taxes on dividends are greater than taxes on capital gains. Generally dividend increase announcement has less effect over a short period of time, but are consistent with the existence of both an information effect and a tax effect. Arjun and Dale (1983) observed that, firms that announced an increase in dividends generally had positive abnormal returns, whereas firms with a positive dividend change and a decrease in the payout ratio tented to have higher abnormal returns than did firms with a positive dividend change and an increase in the payout ratio.

Arjun and Dale (1983) predict that, a change in earnings has influence on the changes in the payout ratios. They said that, a decrease in the payout ratio implies that the earnings increase was proportionally greater than the dividend increase. The abnormal returns surrounding a dividend announcement could be affected by the changes in earnings even though the earnings figure was announced prior to the dividend announcement.

Fairfield (1994) says that “price can alternatively be expressed as a function of capitalized current earnings plus the capitalized present value of changes in future abnormal earnings”. Price/earnings equal the capitalization factor plus the capitalized present value of expected growth in abnormal earnings. He also says that, firms with temporarily depressed earnings that are expected to increase in the future will have high Price/earnings ratios, as well firms with abnormally high current earnings that are expected to increase, because the earnings multiple relates directly to the expected change in abnormal earnings.

Empirical studies that addressed the issue of dividend policy often employed either an event-study methodology (Aharony and Swary 1980, Asquith and Mullins 1983) or time-series regression analysis (Fama and babiak 1968, Watts 1973, Gonedes, 1978, Lee et al. 1987, Chen and Wu 1998). But the interesting thing is that the studies using the event-study methodology usually find a significant relation between dividend and earning changes. On the other hand, studies based on the time-series regression analysis typically find a weak relation between dividend and earnings changes. The main reason behind this problem is that most of the time series regression studies have focused on the relation between dividends and reported accounting earnings rather than dividends and earning changes. However, Lintner (1956) said that dividend changes are more related to changes in permanent earnings. The use of reported accounting earnings figures rather than permanent earnings figures, in the empirical analysis may have produced the puzzling results documented in previous dividend studies (Jumming, Xu-Ming, Chunchi, 1998).

Dividend changes are positively correlated with stock returns in the days surrounding the dividend changes announcement (Aharony and Swary, 1972; Asquith and Mullins, 1983; Kalay and Loewenstein, 1985; and Petit,1972). According to "the information content of dividend hypothesis" (Miller and Modigliani, 1961), dividend changes generate stock returns because they carry new information about the firm's future profitability. Nissim and Ziv (2001) also agree with this hypothesis and find evidence that dividend changes are positively related to future earnings changes, future earnings, and future abnormal earnings.

To get the results whether dividend changes convey new information about future profitability, need to estimate expected profitability. Nissim and Ziv (2001) found same result, what previous researches had found, that dividend changes are not positively related to future earnings changes. But when they extend their experiment then they find the positive relation between the dividend changes and future earnings. To get that result they used different measure of profits: earnings and abnormal earnings. Abnormal earnings are defined as the difference between total earnings and normal earnings, where normal earnings are defined as the required return to the owners based on the cost and level of invested equity (Edwards and Bell, 1961). Future normal earnings that result from future retained earnings and future net stock issues are not relevant for current price. It means that, to affect price, the earnings information that dividend changes convey must be about future abnormal earnings rather than future normal earnings. Nissim and Ziv (2001) observed that dividend decreases are not related to future profits, whereas dividend increases are positively related with the profits, which are comes from the normal and abnormal earnings.

Dividend changes are highly correlated with contemporaneous earnings changes (Benartzi et al., 1997). Nissim and Ziv (2001) also find that the positive relation between dividend changes and earnings changes due to autocorrelation in the earnings changes series. They also mention that management usually increases dividends when they receive information that indicates that future earnings will be higher than previously anticipated. Future earnings are influenced by value creating activities, but they are also influenced by actions that are not directly relevant for current price, such as future retained earnings, stock issues and stock repurchases. Abnormal earnings remove from future earnings the effect of capital contributions, earnings, and dividends between the dividend change year and the future year.

Nissim and Ziv (2001) shows that dividend changes are positively related to the level of future profitability, after controlling for book value, past and current profitability, market expectations of future profitability as reflected in price prior to the dividend changes, past dividends and dividend changes and consensus analysts' earnings forecasts.

Brickly(1983), Healy and Palepu (1988), and Aharony and Dotan (1994) provide evidence that an increase in dividends leads to an increase in future earnings. Fama and French (1998a) claim that variables that proxy future expected earnings are relevant in explaining current dividend payout. Watts (1973) and Gonedes (1978) show there is no relationship between current dividends and future earnings while the evidence in Benartzi, Michaely, and Thaler (1997) suggests that dividend changes provide information about current and past levels of earnings. These points suggest that dividends may respond both to past prices, which, following MM (1987), act *as forecasts* of current and future permanent earnings, and to unexpected current permanent earnings. Garrett and Priestley (2000) found that information about the expected future permanent earnings is captured by lagged stock price and dividends convey information about current unexpected permanent earnings. They also indicate that, only positive changes to unexpected permanent earnings affect the current dividend.

In summary, usually dividend decisions are influenced by information issues and tax effects. A higher dividend pay-out strategy implied by higher dividend pay-out ratio should be accompanied by a decrease in price if taxes on dividends are greater than taxes on capital gains. Price/earnings equal the capitalisation factor plus the capitalised present value of expected growth in abnormal earnings. More-over normal earnings that result from future retained earnings and future net stock issues are not relevant for current price, which means that, to affect price, the earnings information that dividend changes convey must be about future abnormal earnings rather than future normal earnings. Positive changes to unexpected permanent earnings would be expected to affect the current dividend.

2.3.2. DIVIDEND YIELD INFLUENCE ON DIVIDEND POLICY

It is true that higher stock returns are associated with higher dividends, independently of whether income is taxed more or less heavily than capital gain (Litzenberger and Ramaswamy, 1979 and 1982; and Morgan and Thomas, 1998). Lintner (1956) was the first who noted the reluctance to cut dividends; usually managers are reluctant to make dividend changes, which were likely to be unsustainable, but he observed that dividend changes followed shifts in long-run sustainable earnings. So it means that that shifts in dividend policy may be a way of providing information to investors relating to the anticipated future performance of the firm (Bhattacharya, 1979 and 1980). Basically dividend growth follows a period of unusual earnings growth (DeAngelo et al., 1996; and Benartzi et.al, 1997). It is clear that those firms whose maintain or increase the payout ratio on the basis of increased earnings may be viewed as signaling good news to their investors regarding the performance of the earnings growth. Whereas the effect of the situation of declining earnings may be more difficult to interpret, because managers believe that the earnings decrease is permanent rather than temporary, and then they may be reluctant to reduce dividends, and if so the payout ratio will increase.

McManus, Gwilym and Thomas (2004), suggest that there is relationship between the payout ratio and stock returns, dividends, seasonality and size, and this reflects both the importance of earnings related variables in multi-factor models, such as those of Fama and French (1992, 1993 and 1996), and the conjecture that this ratio conveys signalling information in addition to the dividend yield. Lamont (1998) finds that for forecasting short horizon both dividend yield and payout ratio have information, whereas McManus, Gwilym and Thomas (2004) find that the returns payout ratio has an important influence on the statistical significance of the dividend yield, and cast doubt on the more implicit signaling interpretations of the returns-yield relationship.

Empirical studies in the area of relation between dividend yield and stock returns typically form portfolios of stocks ranked by dividend yield and firm size on a monthly or annually basis (Keim, 1985; Levis, 1989; and Christie, 1990) and the data is used to estimate a stacked regression model linking returns, dividend yields, seasonality, firm size, etc. Keim (1985) shows that firm's size and return seasonality have an important influence on the empirical relationship between stock returns and dividend yields. However, McManus, Gwilym and Thomas (2004), says that both firm size and seasonality are found to influence portfolio returns in the regression context, but do not dilute the strong, positive relationship between returns and dividend yield. But it is obvious that, the overall findings cannot be justified by the orthodox explanation of the tax effects mentioned earlier, or the clientele effects of Elton and Gruber (1970), Scholz (1992) and Denis et al. (1994), but is consistent with the dividend signaling models such as those of Bhattacharya (1979), Miller and Rock (1985) and Michaely et al. (1995).

In the related literature the role of earnings, usually has featured frequently in the form of price-to-earnings ratio (P/E) or its inverse, earnings yield (E/P). Basu (1977 and1983) concludes that E/P contributes to explaining the cross-section of average returns, even when controlling for size and beta. Ball (1978) suggests E/P as a proxy for unspecified factors in expected returns.

Ap Gwilym, Morgan and Thomas (2000), say that, they find dividend stability is inversely correlated with systematic risk. They believe that this relationship holds for low, as well as for high, dividend-yielding stocks, but is stronger when dividend stability is measured by the variability of dividend yield than when it is measured by cuts in annual dividend payments.

To assess the relevance of dividend stability to the relation between dividend yields and returns, Gombola and Liu (1993) initially replicate the approach of keim (1985) by forming five yield-ranked portfolios, in addition to a sixth portfolio containing all stocks with zero dividend yield. They obtain similar results to those of keim (1985 and 1986), in observing a U-shaped pattern of absolute returns as yields fall. High returns were associated with high yielding portfolios, and low returns associated with low yielding portfolios. In spite of this, the portfolio containing stocks with zero dividend yields outperformed all other portfolios, resulting in a nonlinear yield-return relationship. When Gwilym, Morgan and Thomas (2000) were calculated the risk-adjusted returns using market model, they observed a linear relationship between systematic risk and return, with estimated beta values rising as yields fall.

Gwilym, Morgan and Thomas (2000) finds that portfolios which have been formed with the highest dividend yield generate significant positive abnormal returns, on the other hand the portfolios based on the lowest non-zero yield portfolio are the only ones to generate significant negative excess returns. In contrast to Keim (1985) and Gombola and Liu (1993), excess returns on the portfolios formed using zero dividend yield stocks are predominantly negative rather than positive. According to Gwilym, Morgan and Thomas (2000) there is a clear inverse correlation between beta and stability; within dividend yield portfolio, higher systematic risk is a feature of stocks with a relatively unstable history of dividend payments.

However, it is important to note that the inverse relation between beta and stability does not apply to portfolios comprised of stocks with a zero dividend yield, a finding that holds with both definitions of stability. Gwilym, Morgan and Thomas (2000) finds correlation between dividend stability and beta for all non-zero yield groupings but do not suggest a causal relationship. Dividend signalling is not only a phenomenon, which affects high-yielding stocks, rather a low level of exposure to systematic risk may be signalling outsiders by combining a stable dividend policy with a relatively low yield. This can be very hefty, because a stock's yield is not wholly under the control of its managers, and so stocks in industrial sectors which tend to earn a relatively low yield are also able to signal low systematic risk by maintaining dividend stability.

Whether the dividend yield has predictive power for stock market returns remain one of the most open and debated questions in empirical finance. But Hjalmarsson (2010) investigates the predictability of the dividend-price ratio, earnings-price ratio, short-term interest rate and term spread with respect to stock returns and develops new methods for panel estimation and his analysis includes both full sample results and some recursive estimation to illustrate changes over time in predictability. He finds that the short-term rate and the term spread are robust predictors of stock returns in developed economies, with no predictability found for earning yield and dividend-to-price ratio.

The belief that stock returns can be predicted by dividend yields largely dates back to research by Campbell and Shiller (1988a, 1988b) and Fama and French (1988). Since then research has debated whether such predictability exists, or whether the findings are spurious, perhaps due to possible non- stationary behavior within the dividend yield or the short sample sizes used in the empirical work. For a flavor of the debate, Campbell et al. (1997), Campbell and Shiller (2001) and Campbell and Yogo (2006) have provided further supporting evidence. In contrast, several authors have argued against such predictability (Wolf, 2000; Lanne, 2002; Valkanov, 2003; Ang and Bekaert, 2007). More recently, Campbell and Yogo (2006) have argued that the over rejection of the null of no predictability can arise due to persistence in the regressor variable. Cochrane (2008) has argued that the dividend yield must have predictive power for returns (or dividend growth) otherwise in the context of the present value model the dividend yield would be a constant.

Most recently, Chen (2009) has reported evidence that the dividend yield may predict dividend growth as well as returns, although across different time periods. Furthermore, building on the work of Campbell and Yogo (2006), Park (2010) argues that in a sub-sample of US data that includes the 1990s the predictive power of the dividend yield disappears. This is again related to the possible non-stationarity of the dividend yield over this time frame.

McMillan and Wohar (2013) show that the predictive power of the dividend yield for returns and dividend growth is time varying. Chen (2009) and Engsted and Pedersen (2010) have argued in favor of dividend growth predictability and indeed argued that the nature of predictability for returns and dividend growth varies over time. While the work of Chen, on the one hand, and Engsted and Pedersen, on the other hand, suggest differences in the exact nature of that time variation, a key point in this line of research is both that they recognize the existence of such time variation and that predictability for dividend growth does occur. McMillan and Wohar (2012) results confirm both the existence of dividend growth predictability and that the nature of predictability for returns and dividend growth varies over time.

Dividend growth follows a period of unusual earnings growth. It is clear that those firms that maintain or increase the payout ratio in the light of increased earnings may be viewed as signalling good news to their investors regarding the performance of the earnings growth. Dividend yield may predict dividend growth as well as returns, but some researchers show that the predictive power of the dividend yield for returns and dividend growth is time varying.

2.3.3. CORPORATE GOVERNANCE EFFECT ON DIVIDEND POLICY

A number of theories have been advanced to unwind Miller and Modigliani's (1961) seminal work on dividend irrelevance assumptions of perfect capital markets. But one very important theory that has been extensively examined in the literature and has received supporting evidence is agency theory. It has been established in the literature that agency considerations play a significant role in payout ratio (Lie, 2000; Aivazian *et al.*, 2003 and 2006; and DeAngelo *et al.*, 2006). As La Porta *et al.* (2000)

summarize, corporate governance, as the mechanism to mitigate agency problems, can potentially have two opposing effects on payout policies. One possibility is that firms operating under better corporate governance system pay more dividends because of the pressure from shareholders (outcome model). Or another possibility is that firms operating under poor governance systems and weaker shareholder rights need to pay higher dividends to maintain good reputation with shareholders (substitution model). According to Jensen's (1986) agency theory, dividend policy is determined by agency costs arising from the divergence of ownership and control. Due to agency costs, managers may not always adopt a dividend policy that is value-maximising for shareholders. Rather, they may choose a dividend policy that maximise their own private benefits.

Dividend payouts are argued to reduce agency conflicts by reducing the amount of free cash flow, which could be used by managers for their private benefits rather than for maximizing shareholders' wealth (Grossman and Hart, 1980; Easterbrook, 1984; Jensen, 1986; DeAngelo, DeAngelo, and Stulz, 2006). On top of that dividends help mitigate agency conflicts by exposing firms to more frequent monitoring by the primary capital markets, as paying dividends increases the probability that new equity has to be issued more often (Easterbrook, 1984). Under the agency framework, the direct link between corporate governance quality and dividend policy has been extensively examined but yielded mixed evidence (Jiraporn, Kim and Kim, 2011). For example, some previous studies find that strong governance is associated with larger dividend payouts (La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 2000; Michaely and Roberts, 2006; Renneboog and Szilagyi, 2006) while other studies find the opposite (Jiraporn and Ning, 2006; Nielsen, 2006; Officer, 2007; Jo and Pan, 2009).

Corporate governance exists to provide checks and balances between shareholders and management and thus to mitigate agency problems. Hence, firms with better governance quality should incur less agency conflicts (Jiraporn, Kim and Kim, 2011). As a result, the quality of corporate governance should have an impact on dividend policy. Todd Mitton (2004) says that the agency theory suggest that outside shareholders have a preference for over retained earnings because insiders might squander cash retained within the firm. This preference for dividend may be even stronger in emerging markets with weak investor's protection, if shareholders perceive a greater risk of expropriation by insides in such countries than the developed countries where investors enjoy more protection. La Porta et al. (2000) show that dividend payouts are higher, on average, in countries with stronger legal protection of minority shareholders.

La Porta et al. (2000) documented two agency costs of equity models of dividends, namely, the outcome and substitution models. The outcome model suggests that dividends are an outcome of effective governance, where governance can be either country and/or corporate governance (Mitton, 2004; and Bartram *et al.*, 2012). Given the agency costs associated with free cash flow, shareholders prefer dividends to retained earnings since dividends reduce the pool of funds, which can be consumed privately by controlling insiders (Easterbrook, 1984; and Jensen, 1986). In turn, the outcome model suggests that it is the shareholders with the greatest legal rights (and/or belonging to better-governed firms) who can extract the largest dividends from firms. Hence, the theoretical prediction of the outcome model is that, all else equal, dividend payout increases with the strength of shareholder rights (O'Connor, 2013).

On the other hand, the substitution model predicts that corporate dividend payout decreases with the strength of shareholder rights (O'Connor, 2013). In emerging markets where firm-level bonding mechanisms are few, the substitution model suggests that financially-constrained poorly governed firms pay large dividends in the hope that these reputation ally-enhancing dividends will reduce their cost of external finance (Benos and Weisbach, 2004). In contrast, well-governed firms, that are presumably less financially-constrained, pay much lower dividends. From the study of La Porta *et al.* (2000), the extant literature has found empirical support in favour of both the models. For example, Mitton (2004), Brockman and Unlu (2009 and 2011), Chae *et al.* (2009), Sawicki (2009) (in post-Asian crisis Asia), Shao *et al.* (2009), Adjaoud and Ben-Amar (2010), Jiraporn *et al.* (2011), Bartram *et al.* (2012), and Byrne and O'Connor (2012), all support the view that dividend pay-outs increase with shareholder rights. On the other hand, Jiraporn and Ning (2006), John and Knyazeva (2006), Officer (2007), Chae *et al.* (2009), Jo and Pan (2009), and Sawicki (2009) (in pre-Asian crisis Asia), uncover evidence which supports the substitution model, i.e., dividend pay-outs decrease with shareholder rights.

Brockman and Unlu (2009) extend the agency costs of equity version of the outcome and substitution models by integrating the agency costs of debt. The result is that the theoretical predictions of the agency costs of equity and debt version of the outcome model of dividends are different. Now, given the agency costs of debt, the outcome model predicts that dividend pay-out increases with the strength of shareholder and creditor rights (O'Connor, 2013). This means that where creditor rights are weak and shareholder rights are strong, creditors demand and firms consent to lower dividend pay-outs to shareholders. In effect, creditors substitute poor legal rights for lower dividends. Using country-level measures of shareholder rights, both

Shao *et al.* (2009) and Byrne and O'Connor (2012) find support in favour of this prediction; the outcome model of dividends holds where shareholder and creditor rights are strong.

O'Connor (2013) examine firm-level measures of shareholder rights, i.e., corporate governance, is used in contrast to the country-level measures employed by Shao *et al.* (2009) and Byrne and O'Connor (2012). Since the predictions of the agency costs of equity and debt version of the outcome model of dividends should hold for both country and corporate measures of shareholder rights. O'Connor (2013) found that the creditors exert a profound influence on corporate dividend policy. O'Connor (2013) says that, creditors demand and firms consent to pay lower dividends to their shareholders, where creditors' rights are poorly enforced. Shareholders can use their rights to extract large dividends from firms, but can only do so where shareholders rights and the enforcement of creditors' rights are strong. O'Connor (2013) also mentions that the shareholders of better-governed firms do not appear to be able to extract large dividends from firms where creditor rights are poorly enforced. O'Connor (2013) said that the outcome model fails to hold irrespective of the strength of creditor rights, but on the other hand outcome model prevails under strong enforcement of creditor rights.

Todd Mitton (2004) argued that, "if protection of minority shareholders does have a positive impact on dividend payouts then shareholder protection should help explain not just country-level differences in dividend payouts, but also firm-level differences in dividend payouts within countries". He also suggests that while country-level investor protection is an important factor in preventing expropriation, firm-level corporate governance could carry equal or greater importance. And corporate governance practices can vary widely even among firms in the same country operating under the same legal regime. Todd Mitton (2004) uses firm-specific corporate governance ratings developed by Credit Lyonnais Securities Asia (CLSA) to study the impact of firm-level corporate governance on dividend payouts.

Todd Mitton (2004) also says, when shareholders are well protected, they may not prefer higher dividend pay-outs if they believe that the firm has good investment opportunities available for excess cash. La Porta et al. (2000) found that in countries with strong investment protection and corporate governance, there is a stronger negative relationship between growth opportunities and dividend payouts. Todd Mitton (2004) documented that firms with stronger governance have higher profitability, but improved profitability explains only part of the connection between governance and dividends.

Jiraporn, Kim and Kim (2011) explore the impact of The Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA). JGTRRA reduces the maximum tax rate on dividends and therefore alleviates the tax disadvantage of dividends. They say that this Act make dividends more attractive as a means of cash disbursement. Jiraporn, Kim and Kim (2011) tests, reveal that this legislation does not seem to have a significant impact. Jiraporn, Kim and Kim (2011), argue that the quality of corporate governance affects dividend payout. They also says that corporate governance and dividend policy are endogenously determined, for that reason dividend payout might influence the quality of the corporate governance and vice versa.

Dividends and repurchases are parallel because both of them entail cash disbursement. In recent times, repurchases have become more popular and have replaced dividends in many firms. One key difference between dividends and repurchases, nevertheless, lays in the fact that repurchases are much more discretionary cash distributions relative to dividends. Prior research shows a strong negative market response to dividend cuts and omissions. Accordingly to Jiraporn, Kim and Kim (2011), dividends significantly constrain managers through the high cost of dividend reduction or discontinuation, making dividends a more effective pre-commitment mechanism in the presence of an agency conflict. By contrast, the flexibility associated with repurchases gives managers much more discretion, thereby diminishing their effectiveness in alleviating the agency conflict. Recent evidence about the difference between dividends and repurchase can be found in Kooli and L'Her (2010).

Jiraporn, Kim and Kim (2011) say that, firms with weak governance, managers may avoid paying dividends in favour of repurchases because they can exercise more discretion over repurchase decisions. This result would be consistent with the outcome hypothesis. On the contrary, in firms with poor governance quality, managers may choose dividends over repurchases because dividends constitute a strong governance mechanism and send a stronger signal to the capital markets that managers do not expropriate from shareholders (because dividends reduce what is left for expropriation). This result would be consistent with the substitution hypothesis. But John and Knyazeva (2006) as they report that stronger governance is associated with a stronger propensity for dividends over repurchases.

Jiraporn, Kim and Kim (2011) say that the association between dividend payouts and governance quality is conditional on external financing constraints. Chae, Kim, and Lee (2009) argue that firms with better governance pay larger dividends only when they are not subject to external financing constraints. On the contrary, when subject to financing constraints, they do not pay out more dividends. Larger dividend layouts increase the likelihood for firms to raise external capital in the future.

Therefore, firms with difficulty raising external capital (i.e., those with financing constraints) would be less likely to pay out larger dividends.

Jiraporn, Kim and Kim (2011) find that, firms with more free cash flow are more vulnerable to the agency conflict. In addition, they conjectured that firms with higher information asymmetry likely incur higher costs when raising external capital, as it is harder for external capital providers to monitor these firms. Jiraporn, Kim and Kim (2011) use the residual volatility of daily stock returns to proxy for information asymmetry; the more volatile, the higher the information asymmetry.

One very important theory that has been extensively examined in the literature and has received supporting evidence is agency theory. It has been established in the literature that agency considerations play a significant role in payout ratio. Dividend payouts are argued to reduce agency conflicts by reducing the amount of free cash flow, which could be used by managers for their private benefits rather than for maximizing shareholders' wealth. Shareholders of better-governed firms do not appear to be able to extract large dividends from firms where creditor rights are poorly enforced. In the case firms with weak governance, managers may avoid paying dividends in favour of repurchases because they can exercise more discretion over repurchase decisions.

2.3.4. CAPITAL STRUCTURE AND DIVIDEND POLICY

For more than 50 years the search for the optimal sources of activity financing and their share in the capital structure occupied the debate of the greatest minds in economics and finances. An issue that is firmly connected with the choice of financing sources is dividend policy, which also constitutes a broad research area. The issue of the optimal capital structure as well as the choice of corporate dividend policy remains unsolved. The discussion of capital structure and dividend policy is a controversial debate in corporate finance from long time for the scholars, due to that reason scholars still are interested in investigating using different approached and applying different techniques into different markets.

This debate starts with the seminal work of Modigliani and Miller (1958), who find that given the prefect market assumptions, capital structure is unrelated to the value of the firm and thus managers should have no concern about firm's capital structure when they are making or taking any financial decisions. But, we know that prefect market assumptions will not hold in reality, and therefore it is arguable that Modigliani and Miller (1958) models need modifications. Modigliani and Miller (1958) irrelevance theorem is one of the important and puzzling issues in modern corporate finance theory, which has challenged the traditional view that an optimum leverage exists (Mondher, 2011).

Later Modigliani and Miller (1963) relax their prefect market assumptions and consider corporate tax in their models. Consequently, they find that the value of the firm will increase as the debt level increases, because interest is tax deductible and hence firms will enjoy a debt tax shield from using debt financing. However, one thing they ignore totally, which is bankruptcy costs. The work of Modigliani and Miller in the area of capital structure draws researchers' attention to investigate firms' capital structure. Miller and Modigliani's significantly contribute to the dividend policy literature as well. In 1961 they investigate the theory of dividend policy and conclude that given the existent of the perfect market assumptions, dividend policy is unrelated to the value of the firm. Their argument was that the value of the firm depends on the income produced by its assets and not on how it is split between dividend payments and retained earnings. This is called dividend irrelevance theory in the finance literature. Later scholars challenge the main findings of Miller and Modigliani (1961) since the assumptions of the perfect market will not hold in reality (Al-Najjar, 2011).

In the theory of economics, and specially finances, we can notice different approaches described in the theory of substitution and in the theory of hierarchy (pecking order theory) to the issue of shaping the most favourable sources of activity financing, (Franc-Dabrowska, 2009). The substitution (trade-off) theory assumes that managers look for such a debt capital to equity capital ratio that will allow them to achieve maximum business value (Franc-Dabrowska, 2009). The risk connected with financing enterprise activities with debt capital is compensated by tax advantages (Theobald 1979; Duliniec 1998) resulting from the decrease of the tax base by interest forming a cost element (this theory assumes the existence of benefits as a result of the tax shield mechanism). This approach is consistent with the Value Based Management concept (Franc-Dabrowska 2007). The value creation concept was discussed by Erasmus and Scheepers (2008) not from the capital structure and dividend point of view but highlighting the importance of innovation and entrepreneurship. The substitution theory pays attention to the different aspects of the firm's activities but pays extraordinary attention to the occurrence of costs of financial difficulties and the fact that an increase of the debt capital share in the financial structure increases the risk of losing financial liquidity and of bankruptcy.

It is important for any kind of enterprise to maintain financial liquidity, other wise the loss of financial liquidity creates a danger of imminent bankruptcy (Franc-Dabrowska, 2009). From the point of view of choosing the most favourable dividend policy, a crucial point is highlighting the necessity of maintaining financial liquidity (which is essential according to the substitution theory). It cannot be forgotten that any resolution to pay dividends adopted by the management board becomes a binding liability of the company and has to be settled. For this end it is necessary to collect a certain amount of cash (Ross, Westerfield, and Jordan 2006).

Modigliani and Miller do not take into account the effect of bankruptcy costs in their models of capital structure and dividend policy (Modigliani and Miller 1958, 1961and 1963). However these costs exist in reality and affect financing decisions. Bankruptcy costs exits when a firm's financing decisions, including capital structure, will be restructured. The cost of such transfer are classified into direct costs, including legal and accounting charges, and indirect costs, including the opportunity costs in case of interruption in firm's suppliers and customers' relations (Haugen and Senbet, 1978). Miller (19770 and Senbet (1978) argue that bankruptcy costs are irrelevant in a firm's financing decisions. DeAngelo and Masulis (1980) also did not rely on bankruptcy or agency costs. Their optimal solution rests on the explicit modelling if the non-debt tax shields such as depreciation expenses and investment tax credits (Basil, 2011). However, Titman and Wessels (1988), Holder, Langrehr, and Hexter (1998), Booth et al. (2001), Bhaduri (2002), Ho (2003), Aivazian, Booth, and Cleary (2003) and Huang and Song (2006) find a significant effect of business risk as an indicator for financial distress and bankruptcy in capital structure and dividend policy decisions.

Dividend policy is directed connected with the theories of capital structure, because dividend policy is one of the determinants of capital structure. Firms with a reputation for paying dividends face less asymmetric information when they enter the equity market. Dividend payment represents a signal of improved financial health, and hence of more debt-issuing capacity (Bhaduri 2002; John and Williams 1985;

Miller and Rock 1985). This argument is supported by the signalling theory of capital structure (Al-Najjar, 2011). Easterbrook (1984) documents that dividends exist because they induce firms to float new securities suggesting that firm's dividend decisions linked to firm's financing decisions. Intuitively, it is clear that the firm's pay-out ratio determines its retention ratio and, thus, its capital structure. Thus, a positive relationship is expected between dividend policy and capital structure. On the other hand, capital structure is a determinant of dividend policy. Therefore, a positive relationship is expected between dividend policy and capital structure.

When an enterprise pays dividends, it automatically decreases the degree of financing of equity capital from its internal sources, and as a consequence it may require external financing sources (Franc-Dabrowska, 2009). The theory of Modigliani and Miller indicating the neutrality of dividend policy for the value of the company was hedged around with assumptions that are far from reality (Modigliani and Miller 1961; 1963). Corporate debt levels should be related to the cash flows retained by a firm and to its dividend policy. Indeed, because of the interdependence between dividend policy and capital structure, empirical studies of capital structure, including those that focus on the impact of firm multinationality, are most likely mis-specified unless they include an assessment of dividend policy (Aggaarwal and Kyaw, 2010).

Adedeji (1998) suggests that if firms borrow to pay dividends because they do not want to or they are reluctant to cut dividends, then the financial leverage may have a positive relationship with dividend pay-out ratio, and may have a positive or negative relationship with investments depending on whether firms borrow to finance investments or postpone/reduce the investments. This hypothesized positive relationship between debt and dividend payout is empirically confirmed in Baskin

(1989). Thus, according to pecking order hypothesis, corporate capital structure is positively related to its dividend policy. On the other hand, Jensen (1986) hypothesizes that dividends and debt are substitute mechanisms for controlling agency costs of free cash flows. Empirical finding of Agrawal and Jayaraman (1994) supports Jensen's hypothesis. They find that dividend payout ratios of a sample of all equity firms are significantly higher than those of a control group of levered firms. Jensen et al. (1992) posits that firms with high dividend payouts usually find debt financing less attractive than equity financing leading to a negative relation between debt and dividends. As noted in the comprehensive survey on payout policy by Allen and Michaely (2002), firms also might not want to pay high dividends when they are obligated to pay high levels of other fixed finance charges.

The discussion of capital structure and dividend policy is a controversial debate in corporate finance that scholars were and still are interested in investigating using different approaches and applying different techniques into different markets. Capital structure is unrelated to the value of the firm and hence managers should have no concern about firm’s capital structure when they are making financial decisions. An essential aspect that cannot be omitted in any deliberations concerning the financial situation of enterprises is the necessity of maintaining financial liquidity, the loss of which creates a danger of imminent bankruptcy. Dividend policy is directly connected with the theories of capital structure, because dividend policy is one of the determinants of capital structure. Firms with a reputation for paying dividends face less asymmetric information when they enter the equity market. Dividend payment represents a signal of improved financial health, and hence of more debt-issuing capacity.

2.4. SUMMARY AND CONCLUSION

This chapter is based on the relationship between orthodox finance and dividend policy. In this chapter, I have discussed various dividend policy theories and the key factors that influence dividend policy. For a long time, researchers have been trying to solve the dividend puzzle using different dividend theories and focusing on different key variables, but so far there seems to be no clear solution.

According to Modigliani and Miller, in a perfect capital market dividend payout policy is irrelevant. On the other hand, in imperfect markets, investment decisions can be affected by dividend policy, because when managers have more information about the firm's assets and investment projects than outside investors, asymmetric information problems can constrain the firm's access to external funds. The life-cycle theory suggests that the tradeoff between the advantages and disadvantages of the retention of earnings varies over the life of the firm. Yet again, according to Baker and Wurgler (2004), managers opportunistically modify corporate payout policies when investor sentiment favours the payment of dividends.

After Modigliani and Miller's dividend irrelevancy theory (1958 and 1961) a number of different theories have emerged, but among them the dividend signalling theory, or so called 'information content of dividend' theory, (Bhattacharya, 1979; Miller and Rock, 1985) is the most prominent one. A great deal of research has been conducted on the validity of this theory. What has emerged is that this theory cannot fully solve the dividend puzzle, but there are still gaps in the dividend policy literature that can be addressed using the dividend signalling theory. For this reason, in this thesis I have chosen to shed additional light on the empirical validity of the dividend signalling theory.

3 THE RELATIONSHIP BETWEEN BEHAVIOURAL FINANCE AND DIVIDEND POLICY

3.1. INTRODUCTION

Behavioural finance has important implications in practical corporate finance. All markets participants face several decisions in their financial activities regarding such aspects as investments and funding. Behavioural corporate finance has developed with framing, decision-making, and the perception of many corporate issues. In particular, financial decision-making is one of the central aspects to behavioural finance. According to Baker, Ruback and Wurgler (2004), behavioural corporate finance separates the roles of investors and managers and describes each decision regarding financing and investment patterns (Park and Sohn, 2013).

In this chapter I examine the relationship between behavioural finance and dividend policy. More specifically how different behavioural finance elements influence firms' dividend policy. In this chapter I mainly focus on three different behavioural finance theories and also on the relationship between weather anomalies and calendar anomalies and dividend policy.

Behavioural finance addresses the question of why firms pay dividends, which is a puzzle for orthodox finance. Shefrin and Statman (1984) argued about the behavioural dividend policy of the firms, that firms pay dividends simply because investors exercise better self-control with their expenditure. When investors see a upwelling in dividends, too quickly they believe that the mean dividend growth rate has increased, because they believe dividend growth rate is more variable. Nicholas and Richard (2003) speculated that it is possible that price-dividend ratios and returns might also be excessively volatile because investors generalise past returns too far into the future when forming expectations of future returns. According to Modigliani and Cohn (1979) and Ritter and Warr (2002), in financial market part of the variation in price-dividend ratios and returns may be due to investors mixing real and nominal quantities when forecasting future cash flows.

In standard financial theory it does not matter whether wealth is embodied in the form of a cash dividend or in the form of stock, because they are perfect substitutes. Prospect theory (Kahneman and Tversky's, 1979) contends that the utility function of investors is concave over the domain of gains. The separate valuation by investors of individual gains over a concave utility function influences how a stream of dividend payments will be valued. More specifically, it suggests that the frequency with which dividends are paid will positively affect an investor's valuation of a total dividend distribution. Barberis and Thaler (2003) describe how the concave utility function of prospect theory allows an investor to receive greater utility. According to Kahneman and Tversky's (1979) theory individuals always rank companies according to their chances to get dividend from that company before investment. Because individuals investors always wants to get cash dividends. Later Tversky and Kahneman (1992) presented a new version of the prospect theory, which is called cumulative prospect theory that incorporates the cumulative functional and extends the theory to uncertain as well to risky prospects with any number of outcomes. And finally Schmidt et al. (2008) suggests a new version of prospect theory called third generation of prospect theory and in this theory has three features and two of them are common with the previous two version of the prospect theory, the three features are reference dependence, decision weights and uncertain reference points.

In the recent years researchers are using behaviour finance to solve the stock price puzzle, like they are using air pollution, rain, temperature, sunshine, wind etc. to find out whether this facts has any kind of effect on the stock prices. And we can also see that from 1930 researchers and practitioners are using calendar anomalies to see whether there is any effect of calendar anomalies on the stock prices. But there is no literature available where researchers used behaviour finance elements (i.e. rain, temperature, or calendar anomalies) and dividend-signalling theory together to find out whether investor sentiment (proxed by rain, temperature and air pollution) and calendars anomalies (Halloween, Turn of the Month, Monday, and January) play any role in the relationship between dividend announcements and stock market returns. In this thesis paper I documented that investor sentiment (proxed by rain, temperature and air pollution) and calendars anomalies (Halloween, Turn of the Month, Monday, and January) play a significant role in the relationship between dividend announcements and stock market returns using dividend-signalling theory and behavioural finance elements (i.e. rain, temperature, or calendar anomalies). In this chapter I will focus on behavioural finance theories and behavioural finance elements, especially behavioural finance elements effect on the relationship between dividend announcements and stock market returns while I use dividend-signalling theory.

Section 3.2 presents details about the behavioural finance and section 3.3 introduces the relationship between behavioural finance and dividend policy. Section 3.4 explains the relationship between dividend policy and behavioural finance theories. Whereas section 3.5 presents behavioural finance applications in corporate finance. A comparison between behavioural finance and orthodox finance approaches to dividend policy is offered in section 3.6. Section 3.7 and section 3.8 respectively discuss how behavioural finance elements effect on stock market and present a summary and conclusion.

3.2. BEHAVIOURAL FINANCE

Finance education can be more effective if it sheds specific light on active investing by addressing aspects like – avoiding mistakes while investing and working out the financial markets strategies to obtain superior returns. Those are the main pedagogical goals of behavioural finance, which allows for explanations of financial phenomena based on non-rational behaviour amongst investors (Subrahmanyam, 2007). Modern Portfolio Theory (MPT) and Efficient Market Hypothesis (EMH), represent standard finance, the alternative approach of behavioural finance includes psychological and sociological issues when investigating market anomalies and individual investor behaviour.

Park and Sohn (2013) reports that behavioural finance is a study that brings psychology and economics together, and it also explain various events that take place in the financial markets. It is obvious that in the financial markets there are some phenomena which cannot be explained rationally (Park and Sohn, 2013). It is obvious that in corporate perspectives, company owners and managers do not rely only on logical elements to make critical decisions on dividend policy, mergers and acquisitions and in the case of new investments.

Behavioural finance operates at two levels; macro behavioural finance recognizes anomalies in the Efficient Market Hypothesis (EMH) that behavioural models can explain; micro behavioural finance, instead addresses individual investor behaviour, or biases that are not explained by the traditional model incorporating rational behaviour (Park and Sohn, 2013). More precisely, behavioural finance analyses what happens when individuals unwind some of the tenets that underlie individual rationality. Critics argue that if some agents in the economy are less than fully rational, rational agents will prevent them from influencing security prices for very long, through a process called arbitrage (Hoje and Dong, 2008).

Behavioural finance is a relatively new concept in the financial markets, and is not employed within standard finance models; rather it replaces traditional finance models and it offers a better model of human behaviour. According to Subrahmanyam (2007) traditional finance academics often offer a few common objections to behavioural finance. Firstly, theoretical behavioural models are somewhat ad hoc and designed to explain specific stylised facts. Behavioural models are based on how people actually behave based on extensive experimental evidence and explain evidence better than traditional ones. Secondly, the empirical work is plagued by data mining. Behavioural finance usually examines the impact of psychology on market participant's behaviour and the resulting outcomes in markets (Park and Sohn, 2013). One of the main jobs of behavioural finance is to focus on the individual investor's decision-making process, in particular, how individual investors interpret and act on specific information. Investors' decision-making processes include cognitive biases and affective (emotional) aspects, because investors do not always have rational and predictable reactions when examine through the lens of quantitative models (Park and Sohn, 2013).

Shafrin (2009) pointed out that the root of the global financial crisis of 2008 was a psychological, not fundamental phenomenon. Risk-seeking behaviours were evident in the loss-dominant markets, while excessive optimism and confirmation bias acted as driving factors behind the crisis, and not fundamental factors. People can understand, identify, and address psychological distortions in judgements and decisions by considering behavioural factors to be better prepared for dealing with any psychological challenges (Park and Sohn, 2013).

Behavioural finance has been defined in different way by different researchers. Ricciardi and Simon (2000) defined behavioural finance in the following manner: "Behavioural finance attempts to explain and increase understanding of the reasoning patterns of investors, including the emotional processes involved and the degree to which they influence the decision-making process". Basically behavioural finance explain the what, why and how of finance and investment, from a human prospective. Shefrin (2000), however, mentioned the difference between cognitive and affective (emotional) factors: "cognitive aspects concern the way people organise their information, while the emotional aspects deal with the way people feel as they register information".

3.3. BEHAVIOURAL FINANCE AND DIVIDEND POLICY

Psychology is the second building block of behavioural finance (Shleifer and Summer, 1990). Economists who are working on behavioural finance have done extensive experiments and they gathered extensive number of experimental evidence compiled by cognitive psychologists on the biases that arise when people form beliefs, and on people's preferences, or on how they make decisions, given their beliefs. The determination of dividends has been a long-term puzzle in behavioural finance in spite of the recognition that share repurchases as a means of cash distribution confer tax advantages (Subrahmanyam, 2007). Shefrin and Statman (1984) argued about the behavioural dividend policy of the firms, that firms pay dividends simply because investors exercise better self-control with their expenditure if they get a ‘check in the mail’ in the form of a dividend than if they have take a conscious action, because the latter may allow faster liquidation of the portfolio than is desirable. More recently, Baker and Wurgler (2004) rationalise dividends by arguing that during certain times, investors are more desirous of dividends.

There are several psychological factors that affect investors’ decision-making process: overconfidence (Alpert and Raiffa, 1982) on private information, optimistic and wishful thinking about their ability and prospects (Weinstein, 1980), representativeness, belief perseverance, anchoring: people often start with some initials and adjust away from it, availability biases because investors always search their memories of relevant information before taking any investment decision.

Investors usually believe that the mean dividend growth rate is more variable than it actually is. Investors are usually too quick to believe that the mean dividend growth rate has increased, when they see a surge in dividends. Investor’s enthusiasm pushes prices up relative to dividends, adding to the volatility of returns. Investors relies more on private information than the public information and in particular, on overconfidence about private information. When an investor gets some information about the economy then that investor formed a prior opinion about future cash-flow growth. Then that investor start doing his own research on the basis of the information he gathered and becomes overconfident about the information he gathers. He overestimates its accuracy and puts too much weight on it relative to his prior. If the private information is positive, he push prices up too high relative to current dividends, again adding to return volatility. Nicholas and Richard (2003) found that price-dividend ratios and returns might also be excessively volatile because investors extrapolate past returns too far into the future when forming expectations of future returns. The confusion between real and nominal values first discussed by Fisher (1928), and more recently investigate by Shafir et al (1997). In financial market, Modigliani and Cohn (1979) and more recently, Ritter and Warr (2002), have argued that part of the variation in price-dividend ratios and returns may be due to investors mixing real and nominal quantities when forecasting future cash flows.

A very important question in behavioural finance asks why firms pay dividends. Basically, dividends have been taxed at a higher rate than capital gain. That is why investors who pay taxes always prefer that the firm repurchase shares rather than pay a dividend. Shefrin and Statman (1984) propose a number of behavioural explanations for why shareholders exhibit a preference for dividends on the basis of behavioural finance. Their first idea relies on self-control, because investors always exhibit self-control problems. A second rationale for dividends is based on mental accounting, by designating an explicit dividend payment, firm make it easier for investors to segregate gains from losses and hence to increase their utility. And finally, Shefrin and Statman (1984) argue that by paying dividends, firms help investors avoid regret. Because regret is a frustration that investors feel when they imagine having taken an investment decision that would have led to a more desirable outcome.

Shefrin and Statman (1984) try to explain why firms pay dividends at all. Another question is that how dividend paying firms decide on the size of their dividend. Lintner (1956) proposed a model called behavioural dividend model, according to which firms first establish a target dividend payment rate based on notions of fairness, in other words, on what portion of earnings it is fair to return to shareholders. There are several behavioural aspects to this model. First, the firm is not setting the dividend to maximize firm value or shareholder after tax wealth. Second, sensitivities of fairness are used to set the target payout rate. Third, the asymmetry between an increase in dividends and a decrease is explicitly considered.

Baker and Wurgler (2002b) argue that changes in dividend policy will have reflect changing investor sentiment about dividend-paying firms relative to their sentiment about the non-paying firms. Baker and Wurgler (2002b) argue that, for some investors, dividend-paying firms and non-paying firms represent salient categories and that these investors exhibit changing sentiment about the categories. When investors become more risk averse, they may prefer dividend-paying stocks because of a confused notion that these firms are less risky ("Bird in the hand" theory) (Nicholas and Richard, 2003). Baker and Wurgler (2002b) measure relative investor sentiment about dividend-paying firms as the log market-to-book ratio of paying firms minus the log market-to-book ratio of non-paying firms, and find that in the time series, a high value of this measure one year predicts that in the following year, a higher fraction of non-paying firms initiate a dividend and a larger fraction of newly listed firms choose to pay one.

3.4. THE RELATIONSHIP BETWEEN DIVIDEND POLICY AND BEHAVIOURAL FINANCE THEORIES

In this section I explain the relationship between dividend policy and behavioural finance theories.

3.4.1. DIVIDEND POLICY AND PROSPECT THEORY

Prospect theory (here on PT) (Kahneman and Tversky, 1979) is one of the most well-known and influential models of decision making under uncertainty (Wakker

2010). Prospect theory is one of the most effective theories in behavioural finance and it has been used in finance, consumer choice, and political decision-making. The main important innovation of the PT is reference dependence, and it means that people take their decision on the basis of gains and losses relative to a reference point rather than as final stages of wealth or welfare (see figure 1). In PT reference dependence is observed through three major manifestations: sign dependence, which is the attitudes towards risk/uncertainty captured by the decision weights depend on the sign outcome; diminishing sensitivity for outcomes, that is, people are more sensitive to outcome changes near the reference point than to changes remote from it, and utility revels this and convexity for losses and concavity for gains, and loss aversion, that is a negative deviation from the reference point has a higher impact than a positive deviation of equal size. According to Prospect Theory, individuals are working to maximize the weighted sum of value instead of utility whereby weights are not equal to probabilities (Kahneman and Tversky (1979); Shiller (2001)).

In the recent time dividend policy is one of the most intensely studies areas of behavioural finance. The previous literature in corporate payout policy examines the decision to pay or not to pay dividends (e.g., Fama and French, 2001; DeAngelo et al. 2004; and Baker and Wurgler, 2004a and 2004b), how much to pay (Rozeff, 1982; and Miller and Rock, 1985), or how to pay – repurchases versus dividends (Stephens and Weisbach, 1998; and Jagannathan et al., 2000). Studies such as Ferris et al. (2009), have even examined patterns in international dividend payout across common law and civil law countries. Some of the researchers have done research on corporate governance influence on payout policy (e.g., Mitton, 2004; Jiraporn, Kim and Kim, 2011; O'Connor, 2013; Chang and Dutta, 2012). To do all these research, researcher use different types of theories; like –catering theory, life cycle theory or signalling theory. But only Ferris, Noronha and Unlu (2010), use prospect theory when they examine how frequent firms should pay dividend when they made the decision to pay dividends and Shefrin and Statmen (1986) use prospect theory to examine the dividend pay-out policy.

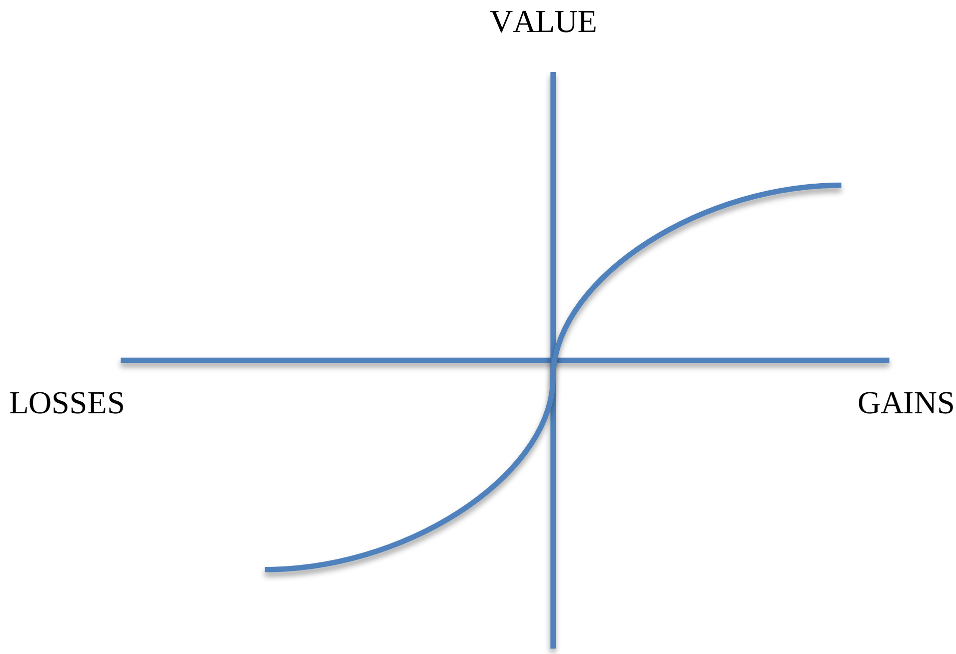


FIGURE 1:VALUE FUNCTION OF PROSPECT THEORY (TVERSKY AND KAHNEMAN, 1979)

Prospect Theory can be defined as a mathematically formulated theory that substitutes “weights” instead of “probabilities” and “value function” instead of “utility function” in expected utility theory. In Prospect Theory, individuals are working to maximize the weighted sum of value rather than utility whereby weights are not equal to probabilities (Kahneman and Tversky (1979); Shiller (2001)). According to Kahneman and Tversky (1979), weights are determined by a function of true probabilities, which assigns zero weight to extremely low probabilities and weight one to extremely high probabilities. In other words, people treat extremely improbable events as impossible and extremely probable as certain (Kahneman and Tversky, 1979). Decision weights are basically incidental from choices between prospects much as subjective probabilities are inferred from preferences in the Ramsey-Savage approach. However, basically decision weights do not follow the probability axioms and these probability axioms should not be interpreted as measures of degree or belief, because they are not probabilities (Kahneman and Tversky, 1979). If we look at the editing phase of prospect theory, then we can see that prospects can lead the individual to remove events with enormously low probability and to treat events of enormously high probability as if they were certain. Because people are usually limited in their ability to understand and evaluated extreme probabilities, and the difference between high probability and certainty is either neglected or exaggerated. As we know that prospect theory is a model of choice, the inconsistency of bids and choices implies that the measurement of values and decision weights should be based on choices between specified prospects rather than on bids or other production tasks. So according to this theory, (in the previous example given by Allais (1953)) people will assign very high weight to event which is very certain and little weight to event which is not very certain irrespective of the price/constant to be the same. "Human behaviour towards risk" can also be studied by replacing probabilities with weights in the expected utility theory.

Investors prefer cash dividends deals with the distinction between 'issues of form' and 'issues of substance'. In standard financial theory it does not matter whether wealth is embodied in the form of a cash dividend or in the form of stock, because they are perfect substitutes. A substantial literature is now growing which indicates that 'form' matters. This literature is discussed by Arrow (1982) who provides a dramatic example from the work of McNeill, Pauker, Sox and Tversky

(1981) to illustrate the importance of form. Kahneman and Tversky (1979, 1981) argue that decision-makers who face risky prospects consistently confuse issues of form and substance.

It might arguable that once the level of payout is decided, it does not matter how frequently dividends are paying, but such an argument, however, ignores the higher utility derived by investors from receiving more frequent payment implied by the prospect theory of Kahneman and Tversky (1979) and Thaler's (1980) mental accounting. These theoretical developments jointly imply important predictions regarding investors prefer to receive dividends. Prospect theory contends that the utility function of investors is concave over the domain of gains. The separate valuation by investors of individual gains over a concave utility function influences how a stream of dividend payments will be valued. More specifically, it suggests that the frequency with which dividends are paid will positively affect an investor's valuation of a total dividend distribution. Barberis and Thaler (2003) describe how the concave utility function of prospect theory allows an investor to receive greater utility.

According to Kahneman and Tversky's (1979) theory individuals tend to rank companies according to their chances to get dividend from that company before investment. Because individuals investors always wants to get cash dividends. Moreover, they postulate that individuals typically display risk-averse behaviour over investment which involve only gains; display risk-seeking behaviour over investment which involve only losses; and have losses loom larger than gains in those investments which admit the possibility of either a gain or loss of equal magnitude. Therefore, in the single-variable case, a standard Kahneman and Tversky value function is concave in gains and convex in losses with a somewhat non-symmetric shape.

Prospect theory is used in finance, consumer choice, and political decision-making. The main important innovation of the PT is reference dependence, and it means that people take their decision on the basis of gains and losses relative to a reference point rather than as final stages of wealth or welfare. In PT reference dependence is observed through three major manifestations: sign dependence, diminishing sensitivity for outcomes, and loss aversion. According to Prospect Theory, individuals are working to maximize the weighted sum of value instead of utility whereby weights are not equal to probabilities. Prospect Theory can be defined as a mathematically formulated theory that substitutes “weights” instead of “probabilities” and “value function” instead of “utility function” in expected utility theory. According to PT (Kahneman and Tversky, 1979) individuals tend to rank companies according to their chances to get dividend from that company before investment.

3.4.2. SELF-CONTROL BIAS AND DIVIDEND POLICY

According to Pompain (2012) Self-control bias is a human behavioural tendency that causes people to fail to act in pursuit of their long-term, supreme goals because of a lack of self-discipline. Money is an area in which people are notorious for displaying a lack of self-control. Self-control theory can be described as a conflict between people’s overarching desires and their inability, stemming from a lack of self-discipline, to act concretely in pursuit of those desires.

The technical description of self-control bias is best understood in the context of the life-cycle hypothesis, which describes a well–defined link between the savings and consumption tendencies of individuals and those individuals' stages of progress from childhood, through years of work participation, and finally into retirement. The foundation of the model is the saving decision, which directs the division of income between consumption and saving. The saving decision reflects an individual's preferences over present versus future consumption. Because the life-cycle hypothesis is firmly grounded in expected utility theory and assumes rational behaviour, an entire life time's succession of optimal saving decisions can be computed given only an individual's projected household income stream vis-à-vis the utility function.

Self-control has a cost, and people are willing to pay a price to avoid controlling in their natural impulses (Pompain, 2012). Consumers act as if they are maintaining separate funds within their individual accounting systems, separating income into current income and wealth. The marginal propensity to consume varies according to the source of income, even if the measure taken to activate or to sustain the source of income is the same. People are more likely to build assets or savings with money they view, or "frame", as wealth, whereas they are less likely to build savings using what they consider to be current income. Many researchers have continues to elaborate on the behavioural life-cycle model, particularly as it relates to retirement savings.

Self-control bias causes investors to spend more to day rather than saving for tomorrow (Pompain, 2012). People have a strong desire to consume freely in the present. This behaviour can be counterproductive to attaining long-term financial goals, because retirement often arrives before investors have managed to save enough money. Asset allocation imbalances problems can be happen due to self-control bias. Investors subject to this bias may prefer income-producing assets, due to a "spend today" mentality. This behaviour can be counterproductive to attaining long-term financial goals because an excess of income-producing assets can prevent a portfolio from keeping up with inflation. Self-control bias also can cause investors to lose sight of very basic financial principles. By failing to reap these discipline profits over time, clients can miss opportunities for accruing significant long-term wealth.

In the Thaler and Shefrin (1981) framework self-control difficulties are regarded as suggesting an internal conflict. The individual wishes to deny himself a present tolerance, yet simultaneously finds that he yields to the temptation. The representation of this conflict in terms of principal- agent theory is accomplished by identifying the individual's desire for self-denial with a principal, and the urge for immediate gratification with an agent.

Thaler and Shefrin (1981) assume that the planner has two kinds of self-control techniques, which can be used to exert an influence over the doer's actions. The first technique is the exercise of 'will'. Specifically, increased will-power serves to induce greater 'self-denial'. Self-denial is assumed to entail some utility cost to the planner; otherwise the exercise of will is simply not problematic. It is precisely because of this utility cost that the planner may wish to use the second technique, manipulation of the doers' opportunities. By imposing additional constraints upon a doer's opportunities, the planner may limit the amount of damage done when the individual is weak-willed (meaning the use of will-power is too costly). In addition, the restriction of a doer's opportunities reduces the temptation, and hence the amount of self-denial to be exercised. Both of these features play an important role in the analysis of dividends.

Brealey and Myers (1981) argue, all the positions advanced to explain favoured treatment accorded firms, which pay handsome dividends, are poorly funded because the sale of stock serves as a perfect substitute for increased dividends. In self-control frameworks the two are not perfect substitutes. Because of possible self-control difficulties, allowing oneself the discretion of selling stock for current consumption may cause the portfolio to be consumed more quickly than is consistent with one's long-term goals.

3.4.3. REGRET AVERSION AND DIVIDEND POLICY

According to Pompian (2012) people exhibiting regrets aversion avoid taking decisive actions because they fear that, in hindsight, because they think that whatever course they select will prove less than optimal. More generally, this bias seeks to avoid the emotional pain of regret associated with poor decision making. Regret aversion bias does not only come into play only following a loss; it can also affect a person's response to investment gains. People exhibiting regret aversion can be reluctant, for example, to buy shares of a company who used to give high amount of dividend in every year, but after buying the shares that company make lose and stop giving dividend, then the shareholder will feel regret, that why he bought this company share.

Pompian in his "Behavioural Finance and Wealth Management" (2012) book says that experimental psychology suggests that regret does influence decision making under conditions of uncertainty. Regret usually forces people to challenge past decisions and to question their beliefs. He also says that people who are regret averse try to avoid distress arising from two types of mistakes: (1) errors of commission and (2) errors of omission. Errors of commission occur when people take misguided actions and on the other hand errors of omission arise from misguided inaction, that is, opportunities overlooked or foregone.

According to Pompian (2012), regret is different from disappointment, because the former implies that the sufferer had some sense of agency in achieving the negative outcome. Moreover, feelings of regrets are more intense when unfavourable outcomes emerge from errors of commission rather than errors of omission. The implications for investor's section use an example to examine more concretely the distinction between errors of omission and errors of commission in the context of regret aversion bias. He also thinks that, regrets are most tangible and take the greatest toll on decision making when the outcomes of forgone alternatives are highly "visible" or "accessible". Pompian (2012) says that, by the same token, regret become a less influential factor when consequences of mistake are less discernible.

Regret aversion causes investors to anticipate and fear the pain of regret that comes with incurring a loss or forfeiting a profit. The potential for financial injury isn't the only disincentive that these investors face; they also dread feeling responsible for their own misfortunes. The anxiety surrounding the prospect of an error of commission, or a "wrong move," can make investors timid and can cause then to subjectively and perhaps irrationally favour investments that seem trustworthy.

Regret theory bears some similarities to prospect theory (Tversky and Kahneman, 1986) and many of its predictions are consistent with the empirical observation of human behaviour that constitutes the building block of prospect theory. Because Tversky and Kahneman (1986) indicate that that for most people the sale of stock cause more regret. Thaler (1980) discusses a related point. He considers why the possibility of regret discourages decisions in which the individual feels he must take responsibility for the final outcome. This idea can be used to relate Kahneman and Tversky's (1979) treatment of regret to their formal analysis of prospect theory. Suppose that a favourable outcome enable the decision maker to take pride in his action, while an unfavourable outcome involves regret. As Kahneman and Tversky (1979) argue the reasons for regret and pride stem from the consideration of what would have occurred had another decision been made. If regret generates stronger emotions than pride, then decisions involving responsibility will tend to be avoided.

Shefrin and Statman (1984) highlighted regret as a reason why investors prefer stocks that pay dividends. Their argument was that by paying dividends, investors can avoid some frustration that is felt when taking an action that leads to a less than expected outcome. Regret is stronger for errors of commission than for errors of omission. According to Pompian (2012) investors usually sell their investment or shares if they do not get a dividend from that investment or shares. But, if the stock price goes up then investor feels substantial regret because the error is one of commission; he can readily imagine how not selling the stock would have left him better off. But if investor buys the stocks of another company that pays dividends, then a rise in the stock price would not have caused so much regret.

3.5. BEHAVIOURAL FINANCE APPLICATIONS IN CORPORATE FINANCE

Corporate finance tries to explain the financial contracts and the real investment behaviour that emerge from the interaction of manager and investors (Baker and Wurgler, 2013). Due to that reason, a complete explanation of financing and investment patterns requires an understanding of the beliefs and preferences of these two sets of agents. These agents are basically developing unbiased forecasts about future events and use these to make decisions that best serve their best interests. Behavioural finance has important implications in practical corporate finance. Park and Sohn (2013) reports that behavioural finance is a study that combines psychology and economics, and it tries to explain various events that take place in the financial markets. All market participants face several decisions in their financial activities regarding such aspects as investments and funding.

In a nutshell, corporate finance deals with the sources of funding and the capital structure of corporations and the actions that manager take to increase the value of the firm to the shareholders. Behavioural finance can help shed light on corporate finance puzzles. According to Ritter (2002), the foundation of the behavioural finance is laid on two factors i.e. '*Cognitive Psychology*' (people's way of thinking) and '*limits to Arbitrage'* (effectiveness of arbitrage in different circumstances). '*Cognitive Psychology'*, tells us about various factors and theories of human behaviour which tells us about the systematic errors made by the people in the way they think and take decisions regarding their stock selection. As a practical matter, according to traditional finance, managers seem to think that capital markets are efficient, with prices rationally reflecting public information about fundamental values (Baker, Ruback and Wurgler, 2004). Investors can take for granted that managers will act in their self-interest, rationally responding to incentives shaped by compensation contracts, the market for corporate control, and other governance mechanisms. The corporate finance literature can be enriched when, as Baker, Ruback and Wurgler (2004) did, researchers replace the traditional rationality assumption with potentially more realistic behavioural assumptions. Baker, Ruback and Wurgler, (2004) divide the literature into two approaches, the first approach emphasizes the effect of investor behaviour that is less than fully rational, and the second approach considers managers behaviour that is less than fully rational.

Rabin (2002) made some assumptions about how investors take decisions before they made any investment decisions and his assumptions are- “investors have well-defined stable preferences, even if those preferences themselves are never explained or challenged, investors base their preferences between choices on expected outcomes, investors maximise their own well-being or utility and investors discount expected payoff by geometrically increasing amounts to obtain their present value”.

Baker and Wurgler (2013) mention that behavioural finance applications in corporate finance received a boost from the spectacular rise and fall of internal stocks between the mid-1990 and 2000. Even though behavioural finance is a relatively new concept in the corporate finance, but its application is huge in the corporate finance world, because behavioural finance emphasizes investors and managers behaviour. Baker, Ruback and Wurgler (2004) argued that the “irrational investors approach” assumes that securities market arbitrage is imperfect, and thus that prices can be too high or too low. They also argued, “the rational managers are assumed to perceive mispricing, and to make decisions that may encourage or responding to mispricing”. While their decisions may maximise the short-run value of the firm, they may also result in lower long-run values as prices correct. Baker, Ruback and Wurgler (2004) argue that managers balance three objectives: fundamental value, catering, and market timing. Maximizing fundamental value has the usual ingredients. Catering refers to any actions intended to boost share prices above fundamental value. Market timing refers specifically to financing decisions intended to capitalize on temporary mispricing, generally via the issuance of overvalued securities and the repurchase of undervalued ones.

According to Baker, Ruback and Wurgler (2004) the second approach to behavioural corporate finance, the "irrational managers approach," is less developed at this point. It assumes that managers have behavioural biases, but retains the rationality of investors, albeit limiting the governance mechanisms they can employ to constrain managers. Following the emphasis of the current literature Baker, Ruback and Wurgler's (2004) discussion centres on the biases of optimism and overconfidence. A simple model shows how these biases, in leading managers to believe their firms are undervalued, encourage overinvestment from internal resources, and a preference for internal to external finance, especially internal equity. They also note that the predictions of the optimism and overconfidence models typically look very much like those of agency and asymmetric information models.

Baker and Wurgler (2013) talk about a new approach in behavioural finance which will help managers and investors to take corporate decisions and they call this approach 'behavioural signalling'. This is a response to the many sophisticated signalling models in corporate finance theory that make two questionable assumptions. They assume full rationality and standard preferences and they use the destruction of firm value as the credible signalling mechanism- the better firm is the one that destroys more value, a notion rejected by manager's surveys. Baker and Wurgler's (2013) behavioural signalling model, instead, builds the signalling mechanism on some distortion in beliefs or preferences.

Behavioural finance plays an important role in corporate finance. The second factor of behavioural finance is limited arbitrage, which does not allow investors to take advantage of a price difference between two or more markets: striking a combination of matching deals that capitalize upon the imbalance, the profit being the difference between the market prices (Ritter, 2002). It is well known that securities prices reflect fundamental values when informed investors compete aggressively to eliminate mispricing. The classic financial theories, including Modigliani-Miller theorem, hold that they will do so because mispricings between two companies with the same operating cash flows but different capital structures, in a setting of complete and frictionless securities markets, present arbitrage opportunities. On the other hand it is true that securities market mispricings often do not present opportunities for true arbitrage.

Behavioural corporate finance's focus is mostly on the financing decisions of firms. In this decision making process, financial intermediaries often play a critical role between the firms and the ultimate investors. According to Baker and Wurgler (2013) capital market inefficiencies and the role of financial intermediaries are crucial in behavioural corporate finance. To the extent that capital market inefficiencies affect corporate finance. But an interesting question is how intermediaries affect issuance and investment patterns and whether they play a stabilising or destabilising role. According to Shleifer and Vishny's (2010) model, financial intermediaries can play an important role over investor sentiment through securitised lending, creating and selling overpriced assets. It has also been suggested by Baker and Wurgler (2013) that intermediaries can cause financial market 'dislocations' to propagate from one set of firms to another, affecting real activity. Townsend (2011) considers the case of venture capital, where information asymmetry can lead to the firm being locked into a relationship with one capital provider.

Behavioural factors can affect how managers make crucial corporate finance decisions related to dividends, earning management, firm's names, nominal share price and executive compensation. The effect of behavioural factors is also influence by corporate governance, because for less than fully rational managers to have an impact, corporate governance must be limited in its ability to constrain them into making rational decisions.

In summary, there are two main approaches in the literature; the first approach emphasises the effect of investor behaviour that is less than fully rational, and the second approach emphasises manager behaviour that is less than full rational. Empirically, behavioural finance applications in corporate finance received a boost from the spectacular rise and fall of internet stocks between the mid-1990 and 2000.

3.6. COMPARISON OF BEHAVIOURAL FINANCE AND ORTHODOX FINANCE APPROACHES TO DIVIDEND POLICY

The payment of dividends is a long-term puzzle in corporate finance given that share repurchases as a means of cash distribution confer tax advantages (Avanidhar, 2007). Stockholders who pay taxes would often prefer that the firm repurchase their shares instead of paying a dividend. From the very beginning of the dividend paying culture, dividends has been charged a higher tax than capital gain.

However, investors are accepting a significant part of their return in the form of dividends and firms are using behavioural language to choose to frame part of their return as an explicit payment to stockholders. Behavioural dividend policy literature dates back to Shefrin and Statman (1984), who argued that dividends are paid by the firms are because investors exercise better self-control with their expenditures if they get a ‘check in the mail’ in the form of a dividend than if they have to take a conscious action (sell shares), because the latter may allow faster liquidation of the portfolio than is desirable. They also say that the dividend is paid based on the mental accounting. According to Shefrin and Statman (1984) firms try to help investors to segregate gains and losses and hence to increase their utility by designating an explicit dividend payment. On the other hand Baker and Wurgler (2004) rationalise dividends by arguing that during certain times, investors are more desirous of dividends. Their argument is based on that time variations in dividend policy can be effectively explained by the empirical proxy for dividend desire.

Shefrin and Statman (1984) also argue that, firms are paying dividends to avoid their regret, because regret is a frustration that people feel when they imagine having taken an action that would have led to a more desirable outcome (Barberis and Thaler, 2003). According to Baker and Wurgler (2002b), investor's sentiment depend on firms dividend policy, may be investors sentiment about dividend paying firms relative to their sentiment about non dividend paying firms will not same. Their main argument is that investors, dividend paying firms and non-paying firms represent salient categories and that these investors have changing sentiment regarding these categories.

According to prospect theory (Kahneman and Tversky, 1979) utility function of investors is concave over the domain of gains and the separate valuation by investors of individual gains over a concave utility function influences how a stream of dividend payments will be valued. Distinctively, it informs that the frequency with which dividends are paid will positively affect an investor's valuation of a total dividend distribution. Barberis and Thaler (2003) describe how the concave utility function of prospect theory allows an investor to receive greater utility. According to Kahneman and Tversky's (1979) theory individuals typically display risk-averse behaviour over investment which involve only gains; display risk-seeking behaviour over investment which involve only losses; and have losses loom larger than gains in those investments which admit the possibility of either a gain or loss of equal magnitude. Therefore, in the single-variable case, a standard Kahneman and Tversky value function is concave in gains and convex in losses with a somewhat non-symmetric shape.

Orthodox finance theories have fixed assumptions that people act rationally and consider all available information in their decisions related to investments. Followed by the first study of Lintner (1956) and Miller and Modigliani (1961), a number of literatures have been given to the dividend issue and many frameworks have been considered. In corporate finance prospective Modigliani and Miller (1958 and 1961) say that in frictionless markets, if a firm has constant investment policy, then dividend policy is irrelevant because the dividend *per se* has no effect on the firm's share price or its cost of capital. In spite of this, other finance researchers insist on that dividend changes convey information managers could have about a firm's future profitability (Bhattacharya, 1979; John and Williams, 1985; and Miller and Rock, 1985). According to Asquith and Mullins, 1983; Adjaoud, 1984; and Healy and Palepu, 1988, a positive (negative) association between dividends increase (decrease) announcement and stock market reaction. These results hold the signalling explanation of dividend. In the other hand some of the researcher find that the potential agency costs associated with the separation of management and ownership induce a conflict-mitigation role for dividend payments.

Rozeff (1982) and Hu and Kumar (2004) find a negative relationship between dividend yield and the fraction of equity owned by managers. Short et al. (2002) find a negative link between dividend payout ratio and institutional ownership. According to Malcolm Baker, when it comes to supply capital effects, it's all about the combination between the "*investor tastes, limited intermediation and corporate opportunism*". Corporate managers get the right mix between the three factors with the help of an informational advantage about the company earnings.

For corporate finance Baker and Wurgler (2004) argue that managers "catering" to the demands of investors may influence dividend policy. "Catering" means to realizing any actions intended to boost share prices above fundamental value. They found that managers rationally cater investors' demand, by paying dividends when investors put higher prices on payers and not paying when investors prefer non-payers.

Another corporate finance theory for dividend policy is signalling theory. This theory of dividends represents a means to express information about the future profit of a firm. A change of dividend policy is then a signal given to investors concerning expected future cash flows. Kalay (1980) points out that dividends are used as a means to provide investors with financial disclosure information. Dividend payments represent a positive signal sent by managers to shareholders.

3.7. BEHAVIOURAL ELEMENTS' EFFECT ON STOCK RETURNS

In this section I will discuss behavioural elements' effect on stock market returns. Previous literature has shown that behavioural elements such as investor mood have an effect on stock market returns. Chapter 7 of this thesis investigates the role of investor mood in the context of the dividend-signalling theory.

3.7.1. TEMPERATURE AND STOCK RETURNS

Previous literature in psychology suggests that temperature affects mood, and mood changes in turn cause behavioural changes. According to Cao and Wei (2005) lower temperature can lead to aggression, while higher temperature can lead to both apathy and aggression. Watson (2000) conducted a research involving 478 students between 1985 and 1993. He documented that there are no significant links between mood and weather variables suchas temperature, sunshine, barometric pressure and precipitation. Allen and Fisher (1978), and Wyndham (1969) both documented that task-performing abilities are impaired when individuals are exposed to very high and low temperature. This finding was later confirmed in a meta-analytic re-view by Pilcher et. al. (2002).

Wyndham (1969) suggested that under extreme heat behavioural changes are turn into hysteria and apathy. During the hot and cold weather people tend to be less willing to extend help to others (Cunningham, 1979 and Schneider et al., 1980). Connolly (2013) documented that low temperatures increase happiness and reduce tiredness and stress, raising net affect, on the other hand, high temperatures reduce happiness, but these results are consistent with the fact that the survey was conducted in the summer. Before Connolly (2013), Rehdanz and Maddison (2005) looked at that issue using country level data and found that higher mean temperatures in the summer months decrease happiness, while higher mean temperatures in the winter months increase it.

Howard and Hoffman (1984) found that rising temperatures lowered anxiety and skepticism mood scores when they done a research using 24 college students. According to Denissen (2008) higher temperatures raise a person with a low mood up. Klimstra et al. (2011) found that 17% people are happier, less fearful, and less angry on the days with higher temperatures. Chang et al. (2006) argued that, according to some psychologists cold weather commonly makes people impatient or upset, whereas warm weather makes people mood up and happier.

Cao and Wei (2005) examined the impact of ambient temperature alone on mood and behavior. They suggested that stock returns are negatively correlated with temperature, which means the lower the temperature, the higher the returns and vice versa. They also documented that the relationship is slightly weaker in the summer than in the winter, because when the temperature is high apathy dominates aggression, the results show lower returns but statistically significant, and overall negative correlation. According to Keef and Roush (2002) weather might well be multifaceted, due to that reason they extended the prior research by adding more weather variables. After analysing the data from New Zealand all share index they found that temperature has small negative effect on stock returns. Later Keef and Roush (2005) extended their research by examining the effect of New York's weather on the returns of the Dow Jones Industrial Average index and Standard and Poor's index during the period 1st January 1984 to 31st August 2002. Their results suggests that observed temperature does not exhibit any effect on stock returns but when they de-seasonalised the temperature then they observed positive influence of cool days on stock returns. When Keef and Roush (2007) used Australian stock indices they found that temperature has negative influence on the stock market returns.

Using GARCH model Floros (2008) found that in Austria, Belgium and France stock market returns were negatively correlated with the temperature, in the UK there is no evidence of such an effect, and in the Greece there is a positive but insignificant correlation between temperature and stock returns. In the same year Dowling and Lucey (2008) found that temperature has a positive correlation with stock returns. Later Yoon and Kang (2009) also showed that extremely low temperature is positively correlated with the stock returns.

3.7.2. AIR POLLUTION AND STOCK RETURNS

Air pollution is defined as the introduction of particulates, biological molecules, or other harmful materials into the Earth's atmosphere, possibly causing disease, death to humans, damage to other living organisms such as food crops, or the natural or built environment (see Colls 2002 for details on air pollution). According to the definition given by the World Health Organization (WHO), air pollution is contamination of the indoor or outdoor environment by any chemical, physical or biological agent that modifies the natural characteristics of the atmosphere. The physical health effects of air pollution have been studied extensively; its impacts on psychological and mental states of humans have also been widely investigated (Wilson and Spengler, 1996;Holgate et al. 1999). All studies have suggested that an increase in ambient air pollution has been significantly associated with hightened level of annoyance (Klaeboe et al., 2000; Danuser, 2001; Rotko et al., 2002), fatigue (Sagar et al., 2007), depression (Lundberg, 1996), anxiety (Lundberg, 1996) tension (Chattopadhyay et al., 1995) and low spirits (Bullinger, 1989). Most of the above-cited papers indicate that people are in depressed moods when they are exposed to acute levels of air pollution.

The Air Quality Index (AQI), composed by the UK Department for Environment, Food and Rural Affairs, is an index reporting daily air quality and provides recommendation actions and health advice. The index ranges from 1 to 10 and divided into 4 bands. The main reason of the AQI is to inform the public about the risk of the air pollution and help researchers understand the link between air pollution and numerous health problems, including mental health and mood changes.

According to Li and Peng (2016), low mood help people to be more pessimistic. Li and Peng (2016) documented three channels through which the low moods associated with air pollution may impact stock returns. First, people are more pessimistic when they are in a low mood. People are more pessimistic when the level of air pollution rises, and as a result investors may use probability estimates more biased toward negative outcomes and be less inclined to invest in risky assets. According to Hirshleifer and Shumway (2003) people may incorrectly attribute their bad mood to negative economic prospects rather than to air pollution; Li and Peng (2016) results also suggest that air-pollution level is negatively correlated with stock returns. Second, depressed mood and air pollution both can increase risk aversion. Increased risk aversion resulting from air-pollution can be expected to reduce demand for stocks, which turn results in lower stock prices. And third, depression also leads to a lower investor elasticity of intertemporal substitution (EIS). Investor with lower EIS caused by air pollution would have a higher tendency to prefer consuming in the present, in turn depressing today's demand for investment in the stock market. Stock prices are therefore expected to drop.

Using data from four industrial countries (Italy, the USA, Spain and Germany) Lepori (2016) showed that air pollution is negatively correlated with stock returns. Lepori (2016) also documented that the relationship between local air pollution and stock returns was likely to be mediated by the behaviour of the trading floor community. Levy and Yagil (2011) documented a negative correlation between daily stock returns and the air-quality index (AQI), when they used U.S. data from 1997 to 2007. Later when Levy and Yagil (2013) extended their study using data from Canada, the Netherlands, Hong Kong and Australia, they found similar results. Li and peng (2016) also found a negative correlation between AQI and daily stock returns, when they conducted their research using Chinese data.

3.7.3. CLOUD, RAIN AND STOCK RETURNS

Psychologists have long known that sunlight, or cloud cover (rain), influences people's moods, thinking, and judgment. According to Saunders (1993) investors are optimistic on sunny days and they are pessimistic on cloudy (rainy) days. Hirshleifer and Shumway (2003) also agree with Saunders (1993) findings and they found that sunlight has positive effect on investor mood. Similarly, according to Schwartsz and Clore, (1983) people tend to rate their life satisfaction much higher on sunny days than on cloudy or rainy days.

Saunders (1993) was the first to study the effects of cloud cover on stock returns. He used three global indices of the US market to investigate whether trader mood has any influence on the stock market. As a proxy for weather condition Saunders (1993) uses the "percentage of cloud cover from sunrise to sunset" according to the New York weather station closest to Wall Street. During the 1927-1962 and 1962-1989 periods, Saunders finds that stock returns are lower on days of 100% cloud cover than on days when cloud cover is 20% or less. He also showed that positive index changes are more likely on days with cloud cover of 20% or less than on days with 100% cloud cover. After adjusting the Monday and January effect Saunder (1993) documented that returns are remain lower on cloudy days.

Trombley (1997) later suggests that the relation between weather and stock returns is not as obvious as suggested by Saunders (1993). After replicating Saunders' results, Trombley (1997) documented that returns on 100% cloudy days are not significantly different from returns on days with 0% cloud cover or 0% to 10% cloud cover. According to Trombley (1997) Saunders' (1993) comparison of 100% cloudy days with 0% to 20% cloudy days " is the only comparison during this period that would produce a statistically significant test statistic….". Kramer and Runde (1997) also found no correlation between cloud cover and stock returns.

Hirshleifer and Shumway (2003) extended Saunders' (1993) research and examine cloudiness and stock returns for 26 countries from 1982 to 19987. Their multiple market focus also allows concentration on a more recent time period when markets are thought to be more efficient. Their results suggest that cloudiness is associated with a lower probability of positive returns for 25 of the 26 cities. These findings ate consistent with the casual intuition that overcast weather is associated with downbeat moods and that moods affect stock prices.

After using all share indexes of the New Zealand Keef and Roush (2005,2007) found that cloud cover is negatively correlated with stock returns. Goetzmann and Zhu (2005) also found a negative correlation between cloud cover and stock market returns. On the other hand, Dowling and Lucey (2005) suggested that rain has a minor but significant negative influence on stock market. Shon and Zhou (2009) documented that sunshine, which can be linked to an investor's psychological state, plays an important role in the way the investor responds to earnings announcements. Their results suggest that market reactions to firms' earnings surprises are higher when earnings are announced on very sunny days in New York City. Using data from 20 countries Lu et al. (2013) suggests that cloudiness has an influence on investor response to firm earnings announcements, on average. They also provide documents in supports of that, cloudiness effects exists, regardless of whether the earnings news type is good or bad, across different countries. Moreover, according to Lu et al. (2013) pooled results, the magnitude of this effect is asymmetric between good and bad news; investors respond more negatively to bad earnings reports when such news is announced on cloudy days than on sunny days, while this effect is nor significant when firms issue good earnings.

3.8. CALENDAR ANOMALIES EFFECT ON STOCK RETURNS

In this section I will discuss the effects of calendar anomalies on stock market returns. Previous literature has shown that calendar anomalies, such as “Sell in May and go away” anomaly, have an effect on stock market returns. Chapter 8 sheds light on the effect of calendar anomalies on the response of the stock market to dividend announcements.

3.8.1. HALLOWEEN EFFECT AND STOCK RETURNS

Usually every year in the month of May, the European financial press refers to a (presumably old and inherited) market saying: “Sell in May and go away.”[1] This saying suggests that the month of May signals the start of a bear market, so it is better for the investors to sell their stocks and hold cash (Bouman and Jacobsen, 2002). According to Bouman and Jacobsen (2002) this saying has two different endings. The first one is: “but remember to come back in September”; and the second one is: “but

[1] Some illustrative quotes: “There is an old axiom about the market: Sell in May and go away” (Forbes,1996). “With all that to wait for, rarely has the old stock market adage to ‘Sell in May and go away’ been more apposite” (The Economist, 1993). “ ‘SELL in May and go away,’ says the old adage” (Economist, 1992). “ ‘ Sell in May and go away’ is one of the best known and most often cited market wisdoms, and many generations of traders grew up hearing this wisdom” (translated from German, www. Bank.de/infos/presse/technical-market-view.htm).

buy back on St. Leger Day"- in which "St. Leger Day" refers to the date of a classic horse race run at Doncaster in England every year. According to the saying, stock returns should be lower during May through September than during the rest of the year. Michael O'Higgins and John Downes (1990) report a closely related and similar strategy related to market timing. Referred to as the Halloween indicator, it is "so named because it would have you in the stock market starting October 31 and through April 30 and out of the market for the other half of the year." Before them Levis (1985) refers to the Sell in May effect but does not examine whether or not it actually exists.

As we know the Halloween effect, or Sell in May effect originates from old European market wisdom first investigated empirically by Bouman and Jacobsen (2002) using 37 countries' monthly return indices. Bouman and Jacobsen (2002) report significant Sell in May effects in 36 out of 37 countries examined. Bouman and Jacobsen (2002) examined different reasons to find an explanation for the anomaly, such as risk, cross correlation between markets, the January effects, data mining, shifts in interest rates, as well as shifts in trading volume and the existence of a seasonal factor in news provision. According to Bouman and Jacobsen (2002) none of these seemed to provide an explanation.

Later Maberly and Pierce (2004) re-examined the Bouman and Jacobsen (2002) results for the U.S. stock market and extended the analysis to S&P 500 futures, and the futures' data set covers the period April 1982- April2003. On re-examination, the documentation of a Halloween effect in the U.S. market disappears after an adjustment is made for the impact of outliers, in particular the larger monthly declines for October 1987 and August 1998 associated with the stock market crash and collapse of the hedge fund Long-term Capital Management, respectively. For the U.S.

market the empirical evidence suggests that the Halloween effect is not an exploitable anomaly, and this is true for both spot and futures prices. But later Maberly and Pierce's (2004) work was criticized by Witte (2010), who argued that Maberly and Pierce (2004) identified the two outliers without formalizing criteria and dealt with them in an unsatisfactory way. Witte's (2010) robust regression analysis suggests that outliers do not drive the results of Bouman and Jacobsen (2002). Marginal as the original results are, they remain marginally statistically significant using methods more resilient to outliers.

After Maberly and Pierce (2004), Galai et al. (2008) also posited a relation between the Halloween effect and outliers. In contrast to the results of Maberly and Pierce (2004), Galai et al. (2008) results suggest that, in daily S&P 500 returns, the Halloween effect is significant only after controlling for outliers. The reason behind this two different sets of results might be due to analyzing daily returns versus monthly, the different time period analyzed (Galai et al. 1980-2002 versus Maberly and Pierce 1970-1998), or even the dropping of return observations from the sample. "Returns on non-consecutive days, other than weekend returns, are excluded, as they are not daily returns" (Galai et al., 2008). Maberly and Pierce (2005) extendee their prior research on the Halloween effect using Japanese equity market data. Maberly and Pierce's (2005) results suggest that the Halloween effect is concentrated in the period prior to the introduction of Nikkei 225 index futures in September 1986. They documented a significant Halloween effect in the Japanese market but only over the period prior to the internationalisation of Japanese financial markets in the mid-1980s.

Lucey and Zhao (2008) examined the U.S. stock data from 1926 to 2002 to determine the robustness of the Halloween effect to consideration of the January effect; they found that equity returns are significantly higher in January than in other months. They also found no evidence of a Halloween effect in their full sample. They found that neither the Halloween effect nor the January effect is consistently significant for value weighted returns when they used sub-period analysis, and that only the January effect is consistently significant for equal weighted returns. Haggard and Witte (2010) documented that the Halloween effect is robust to consideration of outliers and the January effect. Zarour (2007) studies the Halloween effect in the Arabic stock market and suggests that the Halloween effect is present in 7 of the 9 Arabic stock markets in the sample period from 1991 to 2004. Later Lean (2011) studies the Halloween effect using six Asian countries stock markets data from 1991-2008, and he showed that the Halloween effect is only significant in Malaysia and Singapore, if modeled with OLS, but that three additional countries (China, India and Japan) become statistically significant when modeled allowing for time-varying variance.

Using an out-of-sample (1998-2012) period data Andrade el at. (2013) find that all 37 countries in the original study (Bouman and Jacobsen, 2002) have performed better in November through April than during the remainder of the year and 14 have done so significantly. Moreover, Jacobsen et al. (2005) documented that the Halloween effect is a market-wide phenomenon, which is not related to the common anomalies, such as size or book to market ratios and/or dividend yield. Jacobsen and Visaltanachoti (2009) examine the Halloween effect among U.S. stock market sectors and find substantial difference across sectors. Dichti and Drobetz (2014) implement the ‘superior predictive ability’ on the Halloween effect and find that an investment strategy based on the effect cannot significantly outperform the buy-and–hold strategy. Later Dichti and Drobetz (2015) confirmed that the existence of a Halloween anomaly in their regression analysis, when they use the maximum history of available index date, but when they account for the availability of adequate investment instruments and the publications date of the Bouman and Jacobsen (2002) study, Dichti and Drobetz (2015) found that the Halloween effect became weaker and in some markets even disappeared. On the other hand Carrazado el al. (2016) found economically and statistically empirical evidence that the Halloween effect is significant. Their results suggest that the Halloween anomaly works persistently and outperforms the buy and hold strategy in 8 out of 10 indices in their sample.

3.8.2. TURN-OF-THE-MONTH EFFECT AND STOCK RETURNS

Some previous studies have shown that returns are higher during the first few trading days of each month (Sharma and Narayan, 2014). This type of behavior is consistent with the turn-of-the-month (from here on TOM) effect (for instance, Lakonishok and Smidt, 1988; McConnell and Xu, 2008; Nikkinenet et al. 2007). Arial (1987) first found the TOM effect on stock returns in the U.S. stock market. Using equally-weighted and value-weighted daily stock returns from the NYSE during the period 1963 to 1981 Arial (1987) found that mean daily stock returns are positive at the beginning of the month and continuing through the first half of the month. He also found that returns after this point are predominantly negative. Lokonishok and Smidt (1988) investigate the DJIA from 1897 to 1986 and discovered that the rate of return is especially high for the last trading day to the next month. More specifically, they find that returns during the TOM are 0.475% compared to 0.061% for non-TOM days. Later McConnell and Xu (2008) extend Lokonishok and Smidt (1988) study to include data up to 2005 for the DJIA and find that the TOM effect is still significant. Even their results were suggested significant TOM effect with all of the positive returns to equities occurring during the TOM interval. Moreover they documented that on average, during the other trading days of the month investors receive no reward for the risk they took. They also documented that it is not due to the concentration of buying shares at the TOM, or just confined to the U.S. McConnell and Xu (2008) was not able to give any explanation for this profitable calendar effect. Their results also suggest that TOM effect is significant in the 31 of the 35 countries they examine.

Using the daily stock market indices of 10 countries between 1962 and 1989 Cadsby and Radner (1992) examine the TOM and holiday effect to see whether the effects are independent of, or related to, patterns observed in the U.S. market. They found TOM pattern in six countries that is independent of the turn-of-the-year effect. However, they were unable to directly examine the spillover of the TOM effect since the period occurs simultaneously across countries. Later Kunkel el at. (2003) was able to show that the pattern is not due to spillover from U.S. market. Their results was show that the TOM effect persists throughout the 1990s in at least 16 of 19 countries in their study. Their parametric and nonparametric tests indicate a significant TOM pattern that is independent of any monthly seasonal and cannot be explained by outlier observations in a few months.

Sharma and Narayan (2014) examine the TOM effect using on 560 firms listed on the NYSE and they found the evidence that the TOM effects returns and returns volatility of firms. They also suggested that the effect are different for different firms, firm size and sectors. So their results are suggests that the TOM has a heterogeneous effect on firm returns and firm return volatility. With the linear trend line downward sloping Marquering et al. (2006) found that the TOM effect is slightly weaker than pre-1987 data for the DJIA. Later using daily returns for the Russell 2000 and

S&P500 futures market and through the subperiod analysis Dzhabarov and Ziemba (2010) found that the TOM effect still exists, but with a bit of anticipation.

Atanasova and Hudson (2010) found the evidence of the TOM effect on the stock returns for the FT-30 using -1 and +3 days for the period July 1935 to March 2009. Using 50 international stock indices during the period 1994-2006 Khaled and Keef (2012) examine the TOM effect and found the evidence of the TOM effect which is found even after controlling for a number of factors. McGunness and Harris (2011) documented a notable TOM effect for various sectors of the Hong Kong market as well as for the Shanghai and Shenzhen B-markets. Using the daily data from January 2001 to December 2011 of the S&P 500 index fund SPY, Liu (2013) found that the TOM effect is exists in the U.S. equity market but the date of its occurrence have moved earlier.

3.8.3. JANUARY EFFECT AND STOCK RETURNS

The January effect was first documented by Rozeff and Kinney (1976) and later gained alot of attention from academics as well as practitioners. Jacobsen and Zhang (2013) examined over 300 year of UK stock returns and found that the January effect only emerges around 1830, which coincides with Christmas becoming a public holiday but is no longer significant from 1951 to 2009. The January effect states that returns in January appear to be higher than in other months of the year (Urquhart and McGroarty, 2014). According to Klock and Bacon (2014) investors obtain abnormally large returns on small cap stocks at the turn of the calendar year; in this process investors buy stocks and their prices rise in January. Rozeff and Kinney (1976) examine the January effect using the NYSE data for the period 1904 to 1974 and found that the average returns for the month of January was 3.48% compared to only 0.42% for the other months. Keim (1983) documented that around 50% of the average magnitude of the risk-adjusted premium of small firms relative to large firms is due to January abnormal returns using the NYSE data from 1963 to 1979. Keim (1983) also suggests that 50% of the January premium is due to abnormal returns during the first week of trading in the year. Keim (1983) findings for small firms were supported by Roll (1983) and Reinganum (1983), particularly for small firms with low share prices.

On the other hand, Kohers and Kohli (1991) found that the January effect is not related to the small firm effect. Lakonishok and Smidt (1988) found no evidence of the January effect in the DJIA for the whole of January, and only found mild support for rates of return being larger in the first half of the month than last half of the month. Even though some studies documented that the January effect is disappearing (Gu, 2003; He and He, 2011; Hensel and Ziemba, 2000) numerous others provide evidence that the January effect continues to appear in the modern U.S. capital markets (see for instance, Anderson et al., 2007; Brown and Luo, 2006; Ciccone, 2011; Easterday et al., 2009) although it does not occur every year (Easterday et al., 2009; Hulbert, 2008). Using Tokyo Stock Exchange data Kato and Schllheim (1985) examined the excess returns in January and they found evidence of excess returns in January and a string relationship between returns and size, with the smallest firms returning 8% and the largest firms returning 7%.

Mills and Coutts (1995) examined the January effect for the FTSE-100, Mid 250 and 350 indices from January 1986 to October 1992. Their results suggest the January effects, with daily returns being positive and significant for January and February in the FTSE 100 and for January in the Mid 250. However, Sun and Tong (2010) documented that in January volatility is not higher than other months of the year and the higher January returns reflect greater compensation for risk. According to Easter and Sen (2016) January effect is correlated with accounting earnings and expectations about future earnings. They extend the work of Henker and Debapriya (2012), who argue against "irrational noise trader" explanation of the January effect. Tax management is the most usual explanation for the January effect: investors usually take advantage of capital gain losses at year end for the tax purpose, which create temporary downward mispricing resulting larger January returns when pieces rebound after turn of the year (Branch, 1977: Brown et al., 2010; Dalton, 1993; Phua et al., 2010; Sikes, 2014).

3.8.4. MONDAY EFFECT AND STOCK RETURNS

The Monday effect was one of the first calendar anomalies to be discovered and previous studies suggest that it is still quite strong (Urquhart and McGroarty, 2014). According to Maberly (1985), financial practitioners were aware of the Monday effect as early as 1920s, with the first documented finding by Kelly (1930) who found Monday to be the worst day to buy stocks based on a three-years statistical study. The Monday effect refers to the fact that asset returns are negative on Mondays (Urquhart and McGroarty, 2014). Negative Monday returns have been found to be robust over time and different markets (see, Jaffe and Westerfield, 1985; Keim and Stambaugh, 1984). French (1980) found early evidence of unusual price patterns in the weekends in the U.S. market during the 1950s and to 1970s. After him numerous studies confirmed the Monday effect using various time periods and different stock returns indexes.

Cross (1973) was the first academic who documented the Monday effect using S&P 500 data from 1953 to 1970. Over this period, the index advanced on 62% of the Fridays and the mean return was +0.12%; on the other hand the index advanced on just 39.5% of the Mondays and the mean was -0.18%. Cross also suggests that Monday return are dependent on previous Friday returns. French (1980) documented day-of-the-week evidence in the U.S. market, including negative and statistically significant Monday returns, when he used the S&P 500 from 1953 to 1977. Gibbons and Hess (1981) also documented similar results when they use the S&P 500 and CRSP value and equally-weighted index from NYSE and AMEX securities from 1962 to 1978, as did Kim (1987) for the U.S. indexes from 1963 to 1985. Lakonishok and Smidt (1988) found negative Monday returns for their entire sample period (1897-1986), and they also suggests that all but two of their subsamples were statistically significant. Rogalski (1984) documented that the average negative Monday returns occur during the nontrading period from Friday's close to Monday's open. Later Damodaran (1989) showed that firms usually report bad news on Fridays and this late announcement of bad news might cause the negative Monday returns. Wang, Li and Erickson (1977) show that the Monday effect (negative returns) occurs primarily in the last two weeks of the month for a number of stock indexes consistently over the period 1962-1993, while the Monday returns for the first part of the month are not statistically significantly different from zero.

A number of previous studies found that the Monday effect is diminished and in some cases even reversed over time. Connolly (1989) suggested that Monday returns were statistically significant before 1974, but were not statistically significant after 1974, but they remained negative. Chang et al. (1993) also found similar results. On the other hand, Kamara (1997) documented that the Monday effect has diminished significantly after introduction of the S&P 500 futures contracts in 1982. Coutts and Hayes (1999) showed empirically that the Monday effect exists but is not as strong as has been previously documented for the UK stock indexes; see also Steeley (2001). Marquering et al. (2006) studied the DJIA from 1960 to 2003 and found that the Monday effect has declined in recent years. Bakar et al. (2014) documented that Monday effect disappears after controlling for mood when they use daily mood data from Facebook across 20 international markets. Brusa and Pu (2000) found that the Monday returns for the large U.S. stocks were positive and largest of any day of the week during 1990. Later Mehdian and Perry (2001) found this 'reversal' in returns for the large U.S. stocks from November 1987 to August 1998, but they did find negative Monday returns for small stocks. Brusa and Liu (2004) documented that this reversal in returns is concentrated on positive returns in the first and third weeks of each month, while Brusa, Pu and Schulman (2005) found that the positive weekend returns are correlated with the previous Friday's return, suggesting that the positive Monday returns are likely to be observed after a positive Friday return. Alt et al. (2011) examined the Monday effect in the U.S., UK and German stock markets using a testing procedure based on the closure test principle that controls for multiple type I errors. They found a Monday effect in the 1970s and 1980s, while it disappear in all three markets in the 1990s and 2000s.

3.9. SUMMARY AND CONCLUSION

The main aim of corporate finance is to explain the financial contracts and the real investment behavior that emerge from the interaction of manager and investors; because of that reason, a complete explanation of financing and investment patterns requires an understanding of the beliefs and preferences of these two sets of agents. On the other hand behavioral finance is based on two pillars called '*Cognitive Psychology*' (people's way of thinking) and '*limits to Arbitrage'* (effectiveness of arbitrage in different circumstances). Baker and Wurgler, (2013) believe that behavioural finance applications in corporate finance are extensive and received a boost from the spectacular rise and fall of Internet stocks between the mid-1990 and 2000. Behavioural finance is a relatively new concept in corporate finance, but its application has been gaining more and more recognition in the corporate finance world, because behavioural finance emphasizes investors and managers' behaviour.

Shefrin and Statman (1984) came out with a new argument about behavioural dividend policy, that firms pay dividends simply because investors exercise better self-control with their expenditure if they get a 'check in the mail' in the form of a dividend than if they have to take a conscious action, because the latter may allow faster liquidation of the portfolio than is desirable. Baker and Wurgler (2004), also think that during certain times, investors are more desirous of dividends.

When researchers think about behavioural finance they typically will first think of Kehneman and Tversky's prospect theory (1979) and cumulative prospect theory (1992). In Prospect theory Kehneman and Tversky give a clear idea about how shareholders and managers make their decisions using psychological biases. In their theory they show that shareholders and managers make decisions using reference points, self-control, or decision weights.

The literature suggests that prospect theory is also useful in corporate finance. In corporate finance, IPO under pricing might be explained based on reference-point preferences, which derive from the value function of Kahneman and Tversky's (1979) prospect theory, which is defined in terms of gains and losses relative to a reference point. Behavioral finance researchers examine political decisions, gambling, asset pricing, etc using prospect theory. But very little work has been done to solve the dividend puzzle problem using prospect theory. Only Stephen, Gregory and Emre (2010) have used prospect theory (Kehneman and Tversky, 1979) to show the importance of the frequency of dividend payment.

Previous researchers have relied on different areas of unorthodox finance, such as investor sentiment and calendar anomalies, to explain stock returns. Some researchers have explored the impact of investor sentiment on the reaction of the stock market to earnings announcements, but to the best of my knowledge, no researcher has yet examined the impact of investor sentiment and calendar anomalies on the reaction of the stock market to dividend announcements. Neither conventional finance nor behavioural finance can fully explain these calendar anomalies. Several explanations have been proposed but none of them seems to be satisfactory.

In this thesis I will examine the dividend signaling theory both from the perspective of orthodox finance and from the perspective of two unorthodox areas of finance (behavioural finance and the literature on calendar anomalies). For this reason in chapter 2 I have discussed orthodox finance and dividend theories and in chapter 3 I have discussed behavioural finance theories and the key literature on calendar anomalies.

4 RESEARCH METHODOLOGY

4.1. INTRODUCTION

"…………The objective of academic research, whether by sociologists, political scientist, or anthropologist, is to try to find answers to theoretical questions within their respective fields. In contrast, the objective of applied social research is to use data so that decision can be made."

Herbert J. Rubin, Applied Social Research, (1983).

The focus of this study revolves around four research questions. First, does dividend changes contain any information about future earnings? Second, do dividend increase (decrease) have a positive (negative) effect on stock returns? Third, does investor sentiment play any role in the reaction of the stock market to dividend announcements? And fourth, do calendar anomalies play any role in the relationship between dividend announcements and stock returns. In order to address these questions, it is necessary to decide suitable research approach and to collect appropriate set of data and to follow proper analytical procedure. This chapter address this issues in details.

4.2. RESEARCH APPROACH AND RESEARCH PHILOSOPHY

There are two research classifications that dominate the research environment, which are the empirical and theoretical research approach (Remenyi et al. 1998). On the base of Oxford English Dictionary we can tell that, ‘Empirical’ is defined as based on, or guided by, the results of observation or experiment only. On the other hand, ‘Theoretical’ is defined as contemplative of the mind or intellectual faculties. We also know that, in empirical research, researchers usually generate ideas using observations and experiments and collect data and related evidence in order to analyse and reach a conclusion.

Theoretical research normally studies the subject through the writings of others and through discussion with informed individuals who can comment on the subject area (Remenyi et al., 1998). Theoretical research does not essentially involve direct observation of behaviour or collection of actual evidence. However, these two approaches are different from each other in their theoretical construction, in reality, they are interconnected in the sense that it is not possible to carry out an empirical study without having a complete theoretical understanding regarding the issues which are being studied and about which evidence are to be collected. Despite this interrelationship, a large amount of academic research conducted today is based on empirical approach. This is true because of the fact that evidence as opposed to thought or discourse, is required to be able to make a satisfactory claim to have added to the body of knowledge (Remenyi et al., 1998). Inspired by this fact, this piece of work will largely follow the empirical approach of research to address the research questions although theoretical approach will also be followed to develop and operationalise the research objectives.

Research philosophy is another important aspect that guides the structure and direction of the research process. According to Easterby-Smith et al. (2002) there is two basic philosophies underpin all research: positivism and phenomenology. From the operational point of view, positivism takes a reductionist approach to exploring the relationship among the variables being studied. Reductionist approach is helpful in controlling an investigation in order to ensure the understanding of behaviour of variables concerned. On the other hand, phenomenological approach of research is holistic in nature and allows much more complicated situation to be examined. It allows researcher to examine as many variable as possible and incorporate as many context of research as possible (Remenyi et al., 1998). For the current study, the choice of research philosophy is positivistic because of the following reasons:

i) Studies that follow positivist approach are easy to replicate to arrive at a general conclusion. On the other hand, studies that use phenomenological approach are difficult to replicate and generalizations are much more difficult (Remenyi et al., 1998). In social science, research issues are continuously changing and different from one place to another. So, one particular result may not fit in two different points of time and two different places. Due to that reason, freedom of replication of a specific study leads the researchers to produce more acceptable generalization.

ii) I chose to use the positivist approach because this is the dominant approach in the stream of literature about the dividend-signalling theory.

4.3. CHOICE OF METHODOLOGY

The choice of research philosophy has an impact on the choice of research methodology. There are three main research methodologies that are widely used, which are, quantitative, qualitative and mixed method. According to Creswell (1994) quantitative studies are characterized by the use of deductive form of logic where in theories and hypotheses are tested in a cause-and-effect order. Ideas, variables, and hypotheses are chosen before the study begins and remain same throughout the study. Creswell (2003) stated that quantitative analysis follows the positivist assumptions and researchers tests a theory by specifying narrow hypothesis and the collection of data to support or refute the hypotheses.

On the contrary, qualitative methodology is an explanatory technique which describes, decodes, translates and infers the meaning, without considering frequency of certain more or less naturally occurring phenomena in the social world (Van Maanen, 1983). According to Creswell (2003) qualitative research follows the assumptions of phenomenology and seeks to establish the meaning of a phenomenon from the views of participants. This means identifying a culture-sharing group and studying how it developed shared patterns of behaviour over time.

Mixed method approach attained its recognition and prominence only during the last two decades. According to Teddlie and Tashakkori (2009), 'the mixed methods research tradition is less well known than the quantitative and qualitative traditions because it has emerged as separate orientation during the only past 20 years'. In very simple terms, mixed methods are an approach, rather a philosophy, to social enquiry that uses two or more methods, processes and philosophies in undertaking a research study. It is based upon the belief that different paradigms and methods have different strengths and, for certain situations, their combined strength would result in improving the depth and accuracy of the findings.

Finance has always borrowed methodologies from other disciplines. Methods developed in mathematics, physics and economics are now standard in finance.

Methods developed in psychology have been important more slowly. According to Muradoglu and Harvey (2012) there are a number of reasons for this, for example they said, experiments are difficult and costly to conduct with investors and markets professionals because their participation in experiments requires funds that exceed those available under standard finance academic research budgets. The primary input to behavioural finance has been from experimental psychology. Methods developed within sociology such as surveys, interviews, participant observations, focus groups have not had the same degree of influence. Usually these methods are more expensive than experimental ones and so costs of using them may be one reason for their lack of impact (Muradoglu and Harvey, 2012). According to Muradoglu and Harvey (2012) behavioural finance has started as a multidisciplinary endeavor but it is now an interdisciplinary field with its own learned societies.

The major objectives of this study are to investigate motivations, determinants and performance of dividend policy. In order to achieve these objectives, this study developed hypotheses and selected variables based on earlier literature and tested those hypotheses by collecting quantifiable data. The variables that are used to represent the aspects of dividend policy in this study are quantifiable and measurable and therefore, provide an ideal situation for the selection of quantitative methodology. Moreover, aspects of dividend policy have been investigated since 1956. An interesting phenomenon of this development is that most of the studies that evaluated the motivations, determinants and performance have used quantitative methodologies rather than qualitative or mixed method. Following the earlier studies, that have gained scholarly support, this study has also used quantitative methodology in examining the stated objectives.

4.4. LITERATURE REVIEW

One of the essential preliminary tasks when we undertake a research study is to go through the existing literature in order to acquaint our self with the available body of knowledge in our area of interest. The literature review involves a paradox. It is not possible to undertake a literature search without some idea of the problem we wish to investigate. The most important function of the literature review is to ensure that we read widely around the subject area in which we intend to conduct our research. It is important to know what other researchers have found in regard to the same or similar question, what theories have been put forward and what gaps exist in the relevant body of knowledge.

Before searching the literature in the field of my interest, it is important that I have some basic idea about the broad subject area. It is also important to have some idea about the population of the study. In this study my subject area is dividend policy. There are four sources that we can use to read our literature, in this thesis I have used all four sources, and the sources are books, journals, conference papers and the Internet. After reading all the related literature in the area of dividend policy I have pulled together all the themes and issues that are relevant to my research hypotheses.

4.5. SECONDARY DATA COLLECTION

We know that there are two types of data, one is primary data and the other one is secondary data. In order to achieve the aims of the study, I have used here secondary data. The analysis of trends, determinants and performance of UK dividend policy used appropriate secondary data collected from various secondary sources.

This section details out the procedure of secondary data collection, sample selection and sources of secondary data.

This study examines the overall and sectorial patterns and trends of the UK dividend policy. Moreover, this study examines the dividend-signalling theory from the perspective of orthodox finance and unorthodox finance. To examine these, this study collected appropriate secondary data from various available secondary sources. This section describes the details of secondary data collection for the study.

4.5.1. DATA COLLECTION

In order to examine the trends and patterns of the UK dividend policy activities over the period of 1990 to 2015, this study has collected data on dividend announcements. Beside the dividend announcements data some other orthodox and unorthodox data also has collected. As indicated earlier the main aim of this study is to investigate the dividend-signalling theory from the perspective of orthodox and unorthodox finance. To do this study yearly dividend announcement data has been collected. Data has also been collected on selected orthodox and unorthodox variables, which are return on equity, market capitalization, earnings of the selected companies, total asset of the companies, temperature in the London area, air pollution in the London area, rainfall in the London Heathrow area, calendar anomalies (January effect, Turn of the month effect, Halloween effect and Monday effect), all 350 companies stock price and 350 companies daily stock returns. Details of these variables and the reasons for their selection are given in the chapter 5, 6, 7 and 8 of this thesis.

4.5.2. SAMPLE SELECTION

In this study I used only those firms meeting the following selection criteria. I impose the following selection criteria because of the time and resource constraint for this study; following selection criteria have been imposed on the dividend announcements firms to become part of the sample.

1. Only final dividend announcements are included, and all other interim dividend and stock dividend announcements during the event period are excluded.

2. Companies in the financial and utility industries are excluded, because these two industries keep their financial records in different way than other industries (claessens and Laeven, 2006, p 111). For the financial industry, profitability and valuation data are difficult to calculate and compare with firm in other industries. For the utility industry profitability and valuation can be strongly influenced by government regulations (claessens and Laeven, 2006, p 111).

3. Dividend changes are between +50% to – 50% to avoid abnormal positive and negative changes and mitigate the effect of outliers.

4. Price data have to be available for the period commencing 200 days prior to the dividend announcement date and ending 1 day after the dividend announcement date.

5. If any other company event is announced (e.g. earnings announcements, stock splits, share repurchases, stoke dividends, right issues, merger and acquisitions) during the event period (t -10, t +10) then those observations are excluded, because they might “contaminate” my results.

6. Shares have to be actively traded. I excluded firms that had no transactions for more than 100 days in the estimation period.[2]

The imposition of these restrictions has produced a sample of 210 firms and 2,783 observations in chapter 5 between January 1990 and December 2015. On the other hand these restriction has produced a sample of 231 firms and 3,621 observations in chapter 6, 7 and 8 between January 1990 and December 2015.

As one of the objectives of this study is to examine the share-price performance of dividend announcements companies, the study would calculate the expected returns using the appropriate methods and would compare these normal returns with actual returns to calculate abnormal returns for dividend announcing firms. To calculate the individual firm’s returns, this study has used daily-adjusted share prices for each individual sample companies. A number of previous studies used monthly share prices to analyze the dividend announcements but using daily share price is more common. Brown and Warner (1985) stated that using daily return data allow a researcher to more effectively isolate the market’s reaction to a particular event with a known event date. Later Lubatkin (1987) point out that daily return data allow abnormal returns to be computed over short horizons (for example, Seiler (2004) said that the average estimation period in case of monthly data is five years and the

[2]It is well known that the thin trading problem can result in biased estimations of the market model parameters (Brown and Warner, 1985).

average for daily data is no more than one year). The shorter the horizon, the less likely that the estimated returns will be biased by peripheral events. The longer the horizon, the more likely that the estimated returns will be biased by extraneous events.

It is important to keep in mind that the sample in this study is not free from the survivorship bias. Survivorship bias is the tendency for failed companies to be excluded from the performance studies due to the fact that they no longer exist. Survivorship bias causes the results of some studies to skew higher because only companies which were successful enough to survive until the end of the period are included.

4.5.3. SOURCES OF DATA

To conduct this study I have collected data from several sources, the main source for orthodox finance data was Bloomberg, and for the behavioral finance data I have used two sources and they are the Department for Environment, Food & Rural Affairs, and Weather Forecast and Reports. Share price data was collected from Bloomberg database, which is a specialized database for daily share prices of various listed companies in the UK. The daily data on LSE FTSE-350 share price index was also collected from Bloomberg database. Information on announcement of any significant events for each of the companies including dividend announcements was collected from Bloomberg. Income statement data, balance sheet data or any other accounting data for the final sample firms has been collected from Bloomberg.

4.6. DATA ANALYSIS

To reach the aims of the study mentioned in the previous sections, it is important to collected an appropriate set of data. And after collecting all the data, the next job is to analyse those data using relevant and appropriate set of statistical procedure. This current study followed various statistical procedures that were used in previous studies to analyze the collected data. To accelerate the analytical procedure, I have used STATA software package. STATA is a very well-known and widely used software package in business research. In addition to the STATA software package, Microsoft Excel was also used to organise and to sort the data. This section will outline the specific statistical analytical procedures that have been followed in the study to reach the main objectives of this study.

4.6.1. ANALYSIS OF SECONDARY DATA

At the beginning of this study all independent and depended variables have been assessed by using descriptive statistics tools. To reach the final goal of this study several regression models were estimated. Details of choice of independent variables and control variables based of available literature and relevant hypotheses along with appropriate statistical analysis are given in chapter 5 and chapter 6.

Performance of the dividend announcements decisions has been measured by using both objective and subjective measures. With the objective measures, one popular way of measuring dividend announcement firm performance is to examine the stock price changes of the dividend announcement firms around the dividend announcement period. The methodology used on this type of performance measure is called an event-study and this has been widely used in finance literature. The second objective measure, which is widely used in the industrial organization literature, is to compare various accounting profitability measures for the dividend announcement firms before the and after the dividend announcement period. Alongside the objective measures of the dividend announcements performance, there are some subjective measures of performance that have been used to assess the dividend announcement performance. Even though there exist some subjective measures of performance most of the dividend announcements related research has employed objective measures of performance, and I will do the same in my thesis.

In chapter 5 I use the dividend-signalling theory and some standard dividend signalling models. The models I use in chapter 5 were first used by Nissim and Ziv (2001) and the later models were modified by Grullon et al. (2005). In chapter 5 I use linear models and nonlinear models. On the other hand in chapter 6, 7 and 8 I use only linear models and the event study methodology. The event study methodology is a very popular method in the finance literature. Event study methodology is popular to examine the share price performance during the dividend announcement period. In this regard, Lubatkin and Shrieves (1986) pointed out that the stock price represents the only direct measure of stockholder value and it encompasses all relevant information aspects of firm performance and also evaluates the risk-adjusted performance of the firm.

Chapter 6, 7 and 8 in this thesis use the event study method of analysing stock price based performance of the UK FTSE-350 firm's dividend announcement. Event study methodology is very popular method of evaluating stock price reaction to a variety of firm specific and economic events such as dividend announcements, mergers and acquisitions, earnings announcements, issues of new debt or equity, announcements of regulatory changes and announcements of macroeconomic variables such as the trade deficit (Campbell, Lo and MacKinlay, 1997). The current version of the method was reintroduce by Ball and Brown (1968) and Fama, Fisher and Roll (1969)[3] who examined the information content of earnings and the impact of stock splits on share prices respectively. Event study methodology is used in this study to identify event date, event window and estimation period, the selection of an appropriate model and the procedure to calculate returns and testing their significance are discussed in chapters 6, 7 and 8.

In this thesis, in chapter 5, 6, 7 and 8 I employ panel data. In chapter 5 I use a variety of dependent variables, while in chapter 6,7 and 8 I use $CAR_{-1,+1}$ as my dependent variable in the main empirical analysis and $CAR_{0,+1}$ in the robustness tests. The set of independent variables is chosen based on my examination of the available literature and is described in chapters 5, 6, 7 and 8.

4.7. CONCLUSION

This chapter described the research design used in the thesis. The main concentration was on research philosophy, choice of methodology, data collection and data analysis. Considering the nature of research, this piece of work has been carried out with a positivist approach using quantitative methodology. For the purpose of analysis, only secondary data has been used. For the purpose of analysis, this thesis has collected secondary data from appropriate sources based on selected restrictions imposed on choosing the sample events. Orthodox finance methodology and event

[3] Some researchers have claimed that Fama, Fisher, Jensen and Roll have introduced event study methodology in the year 1969 (e.g. Binder, 1998). But Campbell, Lo and MacKinlay (1997) indicated that the first published article using event study was written by Dolley (1933) who examined the price effect of stock spit. Bowman (1983) has indicated that Ashley (1962) conducted an event study to see the stock price reaction to changes in earnings and dividends.

study methodology is used as the primary analytical tool to investigate the LSE FTSE-350 firms dividend announcements. In addition, in this study accounting information has also been used. The study has used appropriate statistical tests to find out the level of significance of the results using suitable statistical packages. The following empirical chapters give more details about each chapter's methodology.

5 DIVIDEND CHANGES AS PREDICTORS OF FUTURE PROFITABILITY

5.1. INTRODUCTION

Whether dividend changes can predict future profitability is one of the important questions in finance. For companies dividends act as an important conveyor of information. According to Lintners' (1956) seminal work on dividend policy firms only increase dividends when management thinks that earnings have permanently increased, which means that a dividend increase implies a rightward shift in distribution of earnings. Later Miller and Modigliani (1961) established "the information content of dividend hypothesis". According to this theory, dividend changes trigger changes in stock prices because they convey new information about the firm's future earnings and profitability. Event studies that evaluate dividend changes announcements and related responses in the stock market (Pettit, 1972; Aharony and Swary, 1980; Dielman and Oppenheimer, 1984) show that dividend increase result in positive abnormal returns for the corresponsing firms. This means that the market considers dividend-increase announcements as a positive signal regarding the firm's future earnings and therefore about the value of the firm's shares.

In this chapter my main aim is to find out whether there is any evidence that dividend changes predict future firm profitability. There are a number of studies available where researchers have tried to answer this question and different studies have found different results. Most of the research conducted in this area was based on US data. To the best of my knowledge no studies has been conducted on UK data. To conduct this research I will use data for a sample of firms included in the UK FTSE-350 index. The sample period that I consider is 26 years long.

In this chapter I use two different types of linear and non-linear model specifications based on the dividend-signalling theory and previous literature. My first model specification is an interaction model (linear and nonlinear), which is based on previous literature (Nissim and Ziv, 2001 and Grullon, Michaely, Benartzi and Thaler, 2005). My second model specification is a binary (linear and nonlinear) model specification, which is a partially novel model specification. My main contribution to the literature is that, using a UK data set and a binary (linear and non-linear) model specification, which is a partially novel model specification, I found very weak evidence that dividend decreases tend to be followed by earnings decreases two years later, and most of my results do not provide support for the dividend-signalling theory.

If we look at previous studies in this area then we can see that researchers were unable to reach a unified conclusion. Griffin (1976), Charest (1978), and Nissim and Ziv's (2001) research suggests that dividend changes convey information about the firm's future earnings and profitability. Studies by Watts (1973), Gonedes (1978), Penman (1983), DeAngelo, DeAngelo, and Skinner (1996), Benartzi, Michaely, and Thaler (1997), Grullon, Michaely, and Swaminathan (2002) and Grullon, Michaely, Benartzi and Thaler (2005) find little or no evidence that dividend changes predict abnormal increases in earnings.

Initially I will conduct my study using Nissim and Ziv (2001) and Grullon, Michaely, Benartzi and Thaler's (2005) method, which is my first model specification (linear interaction model specification) and then I will use a second model specification (linear binary model specification). In cross-sectional regressions after controlling for ROE (Return on Equity), I have not found any evidence that dividend changes are positively correlated with future firm earnings in the linear interaction model specification and in the linear binary model specification. On the other hand, I also run the same cross-sectional regression after controlling for nonlinear earnings patterns, and my results are similar in that the relation between dividends changes and future earnings disappears when I use the interaction model specification, but there is minor evidence that dividend-decrease announcements predict future earnings decreases according to the binary model specification. However, for robustness purposes, when I run a cross-sectional regression using Grullon et al.'s (2005) linear and nonlinear interaction model, to find out the relation between dividend changes and future earnings after controlling for ROE, I show that dividend changes are not significantly positively correlated with future earnings. These results are similar in the linear and nonlinear binary model.

The rest of this chapter is organized in the following way, where in the section 5.2 I present a literature review and in the section 5.3 I describe the testable hypothesis. Section 5.4 discusses the methodology, while section 5.5 describes the data. In section 5.6 I documented the empirical analysis and in section 5.7 I conduct a robustness test. Section 5.8 and 5.9 offer a general discussion and a conclusion, respectively.

5.2. LITERATURE REVIEW

The basis of the dividend-signalling theory derives from a study by Lintner (1956), in which 28 companies' managers were interviewed to find out which factors were most instrumental in firms' payout policies. Lintner was convinced that dividends are not only important for the amount of cash needed to finance projects in short-term, but they also show managers confidence over the sustainability of company earnings in the long-term. For that reason managers tended to increase or initiate pay-outs only when they believed that subsequent earnings would be high. John and Williams (JW) (1985) and Miller and Rock (1985) found evidence that the level of dividends provides signals about the level of a firm's cash flows.

According to Bhattacharya (1979) and Miller and Rock (1985), dividend changes signal future profitability. Higher dividend payments signal higher earnings and vice-versa. Benartzi, Michaely, and Thaler's (1997) findings suggest that the earnings growth rates of firms that increase dividends do not subsequently increase. On the other hand, Watts (1973) and Gonedes (1978) report that firms that decrease dividends experience significant decrease in earnings growth rates in the two years following the dividend decrease. Watts (1973) and Gonedes's (1978) findings and Grullon, Michaely, and Swaminathan's (2002) findings contradict the central supposition of the dividend information/signaling models, namely that dividend changes signal changes in profitability in the same direction.

Empirical evidence suggests that investors pay attention to dividend increases and initiations; the stock prices of firms that initiate dividends tend to increase around the time of the initiation announcement (Asquith and Mullins, 1983; Healy and Palepu, 1988). Similarly, the signaling theory implies that any subsequent decrease or elimination of dividends will be viewed with extreme disfavour by the financial markets (Healy and Palepu, 1988; Michaely et al., 1995; Benartzi et al., 1997).

DeAngelo et al. (2004) find that the cumulative level of real dividends has been increasing but dividends have become increasingly concentrated instead of widely distributed. According to the signaling theory, by paying dividends companies send a positive signal to the capital markets about their high future cash flows and profits, and this signal represents a message (c.f. Lintner, 1956) that the initiation of dividends represents a commitment to sustained payments. Therefore, the firms that are expected to generate higher future cash flow and pay dividends are the firms that are most rewarded by investors at the time of the initiation announcement.

When many researchers suggested that company managers use dividends to signal their views of future earnings prospects (Miller and Modigliani, 1961; Bhattacharya, 1979; John and Williams, 1985; and Miller and Rock, 1985), DeAngelo *et al.* (1996) tried to assess the empirical importance of dividend signalling in a sample of 145 NYSE firm's whose annual earnings decline after nine or more years of continuous growth. DeAngelo *et al.* (1996) used a variety of models and definitions but their tests yield no indication that favourable dividend decisions represent reliable signals of superior future earnings performance for those firms. DeAngelo *et al.* (1996) present a variant of the dividend-signalling hypothesis in which dividend decisions conform to a separating equilibrium: managers of good prospect firms use dividend increase as differentiator with other firms in similar situation which have less good prospects.

After analysing the sample of 145 NYSE firms DeAngelo *et al.* (1996) explore the six reasons why a firm's favourable dividend actions do not signal future prospects:

1. Current earnings are so informative about future earnings that there is little additional useful signalling content to non-earnings sources.
2. Managers reduce capital outlays, so that the dividend increases are primarily free cash flow payoffs rather than favourable signals about future earnings.
3. The dividend increases are lagged responses to prior earnings increases, not favourable signals about future earnings.
4. Managers mistakenly send favourable dividend signals, but these mistakes are

understandable given the information available at the time.

5. Because managers tend to be overly optimistic about company growth, they send signals that are overly optimistic about future earnings.
6. Managers make only modest cash commitments when they increase dividends, which undermine the reliability of such signals.

DeAngelo *et al.* ‘s (1996) findings do not support (1) to (3), but support (5) and (6) and perhaps (4) can help explain their findings. DeAngelo *et al.*’s (1996) research offers almost no support for the signalling hypothesis.

Hobbs and Schneller’s (2012) findings are an extension of DeAngelo and DeAngelo’s (1990) findings to dividend omissions[4], but their findings show no evidence that dividends signal a rosy future for the firms that initiate them, which is consistent with Grullon et al. (2005), who find little correlation between changes in dividends and subsequent firm profitability. Hobbs and Schneller (2012) show that permanent payers firms are doing better than temporary payers, even though this finding is not true in all the cases, because there is evidence that dividend sustainability is directly related to future performance. The important implication is that firms try to obtain correct market valuation through dividend signalling, but only when shares of equity have to be sold in the market, either by insiders to satisfy personal cash needs or by the firm to raise investment capital. Then the dividend level will signal firm quality and result in the correct valuation of the firm’s shares.

[4] A dividend omission is when a firm would have ordinarily declared and paid but decided against doing so for a certain period of time. For example, a firm usually paid dividend annually but they decided one year they will not going to pay dividend and will hold the dividend.

5.3. TESTABLE HYPOTHESIS

My null hypothesis is that dividend changes do not convey new information about future earnings. If I reject the null hypothesis then it means there is significant evidence that dividend changes convey new information about future earnings during the examined period, which (depending on the sign) could support the dividend-signalling theory. Alternatively if I fail to reject the null hypothesis, then it means there are no evidence that dividend changes convey new information about future earnings, which does not support the dividend-signalling theory. The null and alternative hypotheses are as follows:

H_0: Dividend changes do not contain information about future earnings.

H_a: Dividend changes contain information about future earnings.

5.4. METHODOLOGY

Miller and Modigliani (1961) developed a theory called "information content of dividend (ICD) hypothesis". According to this theory, dividend changes trigger an increase (decrease) in stock returns because they convey new information about the firm's future profitability and cash flows. Event studies that assess dividend change announcements and associated responses in the stock market (Pettit, 1972; Aharony and Swary, 1980; Asquith and Mullins, 1983; Dielman and oppenheimer, 1984) show that dividend increases result in positive abnormal returns. Many researchers agree with this theory including Nissim and Ziv (2001), who find that dividend changes are correlated with future earnings and profitability. On the other hand many researchers including Grullon, Michaely, Benartzi and Thaler (2005) and Choi, Ju, and Park

(2010) found no relation or only partial relation between dividend changes and future firm profitability.

Most previous researchers have assumed that earnings follow a random walk with drift, and measured unexpected profitability as the realized difference between earnings and the estimated drift, and then they examined the association between dividend changes and unexpected future earnings. According to Nissim and Ziv (2001), this is the wrong model and that is the reason why previous research failed to find the true correlation between dividend changes and future earnings profitability. Nissim and Ziv (2001) first used a similar approach and found the same result that previous researchers found, that dividend changes are not positively related with future earnings changes. Then Nissim and Ziv (2001) used a regression analysis that controls for a particular (linear) form of mean reversion in earnings, which resulted in the finding that dividend changes are positively correlated with future earnings changes and profitability.

However, Grullon et al. (2005) argue that Nissim and Ziv's (2001) assumption of linear mean reversion in earnings is inappropriate, because the mean reversion process of earnings is highly nonlinear (see Brooks and Buckmaster 1976; Elgers and Lo 1994; and Fama and French 2000.). To prove that Grullon et al. (2005) corrected the nonlinear evolution in earnings using the modified partial adjustment model proposed by Fama and French (2000), which assume that the rate of mean reversion and the coefficient of auto-correlation are highly nonlinear. After using that model they (Grullon et al.; 2005) found that dividend changes cannot forecast future earnings changes. In this chapter I will use the same model used by Nissim and Ziv (2001) and Grullon et al. (2005) and a partially novel model (binary model) to analyse UK data and I will try to find out whether dividend changes can forecast future earnings.

To calculate $R\Delta DIV$, which refers to the percentages change in dividends, I use Benartzi et al.'s (1997) formula

$$R\Delta DIV_0 = \frac{DIV_0 - DIV_{-1}}{DIV_{-1}} \quad (1)$$

Where DIV_0 represents the dividend paid in the base year or year 0 and DIV_{-1} is the dividend paid in the previous year. Two models will be empirically tested. Model number one is an interaction model (linear and non-linear) and model number two is a binary (linear and non-linear) model. I will call my first model interaction model, which is based on Nissim and Ziv's (2001) and Grullon et al.'s (2005) linear and nonlinear models and I will call my second model the binary model, which is a partially novel model. The reason why I use two models is that the interaction model takes into account both dividend change size and direction, while the binary model only focuses on the dividend change direction. In this chapter I use pooled OLS regression analysis[5].

(a) Baseline linear model

According to Nissim and Ziv (2001), if there is a drift and if one considers only earnings information then the expected changes in earnings may be zero or constant. According to many previous researchers, an important predictor of earnings changes is the ratio of earnings to the book value of equity (ROE) (Freeman, Ohlson and Penman, 1982). In my first linear regression, I use the percentage change in dividends ($R\Delta DIV_0$) and the previous year's ROE (ROE_{it-1}) as independent variables

[5] Future research may also want to use pooled OLS regressions with year- and firm-fixed effects, which is what Nissim and Ziv (2001) did in their robustness tests in their section C.1.

and earnings changes as the dependent variable, to assess the basic relation between dividend changes and future earnings changes.

I use earnings before extraordinary items to calculate the earnings changes and the basic specification used in Nissim and Ziv (2001), with one key difference. Nissim and Ziv (2001), Grullon et al. (2005) and Choi, Ju, and Park's (2010) results suffer from a look-ahead bias when T=2[6]. This means they use ROE as control variable in Year 1, which is unknown in Year 0. But I use ROE in Year 0 instead of the ROE in Year 1 as a control variable to run my equation (2), in which E_t denotes the earnings in year t, B_{-1} is the book value of equity at the beginning of the year (or the end of the previous year), ROE_{t-1} is the return on the book value of equity at $t-1$ for T=1 (that is, one year ahead) and $t-2$ for T=2 (that is, two years ahead), and $R\Delta DIV_0$ is the percentage change in dividends in the year of the dividend change (1990-2015). As control variable I use ROE in equation (2). According to Freeman *et al.* (1982), the return on the book value of equity (ROE=*E/B*) is a significant predictor of the changes in earnings.

$$(E_t - E_{t-1})/ B_{-1} = \alpha_0 + \alpha_1 ROE_{t-1} + \alpha_2 R\Delta DIV_0 + \xi_t \qquad (2)$$

Where E_t denotes the earnings in year t (year 0 is the event year). To test the above hypothesis I use UK data for the period between 1990 and 2015.

(b) Interaction specification

The interaction model will take into account both dividend change size and

[6] Look –ahead bias: The standard look-ahead bias refers to the use of information in a simulation that would not be available during the time period being simulated, usually resulting in an upward shift of the 2 results. An example is the false assumption that earnings data become available immediately at the end of a financial period.

direction. The interaction model specifications have two different types of interaction terms, one for the positive dividend change group and one for the negative dividend change group. In this chapter I will use both a linear and a non-linear interaction model, which have been already used in the previous literature (Nissim and Ziv, 2001; Grullon et al., 2005 and Choi, Ju, and Park, 2010).

To establish a baseline, I first examine the relation between dividend changes and future earnings changes using the linear model of earnings expectation. Due to that reason I have started with Nissim and Ziv's (2001) linear model to see whether their results hold in my sample. Especially, I estimate the following model (equation 3) that allows for asymmetric reactions to dividend increases and decreases:

$$(E_t - E_{t-1})/B_{-1} = \alpha_0 + \alpha_1 ROE_{t-1} + \alpha_2 (E_0 - E_{-1})/B_{-1} + \alpha_{3p} DPI_0 \times R\Delta DIV_0 + \alpha_{3n} DPD_0 \times R\Delta DIV_0 + \xi_t \tag{3}$$

Where E_t is earnings before extraordinary items in year t (year 0 is the event year), E_0 is the earnings before extraordinary items in year 0 (the event year), E_{-1} is the earnings before extraordinary items in year -1, B_{-1} is the book value of equity at the end of year -1, $R\Delta DIV_0$ is the annual percentage change in the cash dividend payment in year 0, DPI (DPD) is a dummy variable that takes the value of 1 for positive (negative) dividend changes and 0 otherwise, ROE_{t-1} is equal to earnings before extraordinary items in year *t-1* for T=1(T=1 refers to the following year's changes in earnings) and *t-2* for T=2 (T = 2 refers to the changes in earnings in two years' time) scaled by the book value of common equity at the end of year *t-1* for T=1 and *t-2* for T=2, means in here ROE_{t-1} is measured as E_{t-1}/B_{t-1} and B denotes the book value of common equity[7]. And $(E_0 – E_{-1})/B_{-1}$ is a control variable[8].

Nissim and Ziv (2001) explain that the relationship between dividend changes and future earnings is positive and significant; their linear model assumes that earnings follow a uniform mean reversion process and their autocorrelation is linear. But many previous studies, including those of Elger and Lo (1994) and Fama and French (2000), have argued that the mean reversion process and the level of autocorrelation in the earnings process are nonlinear. According to them mean reversion is faster for larger changes than for small changes and faster for negative changes than for positive changes in earnings. Therefore, Grullon et al. (2005) suggest an alternative nonlinear specification to control for the potential nonlinearity in the earnings process, as shown in the following equation (equation 4).

$$\begin{aligned}(E_t – E_{t-1})/ B_{-1} = \beta_0 &+ \beta_{1P}DPI_0 \times R\Delta DIV_0 + \beta_{1N}DPD \times R\Delta DIV_0 + (\Upsilon_1 + \Upsilon_2 NDFED_0 \\ &+ \Upsilon_3 NDFED_0 \times DFE_0 + \Upsilon_4\, PDFED_0 \times DFE_0) \times DFE_0 \\ &+ (\lambda_1 + \lambda_2 NCED_0 + \lambda_3 NCED_0 \times CE_0 + \lambda_4 PCED_0 \times CE_0) \times CE_0 \\ &+ \xi_t \qquad (4)\end{aligned}$$

Where DFE_0 is equal to $ROE_0 – E[ROE_0]$, where $E[ROE_0]$ is the fitted value from the cross-sectional regression of ROE_0 on the logarithm of total assets in year -1, the logarithm of the market-to-book ratio of equity in year -1, and ROE_{-1}. $E[ROE_0]$ captures the expected return on equity in year 0 (year 0 is the event year). CE_0 is equal to $(E_0 – E_{-1})/B_{-1}$, $NDFED_0$ ($PDFED_0$) is a dummy variable that takes the value of 1 if DFE_0 is negative (positive) and 0 otherwise, and $NCED_0$ ($PCED_0$) is a dummy

[7] In measuring ROE I follow the Nissim and Ziv (2001) measurement, where I set the book value of equity equal to 10 percent of total assets whenever it was less than that amount.

[8] It would also be interesting to add equity sales as a control variable, given that, according to Hobbs and Schneller (2012), firms try to obtain correct market valuations through dividend signaling only when shares of equity have to be sold in the market. I did not have access to such data, but future research could try to shed light on this issue.

variable that takes the value of 1 if CE_0 is negative (positive) and 0 otherwise.

The following two equations (equation 5 and 6) test the correlation between dividend changes and future earnings level (earnings level scaled by the book value of equity, i.e. ROE). The specification using earnings levels provides an alternative way to examine the relation between earnings and dividend changes. I use the specifications proposed by Grullon et al. (2005) mainly to ensure that my results are robust to alternative specifications; but I am aware that they may be problematic from a statistical point of view as there may be, among other things, a unit root problem. The specifications proposed by Grullon et al. (2005) are:

$$ROE_t = \beta_0 + \beta_{1p} DPI \times R\Delta DIV_0 + \beta_{1N} DPD \times R\Delta DIV_0 + \beta_2 ROE_{t-1} + \beta_3(ROE_0 - ROE_{-1}) + \beta_4 MB_{-1} + \beta_5 SIZE_{-1} + \xi_t \quad (5)$$

Where MB_{-1} is the logarithm of the market-to-book ratio of equity in year -1. $SIZE_{-1}$ is the logarithm of total assets in year -1.

$$ROE_t = \beta_0 + \beta_{1P} DPI_0 \times R\Delta DIV_0 + \beta_{1N} DPD \times R\Delta DIV_0 + (\Upsilon_1 + \Upsilon_2 NDFED_0 + \Upsilon_3 NDFED_0 \times ROE_0 + \Upsilon_4\, PDFED_0 \times ROE_0) \times ROE_0 + (\lambda_1 + \lambda_2 NCED_0 + \lambda_3 NCED_0 \times CE_0 + \lambda_4 PCED_0 \times CE_0) \times CE_0 + \varphi_1 MB_{-1} + \varphi_2 SIZE_{-1} + \xi_t \quad (6)$$

Where CE_0 is equal to $(ROE_0 - ROE_{-1})$.

(C) Binary specification

In the binary model one dummy captures the effect of positive dividend changes and the other one captures the effect of negative dividend changes. The use of this binary model is motivated by two reasons. First, it is possible that what really matters (i.e. the signal being sent by managers) is whether the dividend is being increased or decreased rather than the size of such a change. The binary model ignores the size of the dividend changes and focuses on the direction alone, i.e. whether dividends increase or decrease regardless of the size of the changes. Therefore, the linear binary model complements the linear interaction model. Second, the binary model may further mitigate the impact of outliers on the results. And in equation 6, the omitted dummy represented by the intercept captures companies for which $R\Delta DIV_{it}$= 0, which means there is no change in dividends.

Equation 7 and 8 are similar to equation 3 and 4 but the only difference is that equation 7 and 8 ignore the size of the dividend changes and focus on the direction alone.

$$(E_t - E_{t-1})/B_{-1} = \alpha_0 + \alpha_1 ROE_{t-1} + \alpha_2 (E_0 - E_{-1})/B_{-1} + \alpha_{3p} DPI_0 + \alpha_{3n} DPD_0 + \xi_t \quad (7)$$

$$(E_t - E_{t-1})/B_{-1} = \beta_0 + \beta_{1P} DPI_0 + \beta_{1N} DPD + (\Upsilon_1 + \Upsilon_2 NDFED_0 + \Upsilon_3 NDFED_0 \times DFE_0 + \Upsilon_4 PDFED_0 \times DFE_0) \times DFE_0 + (\lambda_1 + \lambda_2 NCED_0 + \lambda_3 NCED_0 \times CE_0 + \lambda_4 PCED_0 \times CE_0) \times CE_0 + \xi_t \quad (8)$$

Equation 9 and 10 are similar to equation 5 and 6 but the only difference is that equation 9 and 10 ignore the size of the dividend changes and focus on the direction alone.

$$ROE_t = \beta_0 + \beta_{1p}DPI + \beta_{1N}DPD + \beta_2 ROE_{t-1} + \beta_3(ROE_0 - ROE_{-1}) + \beta_4 MB_{-1} + \beta_5 SIZE_{-1} + \xi_t \qquad (9)$$

$$ROE_t = \beta_0 + \beta_{1P}DPI_0 + \beta_{1N}DPD + (\Upsilon_1 + \Upsilon_2 NDFED_0 + \Upsilon_3 NDFED_0 \times ROE_0 + \Upsilon_4\, PDFED_0 \times ROE_0) \times ROE_0 + (\lambda_1 + \lambda_2 NCED_0 + \lambda_3 NCED_0 \times CE_0 + \lambda_4 PCED_0 \times CE_0) \times CE_0 + \varphi_1 MB_{-1} + \varphi_2 SIZE_{-1} + \xi_t \qquad (10)$$

All the above models are estimated using pooled OLS regressions, as in Nissim and Ziv (2001). For statistical inference I will also show cluster-robust standard errors for both models, which generalize those proposed by White (1980) for independent heteroscedastic errors. I show clustered standard error to control for within-cluster error correlation, which can lead to misleadingly small standard errors, and consequently misleadingly narrow confidence intervals, large t-statistics and low p-values. Following Petersen's (2009) and Thompson's (2011) suggestions about estimating standard errors in finance panel data sets, I employ multi-way clustering: more specifically, standard errors are clustered by firm and date. I cluster the standard errors by firm because the error terms may be serially correlated, and I cluster the standard errors by date because the error terms may be correlated across firms at the same point in time.

5.5. DATA

The data sample in this chapter is composed of firms listed in the London Stock Exchange (LSE), more specifically belonging to the FTSE-350 index for the period between 1990 and 2015. The selected firms are the current constituents of the FTSE-350 (at the time when the data were collected). I collected all the data from Bloomberg between June 2016 and August 2016. The sample selection criteria are explained below.

5.5.1. SAMPLE SELECTION CRITERIA

The sample selection criteria are as follows:

1. Only final dividend announcements are included, and all other interim dividend and stock dividend announcements are excluded[9].
2. Companies in the financial and utility industries are excluded, because these two industries keep their financial records in a different way than other industries (Claessens and Laeven, 2006, p 111). For the financial industry, profitability and valuation data are difficult to calculate and compare with firms in other industries. For the utility industry profitability and valuation can be strongly influenced by government regulations (Claessens and Laeven, 2006, p 111).
3. Dividend changes are between +50% to – 50% to avoid abnormal positive and negative changes and minimize the impact of outliers.

I collected dividend announcements data for all FTSE-350 companies from January 1990 to December 2015. More specifically, the firms included in the sample are the constituents of this index in June 2016. Even though my research focuses on the FTSE-350, the final sample contains data about only 210 firms. Some of the data is not available from January 1990; due to that reason some of the firms have more observations than others. For some of the companies listed in the FTSE-350, the

[9] It is possible that there is some information leakage when interim dividends are announced. However, the results in chapter 6 reveal that stock prices do react to the information contained in final dividend announcements, and so the analysis in chapter 5 is aimed at examining whether final dividend announcements contain information about the future trajectory of earnings.

dividend announcement information was missing on Bloomberg, and consequently I had to exclude 140 companies from my final sample. After applying all the above sample selection criteria I have 210 firms in my sample and I have 2,783 annual observations.

5.5.2. DESCRIPTIVE STATISTICS

In this chapter I use annual data, because arguably dividends are set in response to annual rather than quarterly or semi-annual earnings (Watts, 1973). Table 1 includes 2,783 observations: 2,282 dividend increases, 151 dividend decreases and 350 unchanged dividends.

TABLE 1 FREQUENCY OF FRIM-YEAR OBSERVATIONS BY FINANCIAL YEAR

Year	Dividend Increase	Dividend Decrease	Unchanged Dividend	Total
1990	12	1	1	14
1991	36	0	11	47
1992	38	8	10	56
1993	43	9	11	63
1994	69	2	3	74
1995	71	1	11	83
1996	93	1	9	103
1997	98	2	12	112
1998	106	8	6	120
1999	103	6	15	124
2000	129	7	9	145
2001	123	7	20	150
2002	107	12	23	142
2003	116	6	31	153
2004	134	9	19	162
2005	148	5	16	169
2006	135	10	14	159
2007	121	3	12	136
2008	101	10	16	127
2009	55	10	25	90
2010	57	9	20	86
2011	76	5	11	92
2012	81	5	9	95
2013	83	4	13	100
2014	74	5	15	94
2015	73	6	8	87
Total	2,282	151	350	2,783

Note: This table reports the numbers of dividend increases, decreases and constant dividend.

Table 2 represents some descriptive statistics for the whole data sample. Table 2 has 4 different panels. The conditional mean of *RΔDIV* is +13.422% for the dividend increase group and -22.238% is for the dividend decrease group. The kurtosis statistic shows positive signs in both the dividend increases and decrease panels, but the skewness statistic shows a positive sign in the dividend increase panel and a negative sign in the dividend decrease panel. The mean value of the return on equity in the whole sample is +139.844%, the standard deviation value is +92. 531% and the minimum and maximum values are -60.494% and 755.261% respectively. Table 2 shows that Book Value of Equity features a very high kurtosis value, i.e. its distribution features wildly fat tails. This fact is of no concern for regression equations 3-10, as the linear regression model "makes no distributional assumptions about the Xs, other than independence between the Xs and the errors" (Fox, 2015).

TABLE 2 DESCRIPTIVE STATISTICS FOR DIVIDEND EVENT OBSERVATION

Panel A: Whole Sample (*N*= 2,783)

Variable	***N***	**Mean**	**Std.Dev.**	**Min.**	**Max**	**5%**	**25%**	**75%**	**95%**	**Skewness**	**Kurtosis**
Market capitalization (£ billion)	2,627	7.121	1.427	0.666	12.061	4.974	6.133	8.049	9.739	0.263	3.122
ROE (%)	2,782	139.844	92.531	-60.499	755.261	0	86.291	182.117	307.409	1.271	6.926
Book Value of Equity (£ billion)	2,783	0.574	1.9790	0.005	27.802	0.012	0.049	0.332	2.446	8.022	80.156
RΔDIV (%)	2,783	9.799	12.861	-50.00	50.00	-1.510	4.00	15.275	30.769	-0.723	8.075

Panel B: Dividend Increase (*N*= 2,282)

Variable	***N***	**Mean**	**Std.Dev.**	**Min.**	**Max**	**5%**	**25%**	**75%**	**95%**	**Skewness**	**Kurtosis**
Market capitalization (£ billion)	2,166	7.205	1.430	3.008	12.061	5.055	6.185	8.120	9.829	0.315	2.909
ROE (%)	2,281	141.439	91.845	-60.499	684.194	0	88.420	183.273	314.600	1.140	5.880
Book Value of Equity (£ billion)	2,282	0.562	1.937	0.005	27.802	0.012	0.049	0.342	2.446	8.671	93.241
RΔDIV (%)	2,282	13.422	9.370	0.0114	50.00	3.101	7.014	17.241	33.333	1.535	5.634

Panel C: Dividend Decrease (*N*= 151)

Variable	*N*	Mean	Std.Dev.	Min.	Max	5%	25%	75%	95%	Skewness	Kurtosis
Market capitalization (£ billion)	141	6.988	1.398	3.769	10.956	4.802	6.052	7.970	9.337	0.216	2.853
ROE (%)	151	126.351	79.640	-38.459	400.366	0	79.428	164.589	275.922	0.629	3.861
Book Value of Equity (£ billion)	151	43.145	1.195	0.007	11.277	0.015	0.050	0.279	1.741	6.372	51.323
RΔDIV (%)	151	-22.238	16.597	-50.00	-0.011	-49.927	-39.128	-6.456	-0.842	-0.259	1.587

Panel D: Unchanged Dividends (*N*= 350)

Variable	*N*	Mean	Std.Dev.	Min.	Max	5%	25%	75%	95%	Skewness	Kurtosis
Market capitalization (£ billion)	350	6.615	1.314	0.666	10.342	4.616	5.809	7.316	8.805	-0.268	4.324
ROE (%)	350	135.269	101.366	-31.459	755.262	0	72.242	184.413	284.189	2.021	11.872
Book Value of Equity (£ billion)	350	0.714	2.459	0.006	19.281	0.014	0.051	0.262	3.684	5.219	31.581
RΔDIV (%)	350	0	0	0	0	0	0	0	0	-	-

Note: This table reports the firm characteristic for the sample firms. $R\Delta DIV_t$ is the annual change in the cash dividend payment. Market capitalization is the market value of equity. Book value of equity is the book value of equity. ROE is equal to earnings before extraordinary items scaled by the book value of equity. The values of all financial variables are determined at the beginning of the year of the announcement.

5.6. EMPIRICAL RESULTS

5.6.1. LINEAR BASELINE MODEL OF EARNINGS EXPECTATIONS

In the remaining sections of this chapter, all the estimations are based on pooled OLS regressions. Following Nissim and Ziv's (2001), I did not use year- and firm-fixed effects. Unlike Nissim and Ziv's (2001), who used White (1980) standard errors and also the Fama and MacBeth (1973) procedure, I followed Petersen (2009) and Thomson (2011) and I computed cluster-robust standard errors.

Table 3 presents the results from regression equation (2). The average value of earnings changes in T=1 (1 year ahead) is +5.459% and in T=2 (2 years ahead) is +13.289%. This model demonstrates that the regression coefficient on $R\Delta DIV_0$ is α_2= -16.289% when T=1, which is negative but statistically insignificant and α_2= +11.449% when T=2, which is also statistically insignificant. α_2 is economically insignificant but positive in year 2. The regression coefficient on ROE_{t-1} is α_1= -7.601% when T=1 and α_1= +11.906% when T=2. In both time periods ROE_{t-1} is statistically insignificant. α_0 shows a positive sign in year 1 (that is, one year ahead) and negative sign in year 2 (that is, two years ahead). The results also show a very low R^2 value.

TABLE 3 REGRESSIONS OF RAW EARNINGS CHANGES ON DIVIDEND CHANGES (BASELINE MODEL)

$$(E_t - E_{t-1})/ B_{-1} = \alpha_0 + \alpha_1 ROE_{t-1} + \alpha_2 R\Delta DIV_0 + \xi_t$$

Pooled OLS Regression Coefficients

Year		α_0	α_1	α_2	R^2	*N*
T=1	Point Estimate	0.17754[b]	-0.07601	-0.16289	0.06%	2,370
	t-statistics	2.06	-1.01	-0.40		
	Standard error	0.08615	0.07516	0.40478		
T=2	Point Estimate	-0.04607	0.11906	0.11449	0.06%	2,165
	t-statistics	-0.60	0.94	0.46		
	Standard error	0.07663	0.12670	0.24625		

Note: This table reports estimates of regressions relating raw earnings changes to dividend changes. E_{it} denote the earnings in year *t* (year 0 is the event year), B_{-1} is the book value of equity at the end of the year -1, ROE_{it-1} is the return on the book value of equity at *t-1* for T=1 (that is, one year ahead) and *t-2* for T=2 (that is, two years ahead) ROE_{t-1} is measured as E_{t-1}/B_{t-1} and B denotes the book value of common equity, and $R\Delta DIV_0$ is the rate of dividend changes in the year of dividend change (*t*=0). Standard errors are clustered by firm and date. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the 1%, 5% and 10% level, respectively.

According to this baseline model there is no evidence that dividend changes predict future earnings changes. These results suggest that today's dividend changes are not positively correlated with earnings changes over the following two years in the UK market[10]. The results suggest that there is not enough evidence to reject the null hypothesis that current dividend changes do not predict future earnings changes.

5.6.2. INTERACTION MODEL OF EARNINGS EXPECTATION

5.6.2.1. LINEAR INTERACTION MODEL

To establish a baseline, first of all I examine the relation between dividend changes and earnings changes using a linear model of earnings expectations using UK

[10] If I use ROE in *t-1* for T=1 and *t-1* for T=2 as a control variable, my results show no positive relation between earnings changes and dividend changes.

data from 1990 to 2015. I will estimate equation (3) to allow for asymmetric reactions to dividend increases and decreases and control for uniform mean reversion and momentum in earnings. According to Nissim and Ziv (2001) this model assumes that the relation between future earnings changes and past earnings levels and changes is linear.

Table 4 reports the results from equation (3), which shows different results than Nissim and Ziv's (2001) and Choi, Ju, and Park (2010). The linear model shows that dividend changes (dividend decreases) in year 0 are negatively correlated with the following year's earnings changes, but positively correlated with earnings changes two years into the future; however, both coefficients are statistically insignificant. Table 4 reports that current dividend increases are positively correlated with next year's earning changes (T=1) and negatively correlated with earnings changes two year's later (T=2); however both coefficients are statistically insignificant. α_0 shows a positive sign in both years and is statistically significant in Year 1. This result means that, on average, earnings changes are positive in Year 1 (one year ahead) and Year 2 (two years ahead) but only statistically significant in Year 1. The *R2* values are 31.87% and 22.76% respectively in T=1 and T=2. The coefficient on ROE Year 1 is positive and in year 2 is negative, but it is statistically insignificant in both years. Coefficient α_2 is statistically significant at 1% level in Year 1 only.

TABLE 4 REGRESSIONS OF RAW EARNINGS CHANGES ON DIVIDEND CHANGES (LINEAR INTERACTION MODEL)

$$(E_t - E_{t-1})/ B_{-1} = \alpha_0 + \alpha_1 ROE_{t-1} + \alpha_2 (E_0 - E_{-1})/B_{-1} + \alpha_{3p} DPI_0 \times R\Delta DIV_0 + \alpha_{3n} DPD_0 \times R\Delta DIV_0 + \xi_t$$

Pooled OLS Regression Coefficients

YEAR		α_0	α_1	α_2	α_{3p}	α_{3n}	R^2	*N*
T =1	Point Estimate	0.14586[b]	0.06848	-0.54394[a]	0.65781	-0.93847	31.87%	2,370
	t-statistics	2.14	1.27	-2.78	1.12	-1.13		
	Standard error	0.06831	0.05378	0.19544	0.58654	0.82988		
T =2	Point Estimate	0.03004	-0.12226	0.71377	-0.76154	1.07081	22.76%	2,165
	t-statistics	0.42	-1.15	1.47	-0.73	1.10		
	Standard error	0.07161	0.10656	0.48647	1.03686	0.97221		

Note: This table reports estimates of regression relating raw earning changing to dividend changes. E_{it} is the earnings before extraordinary items in year *t* (year 0 is the event year), E_0 is the earnings before extraordinary items in year 0 (the event year), E_{-1} is the earnings before extraordinary items in year -1, B_{-1} is the book value of equity at the end of year -1, $R\Delta DIV_0$ is the annual percentage change in the cash dividend payment in year 0, DPI and (DPD) is a dummy variable that takes the value of 1 for increase (decrease) dividend changes and 0 otherwise, ROE_{it-1} is equal to earnings before extraordinary items in year *t-1* for T=1 (that is, one year into the future) and *t-2* for T=2 (that is, two years into the future) scaled by the book value of equity at the end of year *t-1* for T=1 and *t-2* for T=2, ROE_{t-1} is measured as E_{t-1}/B_{t-1} and B denotes the book value of common equity and $(E_0 - E_{-1})/B_{-1}$ is control variable. Standard errors are clustered by firm and date. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the 1%, 5% and 10% level, respectively.

The pooled OLS regression analysis based on Equation (3) shows that dividend changes provide no information for future earnings changes in the UK market. On the basis of these results I do not have enough statistical evidence to reject the null hypothesis that dividend changes have no predictive power for future earnings changes[11].

[11] If I use ROE in *t-1* for T=1 and *t-1* for T=2, my results are unchanged.

5.6.2.2. NON-LINEAR INTERACTION MODEL

Nissim and ZIv (2001) included the return on equity and past changes in earnings to control for the mean reversion and autocorrelation (e.g., momentum) in earnings. But empirical evidence from Brooks and Buckmter (1976); Elgers and Lo (1994); and Fama and French (2000) indicates that the mean reversion process of earnings and the level of autocorrelation are highly nonlinear. According to them large changes revert faster than small changes, and negative changes revert faster than positive changes.

Grullon et al. (2005) mentioned two alternative methods for controlling for the nonlinearities in the earnings process. The first one is the matched-sample approach, where each firm that changes its dividend is matched to an alternative similar firm that also experienced similar level of earnings and same level of historical pattern in earnings. One would then examine whether the difference in operating performance between the sample firm and the matching firm is related to the dividend changes. Benartzi et al. (1997) and Grullon et al. (2002) used this method in their research paper but neither paper found any evidence that dividend changes predict future changes in earnings.

The second method of controlling for the nonlinearity in the earnings process is regression analysis. According to Grullon et al. (2005), the advantage of regression analysis over the matching sample method is that it allows the researcher to explicitly model the behaviour of future earnings, control for more factors and take advantage of the information contained in the cross-section of earnings. Grullon et al. (2005) use regression analysis to address the nonlinearity of earnings. They use the modified partial adjustment model suggested by Fama and French (2000) as a control for the nonlinearities in the relation between future earnings changes and lagged earnings levels and changes. According to Fama and French (2000), dummy variables and squared terms are designed to solve the nonlinearities in the mean reversion and autocorrelation of earnings. Brooks and Buckmaster (1976) and Elger and Lo (1994) documented that large changes revert faster than small changes, and negative changes revert faster than positive changes.

Table 5 shows the re-estimated coefficients of the nonlinear regression models proposed by Grullon et al. (2005). My results are similar to Grullon et al. (2005) and the results in Table 5 are similar to the ones in Table 4. In both tables there is not enough statistical evidence to conclude that dividend changes contain information about future earnings changes.

TABLE 5 REGRESSIONS OF RAW EARNINGS CHANGES ON DIVIDEND CHANGES (NONLINEAR INTERACTION MODEL)

$$(E_t - E_{t-1})/ B_{-1} = \beta_0 + \beta_{1P}DPI_0 \times R\Delta DIV_0 + \beta_{1N}DPD \times R\Delta DIV_0 + (\Upsilon_1 + \Upsilon_2 NDFED_0 + \Upsilon_3 NDFED_0$$

$$\times DFE_0 + \Upsilon_4\, PDFED_0 \times DFE_0) \times DFE_0 + (ʎ_1 + ʎ_2 NCED_0 + ʎ_3 NCED_0 \times CE_0 + ʎ_4 PCED_0 \times CE_0) \times CE_0 + \xi_t$$

Pooled OLS Regression Coefficients

Year		β_0	β_{1P}	β_{1N}	Υ_1	Υ_2	Υ_3	Υ_4	$ʎ_1$	$ʎ_2$	$ʎ_3$	$ʎ_4$	R^2	N
T=1	Point Estimate	0.17015	0.64293	-0.84228	0.06484	0.80476[c]	0.22361[a]	-0.02099	-0.24264[c]	-0.23422	-0.06923	-0.00901[a]	39.93%	2,236
	t-stat	1.52	1.24	-1.11	0.25	1.70	4.44	-0.60	-1.84	-0.68	-0.50	-5.39		
	Standard error	0.11212	0.51951	0.75621	0.25842	0.47360	0.05039	0.03522	0.13188	0.34648	0.13914	0.00167		
T=2	Point Estimate	0.31433[a]	0.02473	0.92822	0.56802[c]	-0.96592	-0.14696[c]	-0.02472	-0.53697[a]	1.32961[a]	0.29806[c]	0.03699[a]	72.96%	2,042
	t-stat	2.86	0.05	1.37	1.94	-1.45	-1.87	-0.68	-3.83	3.26	1.72	15.99		
	Standard error	0.10993	0.54568	0.67517	0.29211	0.66467	0.07875	0.03656	0.14029	0.40832	0.17286	0.00231		

Note : This table reports estimates of regressions relating raw earnings changes to dividend changes. E_{it} is the earnings before extraordinary items in year t (year 0 is the event year), B_{-1} is the book value of equity at the end of year -1, $R\Delta DIV_0$ is the annual percentage change in the cash dividend payment in year 0, DPI and (DPD) is a dummy variable that takes the value of 1 for increase (decrease) dividend changes and 0 otherwise, ROE_{it-1} is equal to earnings before extraordinary items in year *t-1* for T=1 (that is, one year into the future) and *t-2* for T=2 (that is, two years into the future) scaled by the book value of equity at the end of year *t-1* for T=1 and *t-2* for T=2, ROE_{t-1} is measured as E_{t-1}/B_{t-1} and B denotes the book value of common equity and $(E_0 - E_{-1})/B_{-1}$ is control variable. ROE_{it} is equal to earnings before extraordinary items in year t scaled by the book value of equity at the end of year t. DFE_0 is equal to $ROE_0 - E[ROE_0]$, where $E[ROE_0]$ is the fitted value from the cross-sectional regression of ROE_0 on the logarithm of total assets in year -1, the logarithm of the market-to-book ratio of equity in year -1, and ROE_{-1}. CE_0 is equal to $(E_0 - E_{-1})/B_{-1}$, $NDFED_0$ ($PDFED_0$) is a dummy variable that the value of 1 if DFE_0 is negative (positive) and 0 otherwise, and $NCED_0$ ($PCED_0$) is a dummy variable that takes the value of 1 if CE_0 is negative (positive) and 0 otherwise. Standard errors are clustered by firm and date. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the 1%, 5% and 10% level, respectively.

The average value of earnings changes in year 1 (one year ahead) is +5.459% and in year 2 (two years ahead) is +13.289%. Table 5 shows for that T=1 the coefficient for the dividend increases, β_{1P} is +64.293%. However, β_{1P} is statistically insignificant. At the same time for T=2 β_{1P} is +2.473%, which is economically and statistically insignificant. This suggests that there is no evidence that dividend increases are correlated to earnings changes taking place in the near future. We can also see the same results for dividend decreases in T=1 and T=2, where the coefficient of interest is statistically insignificant. If we look at the other control variables then we can see that seven control variables are statistically significant but only three of them are statistically significant in both years. α_0 is positive in both year but statistically significant only in year 2. This result means that, on average, earnings changes are positive in Year 1 (one year ahead) and Year 2 (two years ahead) but only statistically significant in Year 2. If we look at table 5, then we can see that coefficient λ_4 shows a very interesting result, and it seems to play an important role in the regression. The t-statistics for coefficient λ_4 is 15.99 (T=2), which is quite high. In this case I have got different results than Grullon et al. (2005), as their t-statistic for this coefficient was 0.00. Determining the reason behind this result goes beyond the scope of this thesis, but future research may want to look into this issue in greater detail. The point estimate of λ_4 is 3.699% and λ_4 is statistically significant at the 1% level.

Overall, the pooled OLS regression using the nonlinear model shows that the dividend changes do not provide information about future earnings changes. Consistent with the finding in Fama and French (2000), this evidence indicates that linear model in table 4 may miss important information about the behaviour of earnings. According to Grullon et al. (2005) the reason behind these results is that dividend changes act as a surrogate for the nonlinearity in earnings under a uniform mean reverting model. On the basis of these results we cannot reject the null hypothesis that dividend changes have no predictive power for future earnings changes.

5.6.3. BINARY MODEL OF EARNINGS EXPECTATION

5.6.3.1. LINEAR BINARY MODEL

The binary model only concentrates on the direction of the dividend changes and ignores the size of the dividend changes. If there are any outliers in my data set, then the binary model will mitigate their effects.

Table 6 reports the results from equation (7). Value of the coefficient α_{3p} is economically significant and shows a positive sign in T=1 but it is statistically insignificant. In year 2 coefficient α_{3p} is economically significant, as the value is approximately 3 time larger than the average earnings change but statistically insignificant and shows a negative sign. With regard to T=1, the coefficient α_{3n} is positive and statistically insignificant. On the other hand, in year 2 coefficient α_{3n} is negative and statistically insignificant.

TABLE 6 REGRESSIONS OF RAW EARNINGS CHANGES ON DIVIDEND CHANGES (LINEAR BINARY MODEL)

$$(E_t - E_{t-1})/ B_{-1} = \alpha_0 + \alpha_1 ROE_{t-1} + \alpha_2 (E_0 - E_{-1})/B_{-1} + \alpha_{3p} DPI_0 + \alpha_{3n} DPD_0 + \xi_t$$

Pooled OLS Regression Coefficients

YEAR		α_0	α_1	α_2	α_{3p}	α_{3n}	R^2	N
T =1	Point Estimate	0.10942	0.07350	-0.54307[a]	0.10283	0.49533	31.93%	2,370
	t-statistics	1.19	1.35	-2.78	0.75	1.39		
	Standard error	0.09167	0.05429	0.19538	0.13725	0.35749		
T =2	Point Estimate	0.08265	-0.12253	0.71311	-0.15918	-0.29975	22.73%	2,165
	t-statistics	0.49	-1.14	1.47	-0.75	-0.92		
	Standard error	0.16876	0.10703	0.48605	0.21226	0.32473		

Note: This table reports estimates of regression relating raw earning changing to dividend changes. E_{it} is the earnings before extraordinary items in year t (year 0 is the event year), B_{-1} is the book value of equity at the end of year -1, $R\Delta DIV_0$ is the annual percentage change in the cash dividend payment in year 0, DPI and (DPD) is a dummy variable that takes the value of 1 for increase (decrease) dividend changes and 0 otherwise, ROE_{it-1} is equal to earnings before extraordinary items in year $t-1$ for T=1 (one year ahead) and $t-2$ for T=2 (two years ahead) scaled by the book value of equity at the end of year $t-1$ for T=1 and $t-2$ for T=2, ROE_{t-1} is measured as E_{t-1}/B_{t-1} and B denotes the book value of common equity, and $(E_0 - E_{-1})/B_{-1}$ is control variable. Standard errors are clustered by firm and date. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the 1%, 5% and 10% level, respectively.

α_0 is positive in both year 1 and 2 but statistically insignificant. The coefficient α_2 is statistically significant at 1% level in year 1 only and shows a negative sign in year 1 and positive sign in year 2. On the basis of Table 6, there is not enough statistical evidence to reject the null hypothesis that current dividend changes do not predict future earnings changes. This result is consistent with Table 4 and Table 5 .

5.6.3.2. NON-LINEAR BINARY MODEL

In this section I use the partially modified non-linear model suggested by Grullon et al. (2005) where I ignore the size of the dividend changes and only concentrate on the direction of the dividend changes. Table 7 shows different results compared to Table 6; dividend decreases tend to be followed by negative earnings changes two years later (T=2). Coefficient β_{1P} is economically significant in year 1 as the average earnings change is 5.459% in year 1 but the value is economically insignificant in year 2. β_{1P} is statistically insignificant in both year 1 and 2 and shows the expected positive sign in both years. On the other hand, β_{1N} is economically significant but statistically insignificant in year 1 and shows a positive sign. However, in year 2 β_{1N} is economically and statistically significant (at the 10% level) and shows the expected negative sign, which means that current dividend decreases are followed by negative earnings changes two years later.

TABLE 7 REGRESSIONS OF RAW EARNINGS CHANGES ON DIVIDEND CHANGES (NONLINEAR BINARY MODEL)

$$(E_t - E_{t\text{-}1})/\ B_{\text{-}1} = \beta_0 + \beta_{1P}DPI_0 + \beta_{1N}DPD + (\Upsilon_1 + \Upsilon_2 NDFED_0\ + \Upsilon_3 NDFED_0 \times DFE_0 + \Upsilon_4\ PDFED_0 \times DFE_0) \times DFE_0$$

$$+ (\text{ʎ}_1 + \text{ʎ}_2 NCED_0 + \text{ʎ}_3 NCED_0 \times CE_0 + \text{ʎ}_4 PCED_0 \times CE_0) \times CE_0 + \xi_t$$

Pooled OLS Regression Coefficients

Year		β_0	β_{1P}	β_{1N}	Υ_1	Υ_2	Υ_3	Υ_4	ʎ_1	ʎ_2	ʎ_3	ʎ_4	R^2	N
T=1	Point Estimate	0.15636	0.08470	0.48698	0.07781	0.83316^{c}	0.22916^{a}	-0.02248	-0.24165^{c}	-0.22661	-0.06502	-0.00902^{a}	39.99%	2,236
	t-stat	1.29	0.63	1.43	0.29	1.79	5.07	-0.63	-1.83	-0.65	-0.49	-3.04		
	Standard error	0.12120	0.13499	0.33968	0.26766	0.46648	0.04516	0.03587	0.13180	0.34866	0.13399	0.00297		
T=2	Point Estimate	0.31384^{b}	0.01197	-0.33099^{c}	0.56043^{c}	-0.96882	-0.14822^{c}	-0.02381	-0.53749^{a}	1.32875^{a}	0.29707^{c}	0.03700^{a}	72.97%	2,042
	t-stat	2.15	0.07	-1.86	1.91	-1.47	-1.92	-0,.65	-3.70	3.21	1.70	15.93		
	Standard error	0.14565	0.17661	0.17774	0.29319	0.66116	0.07736	0.03667	0.14526	0.41408	0.17481	0.00232		

Note : This table reports estimates of regressions relating raw earnings changes to dividend changes. E_{it} is the earnings before extraordinary items in year *t* (year 0 is the event year), $B_{\text{-}1}$ is the book value of equity at the end of year -1, $R\Delta DIV_0$ is the annual percentage change in the cash dividend payment in year 0, DPI and (DPD) is a dummy variable that takes the value of 1 for increase (decrease) dividend changes and 0 otherwise, $ROE_{it\text{-}1}$ is equal to earnings before extraordinary items in year *t-1* for T=1(one year ahead) and *t-2* for T=2 (two years ahead) scaled by the book value of equity at the end of year *t-1* for T=1 and *t-2* for T=2, and $(E_0 - E_{\text{-}1})/B_{\text{-}1}$ is control variable. ROE_{it} is equal to earnings before extraordinary items in year *t* scaled by the book value of equity at the end of year *t*. DFE_0 is equal to $ROE_0 - E[ROE_0]$, where $E[ROE_0]$ is the fitted value from the cross-sectional regression of ROE_0 on the logarithm of total assets in year -1, the logarithm of the market-to-book ratio of equity in year -1, and $ROE_{\text{-}1}$. CE_0 is equal to $(E_0 - E_{\text{-}1})/B_{\text{-}1}$, $NDFED_0$ ($PDFED_0$) is a dummy variable that the value of 1 if DFE_0 is negative (positive) and 0 otherwise, and $NCED_0$ ($PCED_0$) is a dummy variable that takes the value of 1 if CE_0 is negative (positive) and 0 otherwise. Standard errors are clustered by firm and date. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the 1%, 5% and 10% level, respectively.

Seven control variables are statistically significant but only three of them are statistically significant in both years. If we look at table 7, then we can see that coefficient λ_4 shows a very interesting result, and it seems to play an important role in the regression. The t-statistics for coefficient λ_4 is 15.93 (T=2), which is quite high. In this case I have got results than Grullon et al. (2005), as their t-statistic for this coefficient was 0.00. Determining the reason behind this result goes beyond the scope of this thesis, but future research may want to look into this issue in greater detail. The point estimate of λ_4 is 3.7% and λ_4 is statistically significant at the 1% level.

R^2 values are a bit higher in both years. β_0 is positive in both year 1 and 2 but only statistically significant in year 2. These results are inconsistent with the ones reported in Table 6. On the basis of these results there is at least minor evidence to reject the null hypothesis in favour of the alternative hypothesis that today's dividend decreases convey information about negative earnings changes that will occur two years later (dividend-signalling theory).

5.7. ROBUSTNESS TEST

5.7.1. INTERACTION MODEL OF EARNINGS EXPECTATION

In addition to the regressions of future changes in earnings on current dividend changes, Nissim and Ziv (2000) and Grullon et al. (2005) also examined the correlation between dividend changes and future earnings levels. Although the specification using earnings levels provides an alternative way to examine the relation between earnings and dividend changes, it has several limitations.[12] Following these

[12] Conceptually, if dividend changes contain ''information'' about earnings, then, by definition, that information have to be about changes because the present level of earnings is already known. Thus, it is not clear what we learn by using earnings levels instead of earnings changes. More important, empirical evidence suggests that changes in profitability or earnings tend to have better statistical properties than levels. For example, Barber and Lyon (1996) found that test statistics using the change in a firm's operating performance yield more powerful test statistics than those based on the level of a firm's operating performance.

authors, I replicate the analyses in previous sections using earnings levels instead of earnings changes to ensure that my results are robust to alternative specifications. Here I use the specifications used by Grullon et al. (2005).

In Table 8 the results are different from Grullon et al.'s (2005). In Table 9 the results are consistent with Grullon et al.'s (2005) results. Both tables show that future ROE (one and two years into the future) is not significantly correlated with current dividend changes. This section's results are consistent with my previous interaction model results; current dividend changes do not forecast future earnings changes. In conclusion, there is not enough evidence to reject the null hypothesis in favour of the alternative hypothesis.

TABLE 8 REGRESSIONS OF RAW EARNINGS CHANGES ON DIVIDEND CHANGES (LINEAR INTERACTION MODEL)

$$ROE_t = \beta_0 + \beta_{1p} DPI \times R\Delta DIV_0 + \beta_{1N} DPD \times R\Delta DIV_0 + \beta_2 ROE_{t-1}$$
$$+ \beta_3 (ROE_0 - ROE_{-1}) + \beta_4 MB_{-1} + \beta_5 SIZE_{-1} + \xi_t$$

Pooled OLS Regression Coefficients

YEAR		β_0	β_{1p}	β_{1N}	β_2	β_3	β_4	β_5	R^2	N
T =1	Point Estimate	-0.25869	0.06067	-0.03339	1.04378[a]	-0.26940	0.07525	0.07811	91.03%	2,236
	t-statistics	-0.65	0.67	-0.44	64.27	-1.49	0.77	0.80		
	Standard error	0.39714	0.09057	0.07562	0.01624	0.18022	0.09805	0.09809		
T =2	Point Estimate	-0.12167	0.09563	-0.0626	1.06161[a]	-0.20720	0.05749	0.06094	84.50%	2,042
	t-statistics	-0.30	0.83	-0.60	51.42	-0.92	0.57	0.61		
	Standard error	0.40753	0.11515	0.10508	0.02065	0.22423	0.10130	0.10051		

Note: This table reports estimates of regression relating raw earning changing to dividend changes. E_{it} is the earnings before extraordinary items in year *t* (year 0 is the event year), B_{-1} is the book value of equity at the end of year -1, $R\Delta DIV_0$ is the annual percentage change in the cash dividend payment in year 0, DPI and (DPD) is a dummy variable that takes the value of 1 for increase (decrease) dividend changes and 0 otherwise, ROE_{it-1} is equal to earnings before extraordinary items in year *t-1* for T=1 (one year ahead) and *t-2* for T=2 (two year ahead) scaled by the book value of equity at the end of year *t-1* for T=1 and *t-2* for T=2. MB_{-1} is the logarithm of the market-to-book ratio of equity in year-1. $Size_{-1}$ is the logarithm of the total assets in year -1. Standard errors are clustered by firm and date. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

TABLE 9 REGRESSIONS OF RAW EARNINGS CHANGES ON DIVIDEND CHANGES (NONLINEAR INTERACTION MODEL)

$$ROE_t = \beta_0 + \beta_{1P}DPI_0 \times R\Delta DIV_0 + \beta_{1N}DPD \times R\Delta DIV_0 + (\Upsilon_1 + \Upsilon_2 NDFED_0 + \Upsilon_3 NDFED_0 \times ROE_0 + \Upsilon_4\, PDFED_0 \times ROE_0) \times ROE_0$$

$$+ (\text{ʎ}_1 + \text{ʎ}_2 NCED_0 + \text{ʎ}_3 NCED_0 \times CE_0 + \text{ʎ}_4 PCED_0 \times CE_0) \times CE_0 + \varphi_1 MB_{-1} + \varphi_2 SIZE_{-1} + \xi_t$$

Pooled OLS Regression Coefficients

Year		β_0	β_{1P}	β_{1N}	Υ_1	Υ_2	Υ_3	Υ_4	ʎ_1	ʎ_2	ʎ_3	ʎ_4	φ_1	φ_2	R^2	N
T=1	Point Estimate	0.13283	0.03129	0.01894	0.95145[a]	0.99181	4.43622[a]	0.02335[a]	0.40208[a]	-0.52209[a]	0.00231	-0.17469[a]	-0.01273	-0.01211	94.24%	2,236
	t-statistics	0.98	0.39	0.35	79.91	1.59	3.82	5.68	5.80	-4.54	0.20	-23.48	-0.38	-0.37		
	Standard error	0.13531	0.07971	0.05425	0.01191	0.62203	1.16199	0.00411	0.06931	0.11491	0.01177	0.00744	0.03314	0.03308		
T=2	Point Estimate	0.19543	0.06393	0.00055	0.94253[a]	1.54152[c]	6.48434[a]	0.03337[b]	0.62862[a]	-0.58303[a]	0.03373	-0.19315[a]	-0.01329	-0.01129	88.31%	2,042
	t-statistics	1.32	0.63	0.01	20.80	1.81	3.28	2.55	5.84	-2.78	1.57	-18.77	-0.36	-0.30		
	Standard error	0.14823	0.10206	0.08612	0.04531	0.85321	1.97873	0.01311	0.10762	0.20941	0.02143	0.01029	0.03706	0.03732		

Note : This table reports estimates of regressions relating raw earnings changes to dividend changes. E_{it} is the earnings before extraordinary items in year *t* (year 0 is the event year), B_{-1} is the book value of equity at the end of year -1, $R\Delta DIV_0$ is the annual percentage change in the cash dividend payment in year 0, DPI and (DPD) is a dummy variable that takes the value of 1 for increase (decrease) dividend changes and 0 otherwise, ROE_{it-1} is equal to earnings before extraordinary items in year *t-1* for T=1 and *t-2* for T=2 scaled by the book value of equity at the end of year *t-1* for T=1 (one year ahead) and *t-2* for T=2 (two year ahead). ROE_{it} is equal to earnings before extraordinary items in year *t* scaled by the book value of equity at the end of year *t*, ROE_{t-1} is measured as E_{t-1}/B_{t-1} and B denotes the book value of common equity. CE_0 is equal to $(ROE_0 - ROE_{-1})$. $NDFED_0$ ($PDFED_0$) is a dummy variable that the value of 1 if ROE_0 is negative (positive) and 0 otherwise, and $NCED_0$ ($PCED_0$) is a dummy variable that takes the value of 1 if CE_0 is negative (positive) and 0 otherwise. MB_{-1} is the logarithm of the market-to-book ratio of equity in year-1. $Size_{-1}$ is the logarithm of the total assets in year -1. Standard errors are clustered by firm and date. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

5.7.2. BINARY MODEL OF EARNINGS EXPECTATION

In this section I use the modified linear and non-linear model used by Grullon et al. (2005) when they examined the correlation between current dividend changes and future earnings levels. Both models ignore the size of the dividend changes and only concentrate on the direction of the dividend changes. Linear binary specification may mitigate the impact of outliers on the results, and therefore it complements specification number one (linear interaction model specification). The omitted dummy represented by the intercept captures companies for which, $R\Delta DIV_{it}= 0$, that is companies that did not change their dividend payments.

In Table 10 the results are inconsistent with Nissim ans Ziv (2000) and Grullon et al. (2005). However, in Table 11 the results are consistent with Grullon et al.'s (2005) results. Both tables show that future ROE (one and two years into the future) is not significantly correlated with current dividend changes. This section's results are consistent with my previous binary model sections results; current dividend changes do not seem to predict future earnings changes. In conclusion, there is not enough evidence to reject the null hypothesis in favour of the alternative hypothesis.

TABLE 10 REGRESSIONS OF RAW EARNINGS CHANGES ON DIVIDEND CHANGES (LINEAR BINARY MODEL)

$$ROE_t = \beta_0 + \beta_{1p}DPI + \beta_{1N}DPD + \beta_2 ROE_{t-1} + \beta_3(ROE_0 - ROE_{-1}) + \beta_4 MB_{-1} + \beta_5 SIZE_{-1} + \xi_t$$

Pooled OLS Regression Coefficients

YEAR		β_0	β_{1p}	β_{1N}	β_2	β_3	β_4	β_5	R^2	N
T =1	Point Estimate	-0.02504	-0.00327	-0.01710	1.04393[a]	-0.26954	0.07573	0.07864	91.03%	2,236
	t-statistics	-0.63	-0.15	-0.79	64.40	-1.50	0.77	0.80		
	Standard error	0.39719	0.02117	0.02172	0.01621	0.18023	0.09778	0.09785		
T =2	Point Estimate	-0.11039	0.02066	0.00892	1.06126[a]	-0.20605	0.05338	0.05685	84.50%	2,042
	t-statistics	-0.27	0.60	0.23	51.40	-0.92	0.54	0.58		
	Standard error	0.40508	0.03465	0.03913	0.02065	0.22395	0.09962	0.09883		

Note: This table reports estimates of regression relating raw earning changing to dividend changes. E_{it} is the earnings before extraordinary items in year t (year 0 is the event year), B_{-1} is the book value of equity at the end of year -1, RΔDIV$_0$ is the annual percentage change in the cash dividend payment in year 0, DPI and (DPD) is a dummy variable that takes the value of 1 for increase (decrease) dividend changes and 0 otherwise, ROE_{it-1} is equal to earnings before extraordinary items in year *t-1* for T=1 and *t-2* for T=2 scaled by the book value of equity at the end of year *t-1* for T=1 (one year ahead) and *t-2* for T=2 (two years ahead), ROE_{t-1} is measured as E_{t-1}/B_{t-1} and B denotes the book value of common equity . MB_{-1} is the logarithm of the market-to-book ratio of equity in year-1. $Size_{-1}$ is the logarithm of the total assets in year -1. Standard errors are clustered by firm and date. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

TABLE 11 REGRESSIONS OF RAW EARNINGS CHANGES ON DIVIDEND CHANGES (NONLINEAR BINARY MODEL)

$$ROE_t = \beta_0 + \beta_{1P}DPI_0 + \beta_{1N}DPD + (\Upsilon_1 + \Upsilon_2 NDFED_0 + \Upsilon_3 NDFED_0 \times ROE_0 + \Upsilon_4\, PDFED_0 \times ROE_0) \times ROE_0$$

$$+ (ʎ_1 + ʎ_2 NCED_0 + ʎ_3 NCED_0 \times CE_0 + ʎ_4 PCED_0 \times CE_0) \times CE_0 + \varphi_1 MB_{-1} + \varphi_2 SIZE_{-1} + \xi_t$$

Pooled OLS Regression Coefficients

Year		β_0	β_{1P}	β_{1N}	Υ_1	Υ_2	Υ_3	Υ_4	$ʎ_1$	$ʎ_2$	$ʎ_3$	$ʎ_4$	φ_1	φ_2	R^2	N
T=1	Point Estimate	0.13743	-0.00727	-0.02470	0.95178[a]	1.00695	4.47863[a]	0.02332[a]	0.40114[a]	-0.51817[a]	0.00259	-0.17471[a]	-0.01140	-0.01079	94.24%	2,236
	t-statistics	0.99	-0.43	-1.35	78.56	1.59	3.78	5.87	5,74	-4.40	0.21	-23.77	-0.33	-0.31		
	Standard error	0.13893	0.01684	0.01836	0.01211	0.63175	1.18474	0.00398	0.06988	0.11787	0.01224	0.00735	0.03438	0.03435		
T=2	Point Estimate	0.20139	0.01994	0.00338	0.94193[a]	1.50029[c]	6.36866[a]	0.03344[a]	0.63069[a]	-0.59416[a]	0.03249	-0.19332[a]	-0.01689	-0.01486	88.31%	2,042
	t-statistics	1.36	0.64	0.09	21.07	1.70	3.12	2.58	5.84	-2.84	1.50	-18.46	-0.45	-0.39		
	Standard error	0.14858	0.03102	0.03836	0.04471	0.88032	2.03806	0.01298	0.10792	0.20916	0.02161	0.01047	0.03766	0.03799		

Note : This table reports estimates of regressions relating raw earnings changes to dividend changes. E_{it} is the earnings before extraordinary items in year t (year 0 is the event year), B_{-1} is the book value of equity at the end of year -1, $R\Delta DIV_0$ is the annual percentage change in the cash dividend payment in year 0, DPI and (DPD) is a dummy variable that takes the value of 1 for increase (decrease) dividend changes and 0 otherwise, ROE_{it-1} is equal to earnings before extraordinary items in year $t-1$ for T=1 and $t-2$ for T=2 scaled by the book value of equity at the end of year $t-1$ for T=1 (one year ahead) and $t-2$ for T=2 (two years ahead). ROE_{it} is equal to earnings before extraordinary items in year t scaled by the book value of equity at the end of year t, ROE_{t-1} is measured as E_{t-1}/B_{t-1} and B denotes the book value of common equity . CE_0 is equal to $(ROE_0 - ROE_{-1})$. $NDFED_0$ ($PDFED_0$) is a dummy variable that the value of 1 if ROE_0 is negative (positive) and 0 otherwise, and $NCED_0$ ($PCED_0$) is a dummy variable that takes the value of 1 if CE_0 is negative (positive) and 0 otherwise. MB_{-1} is the logarithm of the market-to-book ratio of equity in year-1. $Size_{-1}$ is the logarithm of the total assets in year -1. Standard errors are clustered by firm and date. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

5.8. DISCUSSION

In this chapter I used two different model specifications; one is an interaction model specification and the second one is a binary model specification. When I used the interaction model specifications (linear and nonlinear) I found no evidence of correlation between current dividend changes and future earnings changes (up to two years into the future). My linear interaction model specification showed results that are inconsistent with Nissim and Ziv (2001) and Grullon et al. (2005), but when I controlled for the nonlinearity of the model then my results turned out to be consistent with Grullon et al.'s (2005) results.

However, when I ignored the size of the dividend changes and only concentrated on the direction of the dividend changes then the results showed there is at least minor evidence that dividend decreases predict future earnings decreases (two years into the future) in the nonlinear binary model. However, the linear binary model result showed no evidence that dividend changes convey new information about future earnings changes.

On the basis of these results there is not enough statistically significant evidence to reject the null hypothesis according to the interaction model specifications. But there is minor statistically significant evidence to reject the null hypothesis in favour of the alternative hypothesis according to the nonlinear binary model specifications, which provides some support for the dividend-signalling theory.

As an additional test, I examined the correlation between dividend changes and future earnings levels, because earnings levels provide an alternative way to examine the relation between earnings and dividend changes. To conduct this test I used the interaction model specifications (linear and nonlinear) and the binary model specifications (linear and nonlinear). I used ROE as my dependent variable instead of earnings changes. When using the interaction model specification I found that there is no significant correlation between current dividend changes and future ROE (up to two years into the future). The results from the linear interaction model are inconsistent with Nissim and Ziv (2001) and Grullon et al.'s (2005) results but my nonlinear interaction model results are consistent with Grullon et al. (2005) results. When I used the binary model specifications I found similar results. This means the robustness test too, provides no evidence that dividend changes convey new information about future earnings.

5.9. CONCLUSION

Since the significant papers of Miller and Modigliani (1961) and Watts (1973), economists have been looking without success for evidence that current changes in dividends contain information about future changes in earnings. Using different empirical methods, many researchers have been unable to find a reliable link between current dividend changes and future changes in earnings. Using Nissim and Ziv (2001) and Grullon et al.'s (2005) methods I investigated the validity of the dividend-signaling theory for UK firms by testing the correlation between current dividend changes and future earnings changes. In this study I can compare Nissim and Ziv (2001) and Grullon et al. (2005) US market outcome with my UK market outcome using two different model specifications.

For the entire sample, I determined that there is at least minor evidence that dividend decreases predict future earnings decreases (two years into the future) if we ignore the size of the dividend changes and control for the nonlinear patterns in earnings. On the other hand, if we do not ignore the size of the dividend changes and control for the well-known nonlinearity in the earnings process, then we find that dividend changes have no predictive power for future earnings changes in the UK market, which supports Grullon et al.'s (2005) results. Grullon et al. (2005) found that dividend changes are positively correlated with the future earnings levels when they used a linear model but after controlling for the nonlinear patterns in earnings they found that dividends changes do not contain information about the future level of ROE. My findings also suggest that current dividends changes do not contain information about the future level of ROE according to the binary model specifications. One possible explanation as to why I found no evidence that dividend changes predict future earnings changes is that I focused on the short term (1 and 2 years ahead); it is possible that earnings changes take longer time to materialise. In future, the present analysis could be extended so as to examine whether dividend changes predict changes in analyst consensus estimates of future earnings and future cash flows. If dividend increases lead analysts to revise their earnings estimates, this may explain the results presented in chapter 6.

It is very difficult to find support for the dividend-signalling theory on the basis of the empirical research in the US (Nissim and Ziv ; 2001 and Grullon et al.;2005) , Korea (Choi, Ju, and Park; 2010), as well as my own research. According to the dividend-signalling theory, current dividend changes are supposed to predict future earnings changes. Firms tend to change their dividend policy only when earnings changes have been substantial. If firms have done well for long periods, then they increase their dividends, but they cut their dividends if they have a long period of poor performance, which they expect to continue (see Brav et. at. 2003). However, the motives for paying dividends, and the market reaction to them, seem to lie elsewhere[13].

[13] According to Gullon et.al. (2002), dividend changes contain information about unexpected changes in systematic risk.

6 THE EFFECT OF DIVIDEND ANNOUNCEMENTS ON STOCK MARKET RETURNS: A STUDY ON UK DATA

6.1. INTRODUCTION

Over the past six decades researchers have been trying to discover why companies pay dividends or analogously why stockholders are interested in receiving dividends, given that it is well known that dividends are often taxed heavily, especially in the UK where the dividend tax is higher than the capital gain tax[14] (Bozos, Nikolopoulos and Ramgandhi, 2011). Miller and Modigliani (1961) initially argued that dividend policy does not have any effect on a firm's value under perfect capital markets, concluding instead that investment policies have influence on firm value. Following Miller and Modigliani a number of researchers have examined whether dividend change announcements convey any information to the stock market, or whether dividend change announcements have any effect on stock market returns (Pettit, 1972; Aharony and Swary, 1980; Lonie et al., 1996; Bozos, Nikolopoulos and Ramgandhi, 2011; Dasilas and Leventis, 2011).

Determining the optimal dividend policy and its effect on stock returns poses an intricate puzzle for finance researchers. Black, 1976, said that, " [t]he harder we look at the dividend picture, the more it seems like a puzzle, with pieces that just don't fit together". After Miller and Modigliani's (1961) development of dividend irrelevance proposition, a number of other finance researchers have offered different explanations, theories and hypothesis to solve this. Allen and Michaely (1995) believe that more theoretical and empirical research is needed to understand the dividend

[14] UK dividend tax rate for budget year 2016/2017 are, basic income (£0-£32,000) 7.5%, higher income (£32,001-150,000) 32.5% and additional (150,000+) 38.1%. Where UK capital gain tax rates are for budget year 2006/2007, higher 20%/28%, entrepreneurs' relief effective rate 10% and annual individual exemption £11,100.

announcements effect on stock returns. Some of the researchers argued that dividend policy is one of the very important unsolved problems in finance (Bhattacharyya, 2007; Brealey, Myers and Marcus, 2007).

The first reason behind dividend distribution is based on market imperfections, which happen due to information asymmetries (Dasilas and Leventis, 2011). Managers have all kind of important information about the current and future financial position of the firm, and for this reason they use dividends to send signals about the firm's future earnings (Dasilas et al., 2008). As a consequence, firms that pay dividends should face less information asymmetries compared to firms that do not pay any dividends or pay irregular dividends (Howe and Lin, 1992; Khang and King, 2006; Li and Zhao, 2008). All these arguments started on the basis of the so called " information content of dividends hypothesis" or " dividend-signalling theory", initially proposed by Lintner (1956), through his seminal work, then later further developed by Fama et al. (1969) and Ambarish et al (1987).

Dividend announcements may convey some sort of information about the firm value; more specifically researchers believe that dividend increases (decreases) convey positive (negative) information about the firm value (Kato and Loewentein, 1995; Ho and Wu, 2001; Nguyen, 2014; Al-Yahyaee, 2014). Majority of studies have found that dividend announcements have a statistically significant effect on stock returns (Yilmaz And Gulay, 2006; Pan et al. 2014; Dasilas and Leventis, 2011; Kumar, 2017).

Most of the research conducted in this area was based on US data; to the best of my knowledge till now only four research paper have been published based on UK data (Lonie et al., 1996; Bozos, Nikolopoulos and Ramgandhi, 2011; Gunasekarage and Power, 2002 and 2006). In my research I will use a sample of data about firms belonging to the UK FTSE-350 index to test the hypothesis that dividend increase (decrease) announcements have a positive (negative) effect on stock market returns. Compared to the other studies on UK data, my sample period is much longer (26 years), which substantially increases statistical power.

Most of the researchers found that dividend increases (decreases) have a positive (negative) effect on stock returns, which is consistent with the dividend-signalling theory. My results also suggest that dividend increases (decreases) have a positive (negative) effect on stock returns, which is consistent with the dividend-signalling theory and previous researchers' findings. In this chapter I use two different econometric model specifications based on dividend-signalling theory and previous literature. My first model specification is an interaction linear model, which is based on standard dividend-signalling theory model, and some previous researchers used this model (i.e. Nissim and Ziv, 2001; Grullon et. al, 2005). My second model specification is a binary model specification, which is a partially novel model specification. My main contribution to the literature is that, using larger data set and binary model specification, which is a partially novel model specification I provide additional evidence in favour of the dividend-signalling theory.

The rest of this chapter is organized in the following way, where in section 6.2 I review the relevant literature and in section 6.3 I explain the testable hypothesis in details. Section 6.4 presents the methodology, while section 6.5 presents the event window. In section 6.6 I describe the data and in section 6.7 I describe the empirical analysis. Section 6.8 describes a robustness test and section 6.9 describes an alternative test. And finally section 6.10 and 6.11 offer a general discussion and conclusion, respectively.

6.2 LITERATURE REVIEW

A number of different theories have been introduced since Lintner's (1956) seminal work to solve the dividend announcement puzzle. After Miller and Modigliani's (1961) dividend irrelevance theory, Gordon (1963) and Lintner (1962) presented their argument about the risk advantage of dividend payments over capital gains and introduced a theory called 'bird-in-the-hand'. Another popular dividend theory is the agency theory, which is inspired by the dividend cash flow theory, introduced by Jensen (1986). This chapter is based on the 'dividend-signalling theory' or 'information content of dividends hypothesis'. In my literature review chapter I explained in detail the dividend-signalling theory, so in this section I will only repeat the key insights at the heart of the dividend-signalling theory.

Usually company managers hold private information about the company's present financial conditions and future cash flows, in which case dividend policy can play a very vital role in signalling news to shareholders and other market participants (Bozos, Nikolopoulos and Ramgandhi, 2011). Bhattacharyya's (2007) argument behind this theory is that, within institutional settings where dividends are heavily taxed, dividend signalling is important in removing information asymmetries, and the size of the dividend depends on how good or how bad the news is. John and Williams (1985) and Ofer and Thakor (1987) enrich the dividend-signalling theory by arguing that dividend changes may signal the management's assessment of the company's current or future earnings changes.

The majority of previous studies has concluded that there are positive associations between dividend changes announcements and stock returns (Dasilas and Leventis, 2011). In 1972 Petit was the first to provide evidence that positive (negative) dividend changes lead to positive (negative) abnormal returns. Petit's (1972) finding was disputed by Watts (1973), who found no relationship between unexpected dividend changes and positive future earnings changes and subsequent abnormal stock returns.

Aharony and Swary (1980) investigated this matter using 384 U.S. listed firms and reported that on the announcement date (t_0) stocks see an average abnormal return of +0.36% if dividends increase whereas when dividends decrease the abnormal returns is -1.13%. To conduct this study they used two model specifications, their first model was a naïve model and the second model specification was a modified version of the Lintner's (1956) model proposed by Fama and Babiak (1968). After this study a number of studies that followed also reported statistical significant abnormal stock returns surrounding dividends announcements (e.g. see Aharony, Falk and Swary, 1988; Bajaj and Vijh, 1990; Denis, 1990; Denis et al. 1994; Bernheim and Wantz, 1995; Lonie et al., 1996; Dyl and Weigand 1998; WoolRidge, 1982; Gwilym et al. 2000; Nissim and Ziv, 2001; Bozos, Nikolopoulos and Ramgandhi, 2011; Hughes, 2008 and Tsai and Wu, 2015). However, in chapter 5 I only found very weak evidence in favour of the dividend-signalling theory, just like Grullon et al. (2005). Bentarzi et al. (1997) and Choi, Ju, and Park (2010) found very little empirical evidence in support of the dividend-signaling hypothesis. To the best of my knowledge only Grullon et al. (2005) found evidence that current dividend changes are correlated with future firm profitability when they used a nonlinear earnings model.

A number of researchers used the information content of dividends hypothesis to examine dividend initiations and dividend omissions (Asquith and Mullins, 1983; Gorman, Weigand and Zwirlein, 2004; Liu, Szewczyk and Zantout, 2008); most of the researchers report that dividend omissions cause greater negative market reactions than dividend initiations (Bozos, Nikolopoulos and Ramgandhi, 2011). Asquith and Mullins (1983) used 160 NYSE and AMEX listed firms and found 2 days abnormal returns of +3.7% when a firm increases dividends and reports a positive effect of the size of the dividend announced. Ghosh and Woolridge (1991) revealed that when a firm for the first time omits their dividend payment, it means that firm is going through significant capital losses, but when the same firm omits dividends a second time and higher-order omission announcements lead to insignificant valuation effects. When Christie (1994) used 492 dividend omissions and 475 dividend reductions in his study, he observed abnormal returns of -4.95% when dividends are decreased by 20% or less and -8.78% when dividends are decreased by 60%. The average price decline for the omission sample is -6.94%, with 85.5% of firms experiencing a decline in value.

Lonie et al. (1996), said it is difficult to determine the effect of dividend announcements on share prices in markets other than the USA, because researchers were less willing to publish their findings in English and also the data for some countries are not available. Before 1996, there were few research paper published in English (Lonie et al., 1996). In 1991, Easton tested Australian data and reported that there is an interaction effect between dividend announcements and earnings changes on stock returns, which implies that investors are influenced by the interplay of signals in reaching their buying and selling decisions.

In the UK Lonie et al. (1996) were the first researchers who used 620 LSE listed companies to examine whether dividend change announcements have any effect on stock returns. They investigated using a two-day event window (t_{-1}, t_0) and found significant statistical and economical cumulative abnormal returns of +2.03% when dividends are increased and -2.15% for dividend decreases. Gunasekarage and Power (2002, 2006) also report similar results when they use UK data.

Soon after Lonie et al. (1996), Abeyratna et al. (1996) documented that the simultaneous announcement of earnings and dividends can interact with one another. And they also mentioned that in the case of the UK this possibility is even greater, because most UK firms announce their earnings soon after dividend changes announcements or sometimes on the same day. Due to that reason simultaneous signals of earnings and dividends will confuse stockholders and there are chances that, for that reason, it will be difficult for dividend change announcements to convey any information about firm value. Later Bozos, Nikolopoulos and Ramgandhi, (2011) provided more insights into the dividends announcements effect on UK stock returns. In their research they found positive and significant abnormal returns surrounding dividend increases and earnings announcements. They also found significant excess volume activity around dividend change announcements. At the same time Bozos, Nikolopoulos and Ramgandhi, (2011) research reveals that, regardless of the level of earnings and the economic conditions, abnormal returns are accentuated in the same direction as the change in dividends. Finally, they said that dividends change announcements are less important when the firm's economy is stable and growing (i.e. when $\Delta EPS>0$, UKESI (UK Economic Sentiment)>100 or during the steady period 2006-2008).

Due to the possible importance of dividend change announcements on stock returns, researchers across the world, including UK, have done a number of studies to examine this effect. This involved testing the dividend-signalling theory, but still researchers have not managed to reach a unified conclusion. Most of the studies have found that dividend change announcements affect stock returns, or dividend change announcement convey information about firm value. My results also suggest that dividend increases (decreases) have a positive (negative) effect on stock returns, which is consistent with the dividend-signalling theory.

6.3. TESTABLE HYPOTHESIS

This chapter further tests the dividend signaling theory to evaluate if dividend announcements impact upon stock returns using 231 LSE listed FTSE-350 companies. My contribution to the literature consists in using one partially novel empirical specification called binary specification and a larger UK data set compared to previous studies on UK data; my results are consistent with the dividend-signalling theory and previous literature.

My null hypothesis is based on Miller and Modigliani's (1961) dividend irrelevancy theory, so if I fail to reject the null hypothesis then there is no evidence of abnormal stock returns in response to dividend changes during the examined period. Alternatively, if I reject the null hypothesis, then there is evidence that dividends increase (decrease) announcements have a positive (negative) effect on stock market returns, which supports the dividend-signalling theory. I have formulated my alternative hypothesis on the basis of the dividend-signalling theory and my hypotheses are as follows:

H_0: Dividends increase (decrease) announcements have no effect on stock market returns.

H_a: Dividends increase (decrease) announcements have a positive (negative) effect on stock market returns.

6.4. METHODOLOGY AND MODEL SPECIFICATIONS

I use a standard event study methodology. To calculate $R\Delta DIV$, which refers to the percentage change in dividends, I use Benartzi et al.'s (1997) formula just like in my empirical chapter 5.

$$R\Delta DIV_0 = \frac{DIV_0 - DIV_{-1}}{DIV_{-1}} \tag{11}$$

Where DIV_0 represent dividend paid in the base year or year 0 and DIV_{-1} is the dividend paid in the previous year. According to the dividend signaling theory dividend increase (decrease) announcements have a positive (negative) effect on stock returns.

The raw returns are calculated as follows:

$$R_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) \tag{12}$$

where $R_{i,t}$ is the actual return (this is not adjusted for dividend) on stock *i* from day *t*-1 to *t*, $P_{i,t}$ is the price of stock *i* on day *t* and $P_{i,t-1}$ is the price of stock *i* on day *t*-1. I compute abnormal stock returns for each day of the event window as the difference between the actual return and the stock's expected return in the absence of the event, according to the following equation:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{13}$$

where $AR_{i,t}$ is the abnormal returns on stock *i* from day *t*-1 to *t*, $R_{i,t}$ is the actual return on stock *i* on day *t*, and $E(R_{i,t})$ is the expected returns on stock *i* on day *t*. I use the market model to estimate expected stock returns, where the parameters α and β are estimated by OLS using 181 daily returns observations prior to the event window (from t-200, to t-20):

$$E\left(R_{i,t}\right) = \alpha_i + \beta_i R_{m,t} + \mu_{i,t} \tag{14}$$

where $E(R_{i,t})$ is the expected returns on stock *i* on day *t*. $R_{m,t}$ is the market portfolio returns on day t proxied by the FTSE-350 general index. $\mu_{i,t}$ is the random error term and α_i and β_i are the market model parameters.

Then daily abnormal returns are averaged across the portfolios of firms, which increase, decrease or do not change their dividends as follows:

$$AR_{p,t} = \frac{\sum_{t=1}^{N} AR_{i,t}}{N} \tag{15}$$

where $AR_{p,t}$ is the weighted average portfolio abnormal return for dividend increasing firms, dividend decreasing firms and constant dividend firms.

Then I cumulate the $AR_{i,t}$ over a particular time interval and I obtain cumulative abnormal returns (CAR) as:

$$CAR_{it} = \sum_{t=1}^{k} AR_{i,t} \tag{16}$$

where k in the number of days to be cumulated over the event window. I use CAR as a measure of the market reactions to dividend announcements.

For robustness I will consider two different event windows. Two models will be empirically tested. Model number one is an interaction model and model number two is a binary model. I will call my first model the "interaction model" and my second model the "binary model". The interaction model will take into account both dividend changes size and direction, whereas the binary model will only focus on dividend changes direction. For both model specifications I create two dummy variables based on dividend changes, if the dividend changes is positive then the dummy DPI will take value 1, 0 otherwise, and in the same way if the dividend changes is negative then dummy DPD will take 1, 0 otherwise. In both models I use four control variables, which are Size, Reversal, Momentum and Dividend Yield. And finally I use CAR as my dependent variable.

In my interaction model there are two key explanatory variables and both of them represent interaction effects. My first explanatory variable is the percentage change in dividends ($R\Delta DIV$), which is interacted with a dividend increase dummy (DPI), and the second explanatory variable is the percentage change in dividends, which is interacted with a dividend decrease dummy (DPD). On the other hand in my binary model I will use only two dummy variables as my explanatory variables, which are DPI and DPD. In both models I control for year fixed effects, and either firm fixed effects or industry fixed effects. For the industry fixed effects I use Fama and French 17 industry classifications.

Before estimating the two main empirical models I will estimate a baseline linear regression model. The reason behind this is to examine the correlation between the rate of change in dividend per stock at time t and the cumulative abnormal return. After using this model my results suggests that dividend- increase (decreases) announcements have a positive (negative) effect on stock returns. The baseline model is:

$$CAR_{it}^{(-1,+1)} = \lambda_0 + \lambda_1 R\Delta DIV_{it} + \mu_{it} \quad (17)$$

where $CAR_{it}^{(-1,+1)}$ is the cumulative abnormal return for stock *i* on day *t*. And the event window is (-1,+1). $R\Delta DIV$ represents the percentage change in dividends and μ_{it} is the error term.

Interaction specification

The relation between dividend changes and stock returns is likely to be asymmetric for dividend increases and decreases. Thus I create the following interaction model. This model allows asymmetric reactions to dividend increases and decreases and controls for uniform mean reversion and momentum in stock returns. In the following model I have created two different interaction terms, one for the positive dividend-change group and another one for the negative dividend-change group. The results of the following model suggest that dividend-increase (decreases) announcements have a positive (negative) effect on stock returns. I will extend this model in my next two chapters by considering the role of investor sentiment and calendar effects.

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 SIZE_{it} + \lambda_4 REVERSAL_{it} + \lambda_5 MOMENTUM_{it} + \lambda_6 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2\ YEAR\ DUMMIES + \vartheta_3\ FIXED\ EFFECTS + \mu_{it} \quad (18$$

Binary specification

In the binary model one dummy captures the effect of positive dividend changes and the other one captures the effect of negative dividend changes. The use of this binary model is motivated by two reasons. First, it is possible that what really matters (i.e. the signal being sent by managers) is whether the dividend is being increased or decreased rather than the size of such change. The binary model ignores the size of the dividend changes and focuses on the direction alone, i.e. whether dividends increase or decrease regardless of the size of the changes. Therefore, the linear binary model complements the linear interaction model. Second, the binary model may further mitigate the impact of outliers on the results. In equation 6, the omitted dummy represented by the intercept captures companies for which $R\Delta DIV_{it}$= 0, which means there is no change in dividends.

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 SIZE_{it} + \lambda_4 REVERSAL_{it} + \lambda_5 MOMENTUM_{it} + \lambda_6 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2\ YEAR\ DUMMIES + \vartheta_3\ FIXED\ EFFECTS + \mu_{it} \quad (19)$$

Here,

CAR_{it} = Cumulative abnormal returns for firm *i*.

$R\Delta DIV_{it}$ = Percentage change in dividend payment for firm *i*.

DPI_{it} = 1 if the dividends change is positive, and 0 otherwise.

DPD_{it} = 1 if the dividend change is negative, and 0 otherwise.

$SIZE_{it}$ = Firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement (in billions of British pounds).

$REVERSAL_{it}$ = Reversal is measured using cumulative stock returns for firm i over previous month (in percentage).

$MOMENTUM_{it}$ = Momentum is the cumulative monthly stock returns for firm i from month t-12 to t-2.

$DIVIDEND_{YIELD_{it}}$ = Dividend Yield for firm i calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement.

μ_{it} = Error term.

DW = Day-of –the-week effect, where M_d, W_d , T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. Tuesday is the reference day.

$YEAR\ DUMMIES$ = Year fixed effect dummies beginning from 1990 to 2015, and the year 1990 is the reference year.

$FIXED\ EFFECTS$ = Either industry fixed effect dummies or firm fixed effects dummies. The industry fixed effect dummies are based on Fama and French's 17 industry classifications[15]. My reference industry is industry number one, which is the food industry. As for the firm fixed effects, there are 231 firms in my data sample. Firm 888 is my reference firm.

All the above models are estimated using pooled OLS regressions with year- and firm- (or industry) fixed effects. For statistical inference I will also show cluster-robust standard errors for both models, which generalize those proposed by White (1980) for independent heteroscedastic errors. I will show clustered standard error to

[15] According to Bhojraj et al. (2003), Fama and French's industry classification method and the Standard Industrial Classification's (SIC) method "differ little from each other in most applications".

control for within-cluster error correlation, which can lead to misleadingly small standard errors, and consequently misleadingly narrow confidence intervals, large t-statistics and low p-values. Following Petersen's (2009) and Thompson's (2011) suggestions about estimating standard errors in finance panel data sets, I employ multi-way clustering: more specifically, standard errors are clustered by firm and date. I cluster the standard errors by firm because the error terms may be serially correlated and I cluster the standard errors by date because the error terms may be correlated across firms at the same point in time.

6.5. EVENT STUDY WINDOW

I use 2 different event windows, which are (0,+1) and (-1,+1). My event day is day 0, which is the dividend announcement date. It is important to use an accurate event window, which will then give accurate result. Due to that reason several researchers use different event windows and give detailed explanations behind their choice (Vazakidis and StergiosAthianos, 2010).

In this chapter, all the events occur at a distinctly identified time and for that reason it was easy to construct event periods. It is very important to find out how much time the market needs to incorporate new information in the stock returns (Vazakidis and StergiosAthianos, 2010). Krivine et al. (2003) suggested three possible approaches to construct appropriate event window length: a fixed time period, an *ad hoc* approach and an approach that depends on how quickly the market incorporate the given information on the stock prices.

Gurgul et al. (2003) use short event windows compared to other researchers. To explain the impact of corporate dividend change announcement in the Austrian stock market they used a 5-days window (-2,+2). On the other hand Lonie et al. (1996) used a shorter window of only three days (-1,+1) to show the effect of dividend change announcements on UK stock returns. Bozos, Nikolopoulos and Ramgandhi, (2011) went a little further using a two-days event window (-1,0), that is one day prior to the dividends announcements (t_{-1}) to the same day of the dividend announcement (t_0). Kumer (2017) use two event windows: one was three days event window (-1,+1) and another one was two days event window (-1,0). On the basis of Krivine et al. (2003) third suggestion I construct my two event windows for this research paper, which are (-1,+1) and (0,+1). According to Krivine et al. (2003) third suggestion it is important to know how quickly the market incorporate the given information into the stock prices. According to literature, at the LSE dividend changes announcements and earnings announcements sometimes take place on the same day or have few days gap between two announcements, so for this reason I use a 3-days time window rather 21 days or 41 days. Because when there is not enough gap between these two announcements then there are chances that the results would be "contaminated".

I have chosen one event window to conduct the main empirical analysis and the other one for robustness purposes. Event windows (-1,+1) is used in the main analysis, and (0,+1) is used to check the robustness of the results. These windows are between 1 day before the dividend announcement and 1 day after the dividend announcement. The dividend announcement date is day 0, the day before the dividend announcement is day (-1) and the day after the dividend announcement is day (+1).

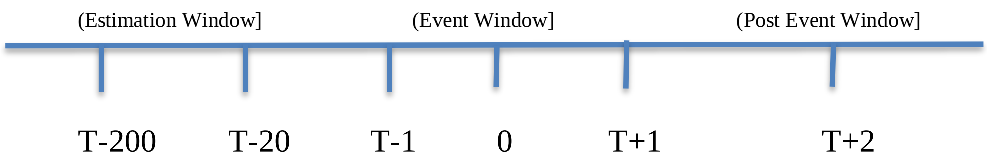


FIGURE-2: TIME-LINE FOR ESTIMATION WINDOW

In Figure 2 I have shown a time line of the event windows. My estimation window start from T-200 days till T-20, which means total estimations days are 181 days. T-1 is the beginning of my event window (-1), T+1 is the end point of my event window (+1) and T+2 represents the post event window. And finally time 0 is the dividend announcement date.

6.6. DATA

The data sample in this chapter is composed of firms listed on the London Stock Exchange (LSE), more specifically FTSE-350 for the years between 1990 and 2015. Selected firms are the current constituents of the FTSE-350 (as of June 2016). I collected all the data from Bloomberg between June 2016 and August 2016. The sample selection criteria are explained below.

6.6.1. SAMPLE SELECTION CRITERIA

The sample selection criteria are as follows:

1. Only final dividend announcements are included, and all other interim dividend and stock dividend announcements during the event period are excluded.

2. Companies in the financial and utility industries are excluded, because these two industries keep their financial records in different way than other industries (Claessens and Laeven, 2006). For the financial industry, profitability and valuation data are difficult to calculate and compare with firm in other industries. For utility industry profitability and valuation can be strongly influenced by government regulations (Claessens and Laeven, 2006).

3. Dividend changes are between +50% to – 50% to avoid abnormal positive and negative changes and mitigate the effect of outliers.

4. Price data have to be available for the period commencing 200 days prior to the dividend announcement date and ending 1 day after to the dividend announcement date.

5. If any other company event is announced (e.g. earnings announcements, stock splits, share repurchases, stoke dividends, right issues, merger and acquisitions) during the period T-10 to T+10 then those observations are excluded, because they might "contaminate" the results. Eliminating these observations from the sample reduces the sample size and the statistical accuracy of my estimates, but at the same time it ensures that the results are not unduly affected by the news contained in earnings announcements and other corporate events.

6. Shares have to be actively traded. I excluded firms that had no transactions for more than 100 days in the estimation period.[16]

[16]It is well known that the thin trading problem can result in biased estimations of the market model parameters (Brown and Warner, 1985).

I collected daily closing prices for all FTSE-350 companies from January 1990 to December 2015. Even though my research focuses on the FTSE-350, the final sample contains data about 231 firms, as I have excluded 119 firms. Some of the firm's data is not available from January 1990, due to that reason some of the firms have more observations than others. Also for some of the companies listed in the FTSE-350 the stock price and dividend announcement information were missing on Bloomberg; due to that I had to exclude 119 companies from my final sample. After applying all the above sample selection criteria I have 231 firms in my sample and I have 3,621 observations.

6.6.2. DESCRIPTIVE STATISTICS

Table 12 and Figure 4 report some descriptive statistics about number of observations, the frequency of dividend increases, decreases and unchanged dividends for both windows.

TABLE 12 DETAILS OF FIRM DIVIDEND CHANGES OBSERVATIONS BY EVENT WINDOW

TABLE 12: 1 **Event Window**	**Number of Obs.**	**Dividend Increase**	**Dividend Decrease**	**Unchanged Dividend**
(-1,+1) & (0,+1)	3,621	2,972	198	451

Note: This table shows the details of firm's dividend changes.

Figure 3 shows dividend changes starting from year 1990 to 2015.We can see from Table 12 and Figure 3 that both event windows (-1,+1) and (0,+1) have a total of 3,621 observations, which include 2,972 dividend increase announcements, 198 dividend decrease announcements and 451 unchanged dividend announcements.

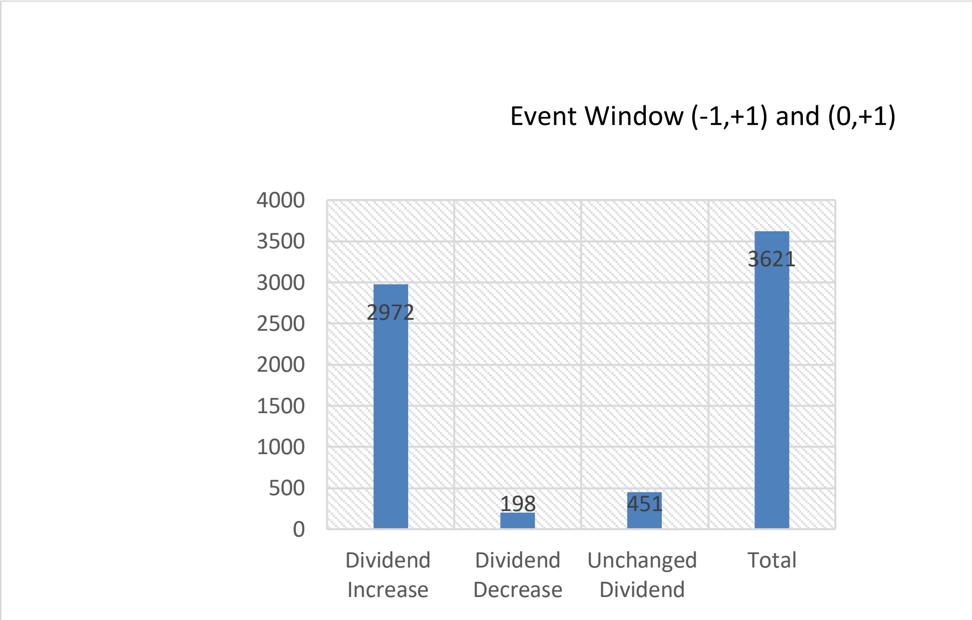


FIGURE 2: DIVIDEND CHNAGES DETAILS WINDOW BY WINDOW

Figure 4 shows the percentage changes in dividends using year-by-year data. Dividend changes reach its lowest (-50.0%) level only 10 times and its highest (+50.0%) level 13 times. Figure 4 also shows that most of the dividend changes values range between +1.0% to +30.0%.

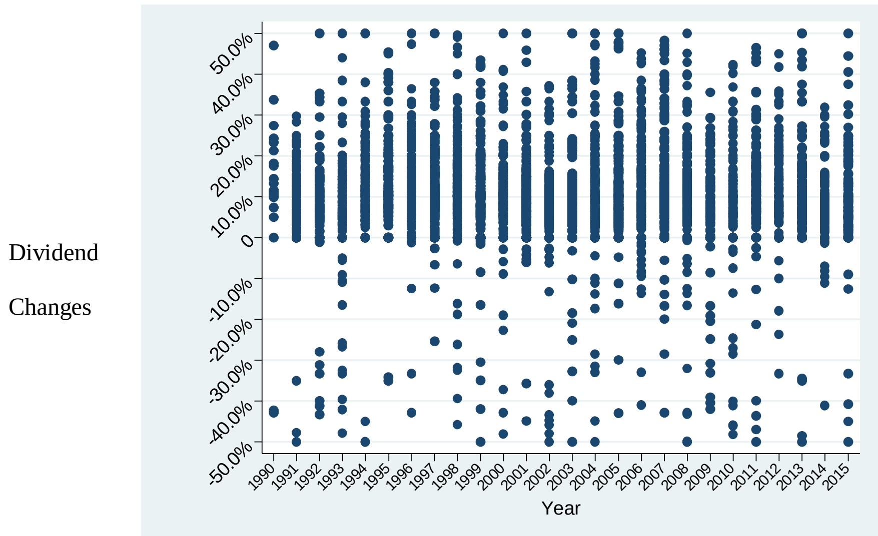


FIGURE 3: DIVIDEND CHNAGES YEAR BY YEAR

Table 13 provides summary statistics for the whole data sample on the basis of two event windows. Table 13 provides information about the percentage change in dividends, Size, Reversal, Momentum, Dividend Yield and Cumulative Abnormal Returns.

In Table 13 the mean value of $R\Delta DIV$ is 9.787% for both event windows. Maximum $R\Delta DIV$ value is +50% and minimum $R\Delta DIV$ value is -50%. $R\Delta DIV$ skewness value is negative and kurtosis value is positive in both event windows. The mean values of size, reversal, momentum and dividend yield variables are same for both event windows. Standard deviation and 4 percentiles values are also same. It is also noticeable that the skewness and kurtosis for size, reversal, momentum and dividend yield are positive and they are identical by construction for both windows.

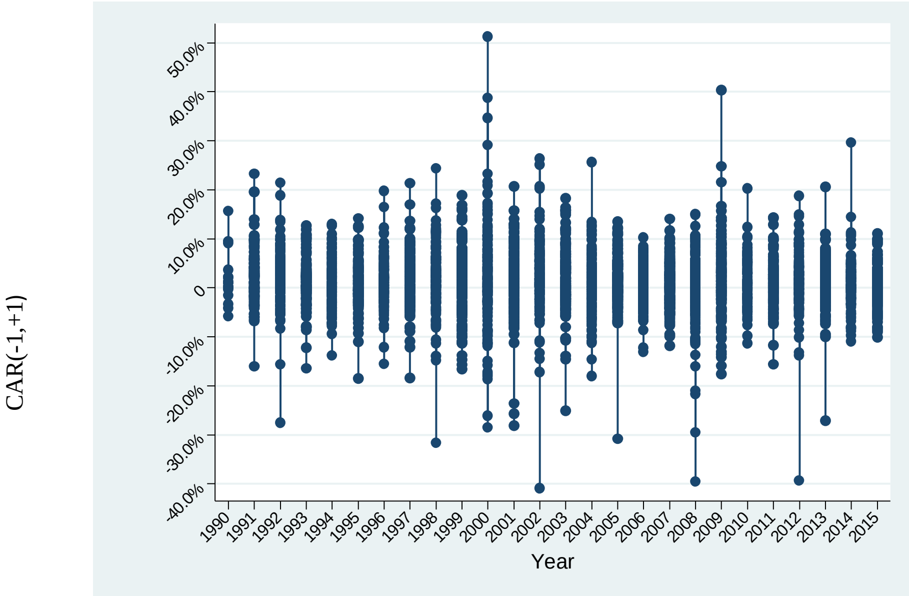
CAR mean values in Table 13 are 1.256% and 1.083% respectively for event window (-1,+1) and (0,+1). In event window (-1,+1) standard deviation is 5.945% and event window (0,+1) the standard deviation is 5.689%, so we can see that both panels mean values are very close to each other. Event window (-1,+1) shows that 5% percentile value is negative but percentile 25%, 75% and 95% is positive. On the other hand event window (0,+1) shows that percentile 5% and 25% is negative and percentile 75% and 95% is positive. Both event windows show negative skewness values and positive kurtosis values.

TABLE 13 DESCRIPTIVE STATISTICS FOR DIVIDEND EVENT OBSERVATIONS BASED ON EVENT WINDOW

Dividend Announcement Event Window (-1, +1) and (0,+1)

Variable	N	Mean	Std. Dve.	Mini	Max	5%	25%	75%	95%	Skewness	Kurtosis
$R\Delta DIV$(%)	3,621	9.787	13.101	-50.000	50.000	-2.522	4.098	15.347	31.034	-0.820	8.134
Size (£ billion)	3,409	7.080	1.453	0.386	12.061	4.891	6.078	8.014	9.708	0.253	3.201
Reversal (%)	3,621	0.055	0.439	-4.039	7.490	-0.618	-0.157	0.281	0.693	0.869	29.924
Momentum (%)	3,618	0.303	1.503	-9.598	6.279	-2.354	-0.507	1.232	2.509	-0.631	5.282
Divi. Yield (%)	3,621	2.035	1.328	0.004	17.248	0.038	1.268	2.639	4.211	2.086	16.467
CAR (-1,+1)(%)	3,621	1.256	5.945	-40.881	51.255	-7.294	1.732	4.224	10.469	-0.034	9.873
CAR (0,+1) (%)	3,621	1.083	5.689	-42.146	56.583	-7.044	-1.701	3.964	9.709	-0.081	11.542

Note: This table reports the firm's characteristic for the sample firms. $R\Delta DIV$ is the annual changes of the dividend payment in percentage terms. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stoke returns over previous months, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. And finally CAR is representing Cumulative Abnormal Return, estimated using the abnormal returns around the dividend announcement date.



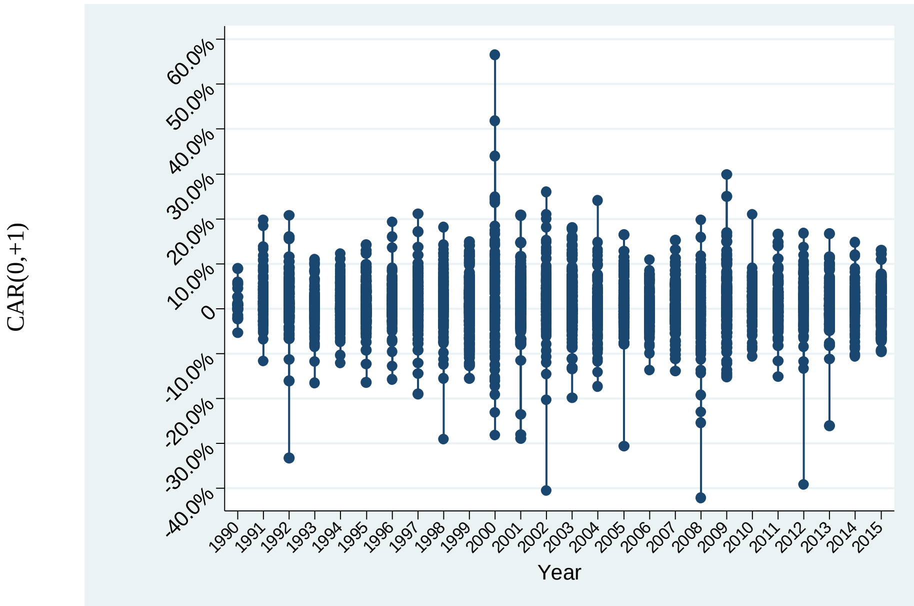
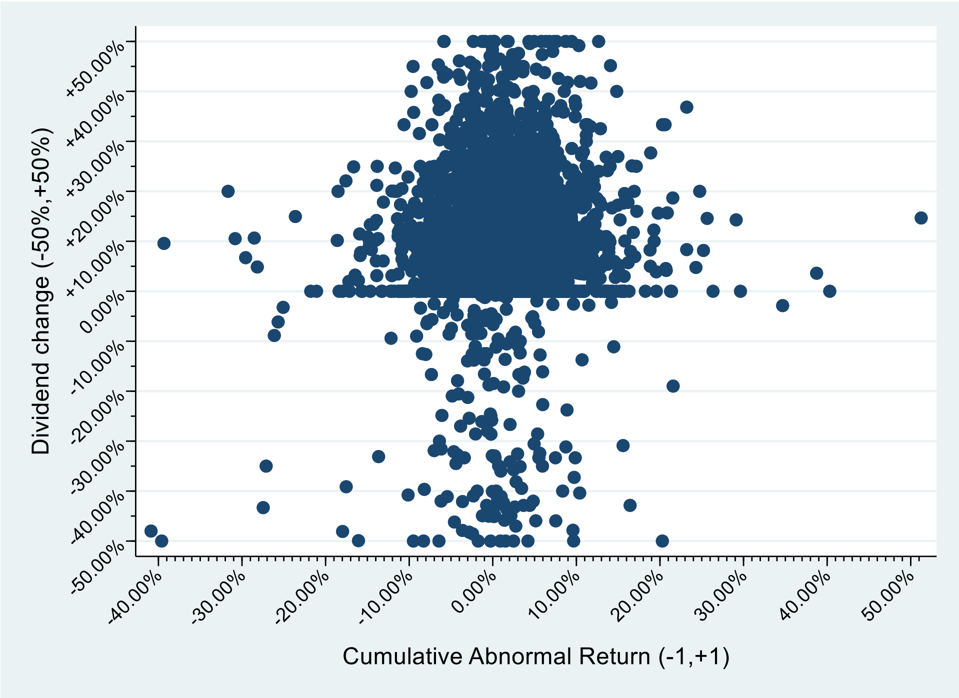


FIGURE 4: CUMULATIVE ABNORMAL RETURNS YEAR-BY-YEAR

Figure 5 shows CAR values by year for the two-event windows from 1990 to 2015. CAR values for both event windows are more concentrated between positive 20% to negative 20%, only few times values are greater than 20% in absolute value. The lowest CAR value was less than (-40%) in event window (-1,+1) and the highest CAR value was around +55% in event window (0,+1).



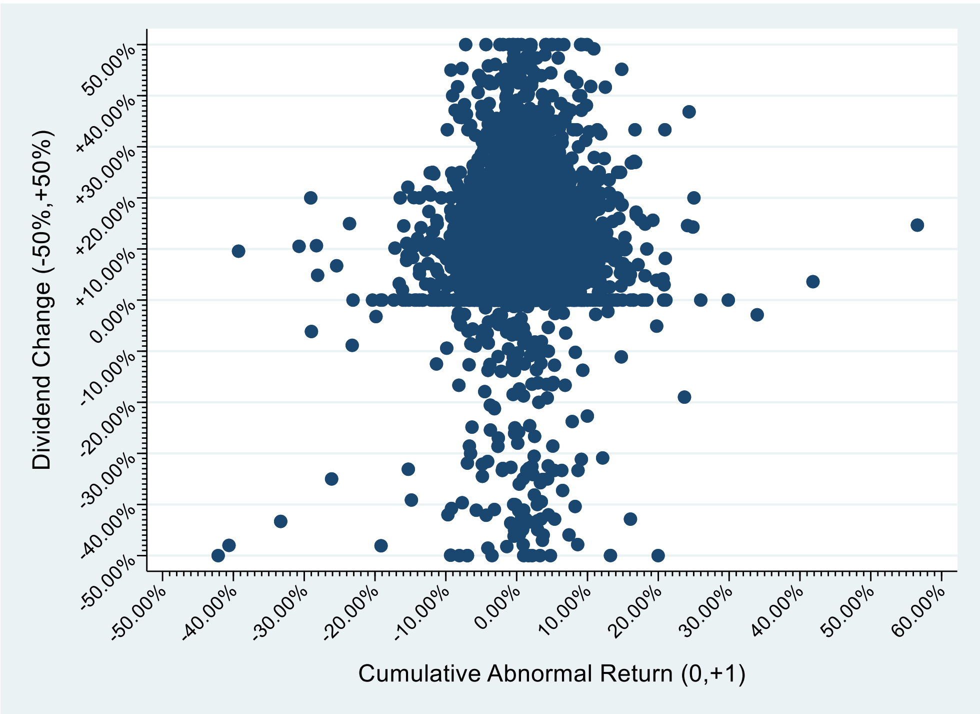


FIGURE 6: CUMULATIVE ABNORMAL RETURNS AGAINST PERCENTAGE CHANGE IN DIVIDENDS

Figure 6 shows the CAR against percentage change in dividends for the event windows (-1,+1) and (0,+1). The scatter plots in figure 6 show that there seem to be some outliers in both event windows. The highest positive outliers in both event windows are greater than 50% and the most extreme negative outliers are less than -40%.

TABLE 14 DESCRIPTIVE STATISTICS FOR CUMULATIVE ABNORMAL RETURN BASED ON DIVIDEND CHANGES

Panel A: All Observations

Event Window	N	Mean (CAR)	Standard Deviation	Mini	Max
(-1, +1) (%)	3,621	1.26	5.95	-40.88	51.26
(0, +1) (%)	3,621	1.08	5.69	-42.15	56.58

Panel B: Dividend Increase

Event Window	N	Mean (CAR)	Standard Deviation	Mini	Max
(-1, +1) (%)	2,972	1.43	5.53	-39.33	51.26
(0, +1) (%)	2,972	1.25	5.29	-39.27	56.58

Panel C: Dividend Decrease

Event Window	N	Mean (CAR)	Standard Deviation	Mini	Max
(-1, +1) (%)	198	-0.66	8.59	-40.88	34.68
(0, +1) (%)	198	-0.46	8.67	-42.15	33.96

Panel D: Unchanged Dividend

Event Window	N	Mean (CAR)	Standard Deviation	Mini	Max
(-1, +1) (%)	451	0.92	6.92	-21.78	40.32
(0, +1) (%)	451	0.68	6.41	-23.10	29.88

Note: This table reports the Cumulative abnormal returns descriptive statistics based on dividend changes for both event windows.

In Table 14, we can see that there are four panels. Panel A shows details about CAR for both event windows based on the whole sample. Table 14 shows that for all observations the CAR mean value for event window (-1,+1) is smaller than for event window (0,+1), but event window (-1,+1) has a larger standard deviation value compared to event window (0,+1). Panel B also shows that event window (0,+1) has a larger mean value than window (-1,+1), on the other hand dividend decrease shows a negative mean value for both event windows. And panel D shows that for event window (-1,+1) the mean value is (0.92%) and for event window (0,+1) the mean value is (0.68%).

TABLE 15 CORRELATION MATRIX FOR NON-DUMMY VARIABLES BASED ON EVENT WINDOW

Panel A: Dividend Announcement Event Window (-1, +1)

Variable Names	$R\Delta DIV$	Size	Reversal	Momentum	Dividend Yield	Cumulative – Abnormal - Return
$R\Delta DIV$	1.0000					
Size	0.0483	1.0000				
Reversal	0.0286	0.0079	1.0000			
Momentum	0.2407	0.0684	-0.0402	1.0000		
Dividend Yield	-0.2221	-0.1686	-0.1379	-0.3569	1.0000	
Cumulative Abnormal Return	0.0973	-0.1306	-0.0632	-0.0344	-0.0642	1.0000

Panel B: Dividend Announcement Event Window (0, +1)

Variable Names	$R\Delta DIV$	Size	Reversal	Momentum	Dividend Yield	Cumulative – Abnormal - Return
$R\Delta DIV$	1.0000					
Size	0.0483	1.0000				
Reversal	0.0286	0.0079	1.0000			
Momentum	0.2407	0.0684	-0.0402	1.0000		
Dividend Yield	-0.2221	-0.1686	-01370	-0.3569	1.0000	
Cumulative Abnormal Return	0.0865	-0.1317	-0.0496	-0.0282	0.0735	1.0000

Note: The table present here represents the correlation matrix of the entire variables used in this chapter to test dividend signaling hypothesis. Correlation matrix is explained using three different even windows. $R\Delta DIV$ is the annual changes of the dividend payment in showing in here as percentage. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stoke returns over previous months, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. And finally CAR is representing Cumulative Abnormal Return, estimated using the abnormal returns around the dividend announcement date.

Table 15 represent pair wise correlation matrix for all explanatory variables and dependent variables except dummy variables based on two event windows. Only Dividend Yield has negative correlation with dividend changes, while Size, Reversal, Momentum and CAR are positively correlated with dividend changes. Dividend Yield is negatively correlated with all other four variables in both panels. Momentum has negative correlation with only Reversal in both panels. Reversal has positive correlation with both dividend changes and Size.

6.7. EMPIRICAL RESULTS

6.7.1. EXPECTED SIGNS

Table 16 shows the expected signs of all variables and the reasons behind those expected sings.

TABLE 16 EXPECTED SIGNS

Variables	Coefficient	Expected sign	Comments
Constant	λ_0 (Equation 17- 19)	+	According to Kalay and Loewenstein (1985) investor requires higher rates of returns to hold stocks around their dividend announcements as compensation for the increased risk per unit of time in this period. Cohen et al. (2007) argue "it is compensation for risk incurred when investors are hold securities during a period when valuation relevant information is expected to be released. Suppose mean-variance pricing, investors require higher announcement returns when a newsworthy announcement is expected and the associated risk is non-diversifiable".
$R\Delta IVI * DPI$	λ_1 (Equation 18))	+	The greater the increase in dividend, the greater the increase in stock return.
$R\Delta IVI * DPD$	λ_2 (Equation 18)	+	The greater the decrease in dividend, the greater the decrease in stock returns.
DPI	λ_1 (Equation 19)	+	Positive dividend changes have a positive effect on stock returns.
DPD	λ_2 (Equation 19)	-	Negative dividend changes have a negative effect on stock returns.

SIZE	λ_3 (Equation 18-19)	-	"Small size effect" where small firms earn higher abnormal returns than large firm (Fuller, 2003 and Dasilas and Leventis, 2011).
REVERSAL	λ_4 (Equation 18-19)	+/-	De Bondt and Thaler (1985) argue that investors overreact to both positive and negative information, pushing the prices away from their fundamental values, and over the next two to three years, prices revert back to their fundamental values generating a reversal in stock returns. Based on that reversal could be positive or negative, empirical work based on CAR and reversal suggests that reversal is negative indicating less favorable reactions for firms with recent stock price increases (Autore and Jiang, 2017).
MOMENTUM	λ_5 (Equation 18-19)	+/ -	Stocks with high (low) unconditional expected rates of return in adjacent time periods are expected to have high (low) realized rates of returns in both periods. Hence, momentum strategies will yield negative average returns even if the expected returns on stocks are in constant over time (Lo and MacKinlay, 1990 and Jegadeesh and Titman, 1999). Based on that reversal could be positive or negative, empirical work based on CAR and reversal suggest that reversal is negative indicating less favorable reactions for firms with recent stock price increases (Autore and Jiang, 2017)
$DIVIDEND_{YIELD}$	λ_6 (Equation 18-19)	+	Dividend yield is the main driver of abnormal returns on dividend announcement dates (Dasilas and Leventis, 2011).
$R\Delta IVI * DPI$ *RECESSION	λ_3 (Equation 20)	-	Reaction of the stock market to dividend increase announcements is less positive than usual during the Great Recession period, because investors are pessimistic, investors are more likely to underestimate future dividend announcements or overestimate the risk of the future dividends of the risky assets, such as stocks, resulting in lower abnormal returns and lower stock prices. According to Hao et al. during recessionary periods, the markets reacts less positively to good performance and more negatively to bad performance.
$R\Delta IVI * DPD$ *RECESSION	λ_4 (Equation 20)	+	Reaction of the stock market to dividend decrease announcements is more negative than usual during the Great Recession period, because firms cannot sustain the dividend payout policy due to deteriorated financial health during the Great Recession (Zia and Kochan, 2017). If the dividend decreases for that reason, then the stock market reaction should be more negative than usual.
DPI * *RECESSION*	λ_3 (Equation 21)	-	Reaction of the stock market to dividend increase announcements is less positive than usual during the Great Recession period, because investors are pessimistic, investors are more likely to underestimate future dividend announcements or overestimate the risk of the future dividends of the risky assets, such as stocks, resulting lower abnormal returns and lower stock prices. According to Hao et al. during recessionary periods, the markets reacts less positively to good performance and more negatively to bad performance.
DPD **RECESSION*	λ_4 (Equation 21)	+	Reaction of the stock market to dividend decrease announcements is more negative than usual during the Great Recession period, because firms cannot sustain the dividend payout policy due to deteriorated financial health during the Great Recession (Zia and Kochan, 2017). If the dividend decreases for that reason, then the stock market reaction should be more negative than usual.

Note: Expected signs for interaction and binary model specification variables.

6.7.2. POSITIVE INTERCEPT

If the market is efficient then security prices should reflect changes in dividends. The empirical evidence in this chapter indicates that the mean realized returns around the dividend announcements period are higher than 'normal' and statistically significant. My results show that standardised mean excess returns are significantly positive in the event period.

The timing of the next dividend announcement can be predicted by market with certainty. As we know that dividend announcements are repetitive and generally made in the same calendar time. So, if the required rate of the returns around the dividend announcement is identical to that in any other random day, one should not be able to make excess returns by trading around these announcements. According to dividend-signalling theory, dividend announcements convey positive (negative) new information. So it means if the market is efficient then the security prices should reflect these changes.

The unconditional expected rate of return during the event period should be higher than normal. A larger required rate of return during the event period is consistent with the theory that the relevant risk per unit of time during the event is higher (Kalay and Loewenstein, 1985). Therefore the reason for positive intercept in all of my model specifications is that investor requires higher rates of returns to hold stocks around their dividend announcements as compensation for the increased risk per unit of time in this period. Some previous literature documents significant positive abnormal returns around predicted news announcements period (Penman, 1984; Chari et al. 1988; Ball and Kothari, 1991)[17]. The explanation given by Cohen et al. (2007) about the abnormal returns is that - "it is compensation for risk incurred when investors are hold securities during a period when valuation relevant information is expected to be released. Suppose mean-variance pricing, investors require higher announcement returns when a newsworthy announcement is expected and the associated risk is non-diversifiable".

6.7.3. BASELINE LINEAR MODEL

I begin my empirical research with a very basic linear model to establish whether dividend increase (decrease) announcements have a positive (negative) effect on stock returns. This model will examine the correlation between the rate of change in dividends per stock at time *t* and the cumulative abnormal returns over the event window. This is my first and benchmark specification, so that I can compare my results with the literature.

In this section I will use equation (17) to test whether dividend increase (decrease) announcements have a positive (negative) effect on stock returns. I will use CAR (-1,+1) as my dependent variable while I will test the dividend signaling hypothesis. In equation (17) I also use $R\Delta DIV_0$ as my explanatory variable, which is the percentage change in dividends. In Table 17 we can see two different types of regression output, one without clustered standard errors and another one is with clustered standard errors.

[17] A few empirical studies fail to show the evidence of announcement-day premium (Peterson, 1990; Brown and Kim, 1993). Whereas majority of the evidence supports the presence of higher returns on predictable disclosure events indicating that investors require an announcement-day premium.

The point estimate for coefficient λ_0 is 0.869%. The average daily stock return is 0.01619%. The point estimate for dividend changes percentages (λ_1) is 3.957%, which is economically significant. Coefficient λ_1 is statistically significant at 1% level in both models. R^2 = 0.76% and number of observations are 3,621 in both models.

TABLE 17 REGRESSIONS OF CUMULATIVE ABNORNAL RETURN ON DIVIDEND CHANGES (BASELINE LINEAR MODEL)

$$CAR_{(-1,+1)} = \lambda_0 + \lambda_1 R\Delta DIV_{it} + \mu_{it}$$

Regression Coefficients on Dividend Changes

Variables and Expected Coefficients Sign		Model-1	Model-2
Constant (λ_0)	Point Estimate	0.00869[a]	0.00869[a]
Expected sign (+)	t-statistics	7.07	5.40
	Standard Error	0.00123	0.00161
$R\Delta DIV_0$ (λ_1)	Point Estimate	0.03957[a]	0.03957[a]
Expected sign (+)	t-statistics	5.27	3.83
	Standard Error	0.00751	0.01033
Clustered by Company ID and Date		NO	YES
R^2		0.76%	0.76%
N		3,621	3,621

Note: this table reports the results of baseline linear model. I use only one event window to calculate my CAR which is 3 days event period (-1,+1). $R\Delta DIV_0$ Represent annual dividend changes percentage. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

The results and signs are consistent with the dividend-signalling theory, as we know according to the dividend signaling theory dividend-increase (decrease) announcements have a positive (negative) effect on stock returns. Constant λ_0 is statistically significant at 1% level and positive. Coefficient λ_0 is economically significant. The positive coefficient λ_0 suggests that investors require higher rates of returns to hold stocks around dividend announcements as compensation for the increased risk per unit of time in this period. Coefficient λ_1 is positive as expected and statistically significant at 1% level. Coefficient λ_1 is economically significant as well; when dividends increase by 10% stock returns are estimated to increase by 0.3957%.

6.7.4. LINEAR INTERACTION MODEL

In this section I use the interaction model which interacts the percentage change in dividends with a dividend increase dummy (DPI) and a dividend decrease dummy (DPD); due to that reason λ_1 becomes the regression coefficient for the positive dividend-change group, and λ_2 becomes the regression coefficient for the negative dividend-change group. In Table 18 I use a three-days event window for the CAR, which is one day before dividend announcement, dividend announcement day and one day after dividend announcement, so my CAR is (-1,+1). Table 18 shows the interaction model results, where I divide my specification into four variations and I call them model 1, 2, 3 and 4. Model 1 results in all four tables are presented without day-of-the-week effects, year fixed effects, industry fixed effects and clustered standard errors; model 2 results are presented with year fixed effects, industry fixed effects and clustered standard errors but without day-of-the-week effects; model 3 results are with day-of-the-week effects, year fixed effects, industry fixed effects and clustered standard errors and model 4 results are with day-of-the-week effects, year fixed effects, firm fixed effects and clustered standard errors.

In Table 18 the signs of the coefficient λ_1 and λ_2 in all four models are consistent with the dividend-signalling theory. Coefficient λ_1 is statistically significant at 1% level in all four models. The average daily stock returns are

0.01619%. The point estimate of Coefficient λ_1 in model three is 6.269%, which is economically significant. In the other three models coefficient λ_1 is also economically significant. This means that when dividends increase by 10% stock returns in model 3 are estimated to increase by 0.6269%. For coefficient $\lambda_1$we can see the similar kind of results in other three models as well. On the other hand coefficient λ_2 is statistically significant at 1 % level in model 1 and at 5% level in model 2, 3 and 4. Coefficient λ_2 results are economically significant in the four models. When dividend decrease by 10% stock returns are estimated to decrease by 0.6439% in model 3. We can see the similar kind of results for three other models as well.

F-test results suggest that there is not enough evidence to reject the equality hypothesis at 10% significant level between coefficient λ_1 and coefficient λ_2 in all four models, because *F*-test result in model 1 is insignificant (*p*-value = 0.6069) and results in model 2, 3 and 4 are also insignificant (*p*-value = 0.9194, 0.9577 and 0.8883 in model 2, 3 and 4 respectively).

Coefficient λ_0 is statistically significant at 1% level in model 1 and in model 4, on the other hand coefficient λ_0 is statistically significant at 5% level in model 2 and 3. Coefficient λ_0 also shows positive sign; the reason behind this positive intercept is explained in section (6.7.2). Control variable size, and reversal are significant in all four models, but momentum is only significant in first three models and their signs are consistent with the literatures. Dividend yield is only significant in model 1 at 5% level, however dividend yield signs are consistent with the literature. So these results indicate that dividends increase (decrease) announcements have a positive (negative) effect on stock market returns. The total number of observation in all three models is 3,407. If we look at Table 17 and other tables then we can see the differences of number of observations, the reason behind is that Table 17 do not have the control variables on the other hand other tables has control variables and control variable size and momentum has less observations than other variables. R^2 value in the four models is 3.70%, 5.03%, 5.29% and 13.07% respectively.

TABLE 18 REGRESSION ANALYSIS OF CUMULATIVE ABNORMAL RETURN ON DIVIDEND ANNOUNCEMENT DATES (LINEAR INTERACTION MODEL)

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 SIZE_{it} + \lambda_4 REVERSAL_{it} + \lambda_5 MOMENTUM_{it} + \lambda_6 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3\ FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.04082[a]	0.03794[b]	0.03594[b]	0.06488[a]
	t-statistics	6.88	2.11	2.00	3.21
	Standard Error	0.00593	0.01794	0.01797	0.02024
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.05402[a]	0.06107[a]	0.06269[a]	0.07281[a]
	t-statistics	4.92	5.14	5.29	5.15
	Standard Error	0.01098	0.01189	0.01186	0.01413
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.06485[a]	0.06434[b]	0.06439[b]	0.06793[b]
	t-statistics	4.10	2.39	2.41	2.37
	Standard Error	0.01584	0.02694	0.02675	0.02866
$SIZE$ (λ_3)	Point Estimate	-0.00518[a]	-0.00472[a]	-0.00499[a]	-0.01335[a]
	t-statistics	-7.35	-4.99	-5.28	-4.90
	Standard Error	0.00070	0.00095	0.00094	0.00272
$REVERSAL$ (λ_4)	Point Estimate	-0.85554[a]	-0.98870[a]	-0.98201[a]	-1.05919[a]
	t-statistics	-3.56	-2.70	-2.70	-2.77
	Standard Error	0.24036	0.36586	0.36423	0.38219
$MOMENTUM$ (λ_5)	Point Estimate	-0.16374[b]	-0.20372[c]	-0.20877[c]	-0.18745
	t-statistics	-2.23	-1.81	-1.86	-1.62
	Standard Error	0.07327	0.11254	0.11563	0.11543
$DIVIDEND_{YIELD}$ (λ_6)	Point Estimate	0.21486[b]	0.17575	0.14910	0.12557
	t-statistics	2.44	1.53	1.29	0.53
	Standard Error	0.08803	0.11502	0.11563	0.23516
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.70%	5.03%	5.29%	13.07%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (-1,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes is positive then DPI=1, otherwise 0, and if the dividend changes is negative then DPD =1, otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stoke returns over previous months, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where

M_d, W_d , T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

6.7.5. LINEAR BINARY MODEL

The binary model only concentrates on the direction of the dividend change and ignores the size of the dividend change to find out whether dividend change direction has any effect on stock returns. By concentrating on dividend change direction, the binary model mitigates the effect of outliers.

Table 19 reveal that the signs of the coefficient λ_1 is positive and λ_2 is negative in all four models and these result is consistent with the dividend-signalling theory. Coefficient λ_1 is statistically significant at 1% level and economically significant in all four models as the average stock returns are 0.01619%. This means that on average across firms that increase dividends stock returns are 1.194% higher in model 1 (1.201% higher in model 2, 1.273% higher in model 3 and 1.300% higher in model 4) than for firms that leave dividends unchanged. Coefficient λ_2 is statistically significant at 5% level in the 1st three models and at 10% in model 4. Coefficient λ_2 is economically significant in all four models. The results reveal that on average across firms that decrease dividends stock market returns are -1.233% lower in model 1 (-1.262% lower in model 2, -1.208% lower in model 3 and -1.429% lower in model 4) than for firms that leave dividends unchanged.

F-test results suggest that there is not enough evidence to reject the equality hypothesis in favour of alternative hypothesis at 10% significant level between coefficient λ_1 and coefficient λ_2 in all four models, because F-test result in model 1 is insignificant (p-value = 0.9588) and results in model 2, 3 and 4 are also insignificant (p-value = 0.9384, 0.9340 and 0.8926 in model 2, 3 and 4 respectively). Coefficient λ_0 is statistically significant at 1% level in model 1 and 4, and at 5% level in model 2 and 3. Coefficient λ_0 also shows positive sign; the reason behind this positive intercept is explained in section (6.7.2). Control variable size, reversal, and momentum shows negative sign in the four models and only dividend yield shows positive sign, which are consistent with the previous literature and are significant in model 1 and signs are consistent with the previous literature and with my expectations. Control variable size, and reversal are statistically significant in the four models and in model 2, 3 and 4 momentum and dividend yield is not significant. The total number of observations in all three models is 3,407. The R^2 value in the four models is 3.34%, 4.50%, 4.75% and 12.39% respectively.

TABLE 19 REGRESSION ANALYSIS OF CUMULATIVE ABNORMAL RETURN ON DIVIDEND ANNOUNCEMENT DATES (LINEAR BINARY MODEL)

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 SIZE_{it} + \lambda_4 REVERSAL_{it} + \lambda_5 MOMENTUM_{it} + \lambda_6 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2\ YEAR\ DUMMIES + \vartheta_3\ FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03937[a]	0.04001[b]	0.03836[b]	0.06748[a]
	t-statistics	6.27	2.21	2.11	3.45
	Standard Error	0.00628	0.01808	0.01818	0.01955
DPI (λ_1)	Point Estimate	0.01194[a]	0.01201[a]	0.01273[a]	0.01300[a]
	t-statistics	3.67	3.53	3.75	3.08
	Standard Error	0.00325	0.00339	0.00339	0.00422
DPD (λ_2)	Point Estimate	-0.01233[b]	-0.01262[b]	-0.01208[b]	-0.01429[c]
	t-statistics	-2.33	-2.04	-1.97	-1.87
	Standard Error	0.00529	0.00617	0.00613	0.00763
$SIZE$ (λ_3)	Point Estimate	-0.00543[a]	-0.00509[a]	-0.00540[a]	-0.01307[a]
	t-statistics	-7.66	-5.27	-5.60	-4.84
	Standard Error	0.00071	0.00097	0.00096	0.00269
$REVERSAL$ (λ_4)	Point Estimate	-0.86158[a]	-0.97335[a]	-0.96623[a]	-1.03885[a]
	t-statistics	-3.58	-2.70	-2.69	-2.72
	Standard Error	0.24080	0.36084	0.35926	0.38206

$MOMENTUM\ (\lambda_5)$	Point Estimate	-0.13699[c]	-0.15839	-0.16263	-0.12718
	t-statistics	-1.88	-1.42	-1.46	-1.09
	Standard Error	0.07298	0.11143	0.11101	0.11649
$DIVIDEND_{YIELD}\ (\lambda_6)$	Point Estimate	0.17206[b]	0.12390	0.09881	0.09825
	t-statistics	1.96	1.07	0.85	0.43
	Standard Error	0.08771	0.11575	0.11624	0.22951
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.34%	4.50%	4.75%	12.39%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (-1,+1). The dummy variables are DPI and DPD. If the dividend changes is positive DPI=1, otherwise 0, and if the dividend changes is negative then DPD =1, otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stoke returns over previous months, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where $M_d,\ W_d\ ,\ T_d\ and\ F_d$ are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

6.8. ROBUSTNESS TEST

An event study attempts to measure the valuation effects of a corporate event, by examining the response of the stock market price around the event. In the previous section I used 3 days event window i.e. (-1,+1), and in this section I will use 2 days event window i.e. (0,+1) to do a robustness test. These two days event window is dividend announcements day t_0 and one day after the dividend announcement day t_1.

One of the underlying assumptions of the event window is that the market processes information about the event in an unbiased manner. Thus, we should be able to see the effect of the dividend announcement on stock market prices, how quickly market can incorporate information and whether this information has any direct effect on stock prices. According to Efficient Market Hypothesis (EMH) the market should react efficiently. Due to that reason in this section I will examine whether there are any empirical evidence that 2 days event window results are different than 3 days event window results. Except for CAR all other variables are the same as in the previous section.

In Table 20 coefficient λ_1 is statistically significant at 1% level and economically significant in the four models as the average stock returns are 0.01619%. These results are consistent with the dividend-signalling theory. When dividends increase by 10% stock returns are estimated to increase by 0.4578% in model 1, 0.5279% in model 2, 0.5477% in model 3 and 0.6654% in model 4. But coefficient λ_2 is statistically significant at 1% level in model 1 and at 5% level in model 2, 3 and 4. This means that when dividends decrease by 10% stock returns are expected to decrease by 0.5891%, 0.5760%, 0.5753% and 0.5992% in model 1, 2, 3 and 4 respectively.

F-test results suggest that there is not enough evidence to reject the equality hypothesis at 10% significant level between coefficient λ_1 and coefficient λ_2 in all four models, because *F*-test result in model 1 is insignificant (*p*-value = 0.5170) and results in model 2, 3 and 4 are also insignificant (*p*-value = 0.8842, 0.9327 and 0.8524 in model 2, 3 and 4 respectively). Empirical results section also suggests similar kind of results. Coefficient λ_0 is statistically significant and shows positive sign. Except for the control variable momentum all other three-control variables are statistically significant in the first three models and dividend yield is not significant in model four, but all four-control variables signs are consistent with the literatures. It means we can tell that dividend increase (decrease) announcements have a positive (negative) effect on stock market returns.

TABLE 20 REGRESSION ANALYSIS OF CUMULATIVE ABNORMAL RETURN ON DIVIDEND ANNOUNCEMENT DATES (LINEAR INTERACTION MODEL)

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 SIZE_{it} + \lambda_4 REVERSAL_{it} + \lambda_5 MOMENTUM_{it} + \lambda_6 DIVIDEND_{YIELD\,it} + \vartheta_1 DW\ Effect + \vartheta_2\ YEAR\ DUMMIES + \vartheta_3\ FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03677[a]	0.03031[b]	0.02689[b]	0.06292[a]
	t-statistics	6.44	2.45	2.18	3.88
	Standard Error	0.00571	0.01238	0.01234	0.01619
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.04578[a]	0.05279[a]	0.05477[a]	0.06654[a]
	t-statistics	4.34	4.48	4.67	4.91
	Standard Error	0.01056	0.01178	0.01173	0.01356
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.05891[a]	0.05760[b]	0.05753[b]	0.05992[b]
	t-statistics	3.87	2.13	2.14	2.06
	Standard Error	0.01523	0.02708	0.02686	0.02907
$SIZE$ (λ_5)	Point Estimate	-0.00495[a]	-0.00461[a]	-0.00489[a]	-0.01342[a]
	t-statistics	-7.30	-5.27	-5.60	-5.10
	Standard Error	0.00068	0.00088	0.00087	0.00263
$REVERSAL$ (λ_6)	Point Estimate	-0.59765[a]	-0.70184[c]	-0.69352[c]	-0.76819[b]
	t-statistics	-2.58	-1.91	-1.90	-1.99
	Standard Error	0.23124	0.36824	0.36580	0.38548
$MOMENTUM$ (λ_7)	Point Estimate	-0.10035	-0.12831	-0.13527	-0.09942
	t-statistics	-1.42	-1.20	-1.27	-0.91
	Standard Error	0.07049	0.10654	0.10677	0.10926
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.26903[a]	0.24050[b]	0.20835[c]	0.25226
	t-statistics	3.18	2.14	1.85	1.14
	Standard Error	0.08468	0.11256	0.11280	0.22051
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.39%	4.66%	5.04%	13.47%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (0,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes is positive then DPI=1, otherwise 0, and if the dividend changes is negative then DPD =1, otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stoke returns over previous months, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where $M_d, , W_d , T_d\ and\ F_d$ are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

In Table 21 the signs of the coefficient λ_1 and λ_2 in the four models are consistent with the dividend-signalling theory and with the results from the previous section. Coefficient λ_1 is statistically significant at 1% level in the four models. Coefficient λ_1 results are economically significant in the four models; across firms that increase dividends stock market returns are 1.311% higher in model 1 (1.328% higher in model 2, 1.409% higher in model 3 and 1.463% in model 4) than for firms that leave dividends unchanged. Coefficient λ_2 is economically significant but statistically insignificant in the four models.

F-test results suggest that there is not enough evidence to reject the equality hypothesis in favour of alternative hypothesis at 10% significant level between coefficient λ_1 and coefficient λ_2 in all three models, because *F*-test result in model 1 is insignificant (*p*-value = 0.4166) and results in model 2, 3 and 4 are insignificant (*p*-value = 0.4396, 0.3287 and 0.4989 in model 2, 3 and 4 respectively). We can observe similar kind of result in empirical results section. Except for the control variable momentum all other three-control variables are statistically significant in all four models, and all four-control variables signs are consistent with the literatures. On the basis of these results it is possible to reject the null hypothesis in favour of the dividend-signalling theory.

TABLE 21 REGRESSION ANALYSIS OF CUMULATIVE ABNORMAL RETURN ON DIVIDEND ANNOUNCEMENT DATES (LINEAR BINARY MODEL)

$$\begin{aligned} CAR_{it} = {} & \lambda_0 + \lambda_1 DPI_{it} + \lambda_2\, DPD_{it} + \lambda_3\, SIZE_{it} + \lambda_4\, REVERSAL_{it} + \lambda_5\, MOMENTUM_{it} \\ & + \lambda_6\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\,Effect + \vartheta_2\, YEAR\ DUMMIES \\ & + \vartheta_3\ FIXED\ EFFECTS + \mu_{it} \end{aligned}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03293[a]	0.02968[b]	0.02652[b]	0.06200[a]
	t-statistics	5.46	2.38	2.13	4.08
	Standard Error	0.00603	0.01245	0.01244	0.01520
$DPI\ (\lambda_1)$	Point Estimate	0.01311[a]	0.01328[a]	0.01409[a]	0.01463[a]
	t-statistics	4.20	4.20	4.46	3.79
	Standard Error	0.00313	0.00317	0.00316	0.00386
$DPD\ (\lambda_2)$	Point Estimate	-0.00723	-0.00729	-0.00661	-0.00828
	t-statistics	-1.42	-1.18	-1.08	-1.08
	Standard Error	0.00508	0.00618	0.00611	0.00765
$SIZE\ (\lambda_3)$	Point Estimate	-0.00522[a]	-0.00502[a]	-0.00534[a]	-0.01319[a]
	t-statistics	-7.65	-5.60	-5.99	-5.05
	Standard Error	0.00068	0.00089	0.00089	0.00261
$REVERSAL\ \ (\lambda_4)$	Point Estimate	-0.60449[a]	-0.69078[c]	-0.68173[c]	-0.74288[c]
	t-statistics	-2.61	-1.89	-1.88	-1.92
	Standard Error	0.23145	0.36455	0.36200	0.38758
$MOMENTUM\ (\lambda_5)$	Point Estimate	-0.08229	-0.09396	-0.10000	-0.04393
	t-statistics	-1.17	-0.90	-0.96	-0.40
	Standard Error	0.07015	0.10449	0.10427	0.10994
$DIVIDEND_{YIELD}\ (\lambda_6)$	Point Estimate	0.24874[a]	0.21174[c]	0.18032	0.25673
	t-statistics	2.95	1.90	1.62	1.19
	Standard Error	0.08432	0.11120	0.11136	0.21512
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.21%	4.32%	4.70%	13.47%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (0,+1). The dummy variables are DPI and DPD. If the dividend changes is positive then DPI=1, otherwise 0, and if the dividend changes is negative then DPD =1, otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stoke returns over previous months, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where $M_d,\ W_d\ ,\ T_d\ and\ F_d$ are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

6.9. DID THE GREAT RECESSION CHANGE THE RELATIONSHIP BETWEEN DIVIDEND CHANGES AND STOCK RETURNS?

In this section I will do an additional test. I will consider the effect of the Great Recession on the UK market, while I will conduct this additional test. In this section I am considering whether the stock market reacts differently to dividend announcements during the Great Recession (2008-2009) period. The 2007 financial crisis followed by the Great Recession (2008-2009) resulted in a loss of confidence among investors, and regaining full trust and confidence has been a challenge for companies. Empirical studies of the signalling theory of dividends reveal that investors react positively to dividend increase and react negatively to dividend decrease. During market downturns information about financial health of firms becomes more important. Investors may wonder if the firms they have invested in are financially sound. At the same time, firms may limit the release of negative information about their financials. During such times, asymmetry of information may increase, and dividend decreases may signal even more strongly than usual that firms are experiencing financial problems.

During the Great Recession (2008-2009), firms become more vulnerable to risk as credit markets tighten up and default rates on loan increase. When a firm decreases dividends, it may be because it cannot sustain the dividend payout policy due to deteriorated financial health, during the Great Recession (Zia and Kochan, 2017). If the dividend decreases are for that reason, then the stock market reaction should be more negative than usual. However, it can be considered a risk-reducing decision as it makes firms more solvent and thus, a positive sign. Whereas the reaction of the stock market to dividend increase announcements may be less positive than usual during the Great Recession period (2008-2009), because investors are pessimistic, investors are more likely to underestimate future dividend announcements or overestimate the risk of the future dividends of the risky assets, such as stocks, resulting in lower abnormal returns. According to Hao et al. during recessionary periods, the market reacts less positively to good performance and more negatively to bad performance. The hypotheses are as follows:

H_0: The reaction of stock returns to dividend increase (decrease) announcements is the same during the Great Recession (2008-2009) as during regular periods (1990-2008 and 2009-2015)[18].

H_a: Stock market returns react less positively to dividend increase announcements and more negatively to dividend decrease announcements during the Great Recession (2008-2009) than during regular periods (1990-2008 and 2009-2015).

I will create a new dummy called recession and this dummy will be interacted with my key independent variables in both the interaction model and the binary model. I have collected Recession period information from House of Commons Library Research[19]. Recession period was in total 6 quarters. Total number of dividend increase announcements during these periods was 106 and total number of dividend decrease announcements was 17. And I will use three days event window (-1,+1) to conduct this additional test. The models are

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[18] More specifically, I am comparing the period between 1st April 2008 and 30th September 2009 (i.e. the Great Recession) with the rest of the sample period, which consists of the period that preceded the Great Recession, between 1st January1990 and 31st March 2008, and the period that followed it, between 1st October 2009 and 31st December 2015.

[19] https://www.parliament.uk/documents/commons/lib/research/key_issues/Key-Issues-Recession-and-recovery.pdf

Interaction model

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * RECESSION_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * RECESSION_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2\ YEAR\ DUMMIES + \vartheta_3\ FIXED\ EFFECTS + \mu_{it} \quad (20)$$

Binary model

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * RECESSION_t + \lambda_4 DPD_{it} * RECESSION_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2\ YEAR\ DUMMIES + \vartheta_3\ FIXED\ EFFECTS + \mu_{it} \quad (21)$$

Where,

$RECESSION_t$ = 1 between 1st April 2008 and 30th September 2009, 0 otherwise

Table 22 shows that the coefficient λ_1 and λ_2 are economically significant as we know the average stock returns are 0.01619%. Coefficient λ_1 and λ_2 are also statistically significant. But coefficient $\lambda_3$is statistically insignificant in all of the four models. So we can tell that there is no evidence that the Great Recession affects the reaction of the stock market to dividend increase announcements.

On the other hand coefficient λ_4 is statistically significant at 1% in model 1, at 5% level in model 2 and 3, and at 10% level in model 4. Coefficient λ_4 is economically significant in the four models; one of the reasons of the high economical significance may be that there are only 17 dividend-decrease observations in the Great Recession period. Computing the partial effect of a dividend decrease on CAR all else constant:

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}\middle| DPD_{it}=1\right)= \lambda_2 DPD_{it}+\lambda_4 DPD_{it} * RECESSION_{\ t} \qquad (22)$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}\middle| DPD_{it}=1\right)=\widehat{\lambda_2}+\ \widehat{\lambda_4} * RECESSION_{\ t}$$

$$=\ \widehat{\lambda_2}+\ \widehat{\lambda_4} * 1 \ \text{ [if } RECESSION = 1]$$

hence, for model 1

=0.04012 + 0.26321 * 1

= 0.30333

for model 2

= 0.04164 + 0.25942 * 1

= 0.30106

for model 3

= 0.04192 + 0.25668 * 1

= 0.29860

and for model 4

=0.04869 + 0.22245 * 1

=0.27114

The results from equation 22 show that a 10% decrease in dividends decreases stock returns by 2.9860% (according to model 3) if it occurs in the Great Recession period, whereas it decrease stock returns by only 0.4192% during other periods of time. We can observe similar kind of results for other three models as well. This means the Great Recession period has a significant influence on the relationship between dividend decrease announcements and stock returns. So these results suggest that the stock market reacts more strongly (i.e. more negatively) to dividend decrease announcements during the Great Recession period than during other periods of time.

On the basis of these results we can conclude that the Great Recession did not affect the reaction of the stock market to dividend increase announcements but the reaction of the stock market was more negative than usual to dividend decrease announcements during the Great Recession period.

TABLE 22 REGRESSION ANALYSIS OF CUMULATIVE ABNORMAL RETURN ON DIVIDEND ANNOUNCEMENT DATES (LINEAR INTERACTION MODEL DURING GREAT RECESSION)

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * RECESSION + \lambda_4 R\Delta DIV_{it} * DPD_{it} * RECESSION + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD\,it} + \vartheta_1 DW\ Effect + \vartheta_2\ YEAR\ DUMMIES + \vartheta_3\ FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.04141[a]	0.03400[a]	0.03310[a]	0.09391[a]
	t-statistics	6.99	3.23	3.15	3.62
	Standard Error	0.00592	0.01053	0.01052	0.02593
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.05297[a]	0.05792[a]	0.05934[a]	0.07064[a]
	t-statistics	4.79	4.81	4.92	4.84
	Standard Error	0.01106	0.01205	0.01205	0.01458
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.04012[b]	0.04164[c]	0.04192[c]	0.04869[c]
	t-statistics	2.43	1.72	1.74	1.83
	Standard Error	0.01649	0.02427	0.02409	0.02656
*RΔIVI * DPI * RECESSION* (λ_3)	Point Estimate	0.04753	0.04889	0.05172	0.06679
	t-statistics	1.24	0.94	1.00	1.21
	Standard Error	0.03835	0.05197	0.05174	0.05514
$R\Delta IVI * DPD * RECESSION$ (λ_4)	Point Estimate	0.26321[a]	0.25942[b]	0.25668[b]	0.22245[c]
	t-statistics	5.10	2.01	1.99	1.70
	Standard Error	0.05165	0.12922	0.12915	0.13118
$SIZE$ (λ_5)	Point Estimate	-0.00526[a]	-0.00507[a]	-0.00534[a]	-0.01338[a]
	t-statistics	-7.47	-5.33	-5.63	-4.48
	Standard Error	0.00070	0.00095	0.00095	0.00274
$REVERSAL$ (λ_6)	Point Estimate	-0.81389[a]	-0.84009[b]	-0.83333[b]	-1.01012[a]
	t-statistics	-3.39	-2.31	-2.30	-2.65
	Standard Error	0.23996	0.36366	0.36241	0.38084
$MOMENTUM$ (λ_7)	Point Estimate	-0.18018[b]	-0.19691[c]	-0.20137[c]	-0.19082[c]
	t-statistics	-2.44	-1.80	-1.84	-1.67
	Standard Error	0.07396	0.10954	0.10965	0.11444
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.20987[b]	0.16435	0.13872	0.13934
	t-statistics	2.39	1.43	1.20	0.59
	Standard Error	0.08776	0.11482	0.11534	0.23548
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		4.48%	5.61%	5.87%	13.59%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (0,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes is positive then DPI=1, otherwise 0, and if the dividend changes is negative then DPD =1, otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stoke returns over previous months, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Recession is a dummy variable, if dividend announced from 1st April 2008 to 30th June 2009 then RECESSION take value 1, otherwise 0. Day-of – the-week effect, where M_d, W_d , T_d *and* F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

Coefficient λ_0 Table 22 is statistically significant and shows positive sign. This suggests that investors require higher rates of returns to hold stocks around dividend announcements as compensation for the increased risk per unit of time in this period. Control variables size, reversal and momentum are statistically significant in four models, but dividend yield is statistically significant only in model 1 at 5% level. The control variable SIZE is statistically significant and it is found to have a negative effect on cumulative abnormal returns. This sign is consistent with the evidence that, other things the same, smaller companies tend to experience higher returns than bigger companies. The signs of the coefficients in four models are consistent with the dividend-signalling theory and with previous literatures. The result of the interaction model is consistent with my previous section.

In Table 23 coefficient λ_1 is economically and statistically significant. Coefficient λ_2 and coefficient λ_3 is economically and statistically insignificant in the three models. Coefficient λ_4 is economically significant in the three models but statistically significant at 1% level in model 1only. Computing the partial effect of a dividend decrease on CAR all else constant:

$$\left(\frac{\partial CAR_{it}}{\partial DPD_{it}}\middle| DPD_{it} = 1\right) = \lambda_2 + \lambda_4 * RECESSION_t \qquad (23)$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta DPD_{it}}\middle| DPD_{it} = 1\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * RECESSION_t$$

$$= \widehat{\lambda_2} + \widehat{\lambda_4} * 1 \text{ [if } REECESSION=1\text{]}$$

hence, model 1

= -0.00802 + (-0.04547) * 1

= -0.05349

for model 2

=-0.00849 + (-0.04728) * 1

= -0.05577

for model 3

= -0.00799 + (-0.04698) * 1

= -0.05497

and, for model 4

=-0.01147+ (-0.03106) * 1

= -0.04253

TABLE 23 REGRESSION ANALYSIS OF CUMULATIVE ABNORMAL RETURN ON DIVIDEND ANNOUNCEMENT DATES (LINEAR BINARY MODEL DURING GREAT RECESSION)

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * RECESSION + \lambda_4 DPD_{it} * RECESSION + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2\ YEAR\ DUMMIES + \vartheta_3\ FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03946[a]	0.03322[a]	0.03242[a]	0.07681[a]
	t-statistics	6.28	3.09	3.03	3.58
	Standard Error	0.00629	0.01075	0.01072	0.02144
DPI (λ_1)	Point Estimate	0.01209[a]	0.01229[a]	0.01298[a]	0.01275[a]
	t-statistics	3.70	3.57	3.77	2.96
	Standard Error	0.00327	0.00344	0.00344	0.00431
DPD (λ_2)	Point Estimate	-0.00802	-0.00849	-0.00799	-0.01147
	t-statistics	-1.47	-1.40	-1.34	-1.56
	Standard Error	0.00547	0.00605	0.00598	0.00738
*DPI * RECESSION* (λ_3)	Point Estimate	0.00175	0.00002	0.00025	0.00606
	t-statistics	0.29	0.00	0.03	0.59
	Standard Error	0.00601	0.00845	0.00842	0.01020
*DPD *RECESSION* (λ_4)	Point Estimate	-0.04547[a]	-0.04728	-0.04698	-0.03106
	t-statistics	-3.02	-1.48	-1.48	-0.97
	Standard Error	0.01508	0.03204	0.03182	0.03192

$SIZE\ (\lambda_5)$	Point Estimate	-0.00548[a]	-0.00537[a]	-0.00567[a]	-0.01303[a]
	t-statistics	-7.72	-5.55	-5.89	-4.81
	Standard Error	0.00071	0.00097	0.00096	0.00271
$REVERSAL\ (\lambda_6)$	Point Estimate	-0.87003[a]	-0.89802[b]	-0.89069[b]	-1.03191[a]
	t-statistics	-3.60	-2.45	-2.44	-2.68
	Standard Error	0.24150	0.36606	0.36473	0.38497
$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.15178[b]	-0.15546	-0.15960	-0.12867
	t-statistics	-2.04	-1.40	-1.44	-1.10
	Standard Error	0.07423	0.11109	0.11082	0.11667
$DIVIDEND_{YIELD}\ (\lambda_8)$	Point Estimate	0.17788[b]	0.12499	0.100058	0.10756
	t-statistics	2.03	1.07	0.86	0.46
	Standard Error	0.08780	0.11641	0.11678	0.23221
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.60%	4.63%	4.89%	12.53%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (0,+1). The dummy variables are DPI and DPD. If the dividend changes is positive then DPI=1, otherwise 0, and if the dividend changes is negative then DPD =1, otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stoke returns over previous months, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Recession is a dummy variable, if dividend announced from 1st April 2008 to 30th June 2009 then RECESSION take value 1, otherwise 0.Day-of –the-week effect, where $M_d,\ T_d, W_d\ , T_d\ and\ F_d$ are the dummy variables for Monday, Tuesday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

Equation 23 suggests that during the Great Recession period across firms decreasing dividends stock market returns are -5.349% lower in model 1 than for firms leaving dividends unchanged, whereas the effect is only -0.802% during other periods of time. As coefficient λ_2 in all four models is statistically insignificant and coefficient λ_4 is statistically significant only in model 1, there is only very weak evidence that the Great Recession affects the reaction of the stock market to dividend announcements.

Coefficient λ_0 is statistically significant at 1% level in all four models and in four models shows the positive sign. Control variable reversal is statistically significant at

1% level in model 1 and 4, and at 5% level in model 2 and 3. On the other hand momentum and dividend yield are statistically significant at 5% level in model 1.

6.10. DISCUSSION

If we look back to my data section then we can see that the number of dividend-increase announcements is quite high compared to dividend decrease announcements (2,972 dividend increase announcements and 198 dividend decrease announcements). This number is also reflected in my empirical results, where I use CAR(-1,+1) as my dependent variable. If we look at Table 17 then we can see the results suggest positive and significant returns surrounding the dividend announcements. My results in Table 18 and 19 also suggest that dividend increase announcements have a positive effect on stock returns, and dividend decrease announcements reduce stock market returns. The interaction model table (Table 18) suggests that when dividends increase by 10% stock returns are estimated to increase by 0.5402% in model 1, 0.6107% in model 2, 0.6269% in model 3 and 0.7281% in model 4. On the other hand when dividends decrease by 10% stock returns are estimated to decrease by 0.6485% in model 1, 0.6434% in model 2, 0.6439% in model 3 and 0.6793% in model 4. F-test results suggest that there is not enough statistically significant evidence to reject the equality hypothesis between coefficient λ_1 and coefficient λ_2 in all four models in Table 18.

In Table 19 we can see that on average across firms that decrease dividend stock market returns are -1.233% lower in model 1, -1.262% lower in model 2, -1.208% lower in model 3 and 1.429% lower in model 4. F-test results suggest that there is not enough statistically significant evidence to reject the equality hypothesis between coefficient λ_1 and coefficient λ_2 in all four models in Table 19. These results are consistent with the dividend-signalling theory. These results are in favour of the alternative hypothesis; and reject the null hypothesis, where the alternative hypothesis is dividend increase (decrease) announcements have a positive (negative) effect on stock market returns.

After seeing the results in Table 17, 18 and 19 where all the results are in favour of the alternative hypothesis and reject the null hypothesis, I decided to conduct a robustness test where I used a two-days event window CAR(0,+1). If we look at Table 20 and 21 both model specifications results suggest that dividend -increase (decrease) announcements have a positive (negative) effect on stock market returns. These results are consistent with the previous literature and with my previous results. We can see that the robustness test is also in favour of the alternative hypothesis and consistent with the dividend-signalling theory.

When I conducted an additional test to check whether the Great Recession changed the relationship between dividend changes and stock returns my interaction model specification (Table 22) showed that the Great Recession did not affect the reaction of the stock market to dividend increase announcements, but the reaction of the stock market is more negative to dividend decrease announcements during the Great Recession period. On the other hand, the binary model specification (Table 23) provides no support in favour of the previous conclusion.

In the previous chapter (chapter 5) I found very weak evidence that dividend changes contain information about future earnings, but on the other hand in this chapter I have found very strong evidence that dividend increase (decrease) announcements have a positive (negative) effect on stock market returns. These two sets of results appear to be in conflict with each other. Explaining these contradictory findings is complex and goes beyond the scope of this thesis. Further research on this topic is needed. Here I simply speculate one possible explanation, which is, in chapter 5 I showed that dividend changes cannot predict earnings changes up to two years into the future, but it is possible that such earnings changes take place at a later date, for example after 3 years or after 5 years. It may be that my analysis focused only on the short term (2years), and for that reason I found only very weak evidence in chapter 5.

All the results in this chapter suggest that dividend increase (decrease) announcements have a positive (negative) effect on stock market returns, which is in favour of the alternative hypothesis and consistent with the dividend signalling theory and the existing literature.

6.11. CONCLUSION

I set out to examine the dividend-signalling theory using dividend announcements at the London Stock Exchange, to find out whether dividend announcements have any effect on the stock market. To do this I employed a traditional event study methodology (e. g. Lonie et al., 1996; Bozos, Nikolopoulos and Ramgandhi, 2011; Vazakidis and StergiosAthianos, 2010). My results suggest positive and significant returns surrounding dividend announcements, in line with the majority of the existing literature in the US and the UK. This is consistent with the interpretation that investors require higher rates of returns to hold stocks around their dividend announcements as compensation for the increased risk per unit of time in this period. According to the dividend-signalling theory dividend increase (decrease) announcements have a positive (negative) effect on stock market returns. My main contribution consists in providing additional support for the dividend-signalling theory using a larger UK data set and a partially novel model specification. In this model specification I used two dummy variables, which focus only on the direction or sign (positive or negative) of the dividend changes and ignore the size of the dividend changes.

Most previous studies were based on US data and only four studies employed UK data. According to the majority of previous studies, dividend decrease announcements have a negative effect on stock returns, which is in line with the dividend signaling theory. My results also suggests that dividend increase (decrease) announcement have a positive (negative) effect on stock returns, which is consistent with the dividend-signalling theory or information content of dividends hypothesis. Overall, the study findings are of significant importance for the body of research on dividend policy, as they confirm the information content of dividends hypothesis in the LSE, one of the world's most important capital markets.

7 INVESTOR SENTIMENT AND THE EFFECT OF DIVIDEND ANNOUNCEMENTS ON STOCK RETURNS: A STUDY ON UK DATA

7.1. INTRODUCTION

"……………..As a result, practically every passing atmospheric disturbance involves a period of stimulation for the individual – if infrequent, the individual may become lax; if sufficiently frequent and severe, stimulation may become optimal; if too frequent and too severe the individual becomes over-stimulated, fatigued; the inadequate individual may succumb."

William F. Peterson 'The Patient and the Weather' (1938)[20]

This chapter builds upon my second empirical chapter's finding, where I found that dividend -increase (decrease) announcements have a positive (negative) effect on stock market returns, which is consistent with the dividend-signalling theory. In this chapter I extend my research by examining the role of three investor sentiment proxies (rain, temperature and air pollution). The question that I want to answer in this part is whether investor sentiment plays any role in the relationship between dividend announcements and stock returns. To conduct this research I am going to use two model specifications (equation number 18 and 19), similar to the one employed in the previous chapter. The key innovation is that in this chapter the investor sentiment proxies are interacted with the two existing model specifications (equation number 18 and 19), from chapter six.

[20] Quoted in Smith (1939,p.29)

Weather is one of the most widespread environmental variables in human life, it is a factor that influences the agricultural economy, and it breaks or makes recreational plans and serves as a perennial topic for superficial conversation (Cunningham, 1979). Many scholars argue that weather has controlling power over both emotion and social behaviour (Campbell and Beets, 1977). Clinical and psychological surveys have uncovered that weather has significant effects on human mood and behaviour. It is also well established in the psychological literature that mood and feelings have a huge effect on the human decision making process (Schwartz, 1990; Loewenstein et al. 2001), and in particular on economic decision making (Etzioni, 1988; Romer, 2000; Hanock, 2002). But the major thread that unites all the mood proxy variables is that psychological researchers have claimed that all these mood proxies are robust, they are developed as a reliable mediating influence on mood and they represent broad measures that have a positive (negative) effect on mood (Dowling and Lucey, 2008).

Behavioural finance researchers have been trying to find out if weather related mood changes have an effect on stock returns for the last two decades. Previous researchers have used some environmental variables as mood proxy such as rain, wind, air pollution, temperature, cloud cover, sun-light, and some of the researches have also managed to establish that there is a significant correlation between investor mood and stock returns (Li & Peng, 2016; Lepori, 2016; Shu & Hung, 2009; etc). For instance, Saunders (1993) used the percentage cloud cover in the New York City as a proxy for investor mood and found a significant relation with stock returns. Saunders' research was extended by Hirshleifer and Shumway (2003) to 26 countries and regions and they also found statistically significant results. Using the stock return volatility and market depth Chang et al. (2008) discovered a significant negative relation between cloud cover and investors behaviour. In addition Kamstra et al. (2003) found that stock returns show a seasonal cycle that is linked to the seasonal affective disorder (SAD), a condition that affects people's behaviour based on seasons (fall and winter) with reduction of daylight length.

Researchers have also used a variety of variables to measure the weather, and they have found significant relationship between these weather variables and investors moods. Howarth and Hoffman (1984) found that humidity, temperature and amount of sunshine exert a significant influence on mood. Shu and Hung (2009) found wind has great influence on stock returns and they also said that wind is better proxy than sunshine for mood, because their study indicating that wind might exert a stronger impact on mood than sunshine. Floros (2008) and Cao and Wei (2005) found temperature has a statistically significant influence on stock returns. Some of the researchers use air pollution as a proxy for the investor's mood (Li and Peng, 2016; Lepori, 2016; Levy and Yagil, 2011;), and all of them found air pollution had a statistically significant influence on stock returns.

Previous researchers have tried to understand the relationship between investor's mood and stock market reaction using different weather related variables. In this chapter I try to answer a completely new question, which is whether investor sentiment plays any role in the response of stock prices to dividend announcements. To the best of my knowledge I am the first person who is addressing this question. The expected answer of this question is investor sentiment plays an important role in the response of stock prices to dividend announcements. To answer this question I have selected three weather variables as proxies for investor sentiment, which are rain, temperature and air pollution, all measured in the city that hosts the LSE, i.e. London.

In this chapter I use FTSE-350 (LSE) companies to test some novel hypotheses related to this question. Empirically I use two slightly different models that are based on the previous chapter's model specifications. Model number one is an interaction model and model number two is a binary model. I will call my first model the linear interaction model and my second model the linear binary model. I will use event window (-1,+1) for hypothesis test and event window (0,+1) for robustness test. My research question is inspired by previous work on the dividend-signalling hypothesis and investor sentiment hypothesis. My main object of investigation is the dividend-signalling hypothesis. So far no previous researchers have tried to test whether investor sentiment plays any role in the reaction of the stock market to dividend announcements.

My results suggest that investor sentiment plays an important role in the reaction of the stock market to dividend announcements. From the empirical result section we can see that high temperature does not affect the reaction of the stock prices to dividend increase announcements, but stock prices react less negatively to dividend decreases when investor mood is positive (proxied by high temperature), when we use interaction model specification. In Both model specifications rain does not affect the reaction of the stock prices to dividend increase (decrease) announcements. When we use binary model specifications then we can see that stock prices react more negatively to dividend decrease when the air pollution level is high (and allegedly investor sentiment is negative).

This work is original in several ways; first no previous researchers have tried to answer the question of whether investor sentiment plays any role in the reaction of the stock market to dividend announcements. Second, I employ a novel model specification based on my second empirical chapter. Third, I employ a larger data-set compared to similar studies in this area, and last, my findings provide an original contribution to the two strands of literature on investor sentiment and the dividend-signalling theory.

Section 7.2 shows brief literature review about the investor sentiment proxies. And then (section 7.3) I have discussed all three testable hypotheses. Section 7.4 presents' methodology and model specifications. Next section (7.5) gives detail statistical information. Section 7.6 presents' empirical results and the very next section presents the robustness test. Section 7.8 and 7.9 presents discussion and conclusion respectively.

7.2. LITERATURE REVIEW

7.2.1. WEATHER, INVESTOR SENTIMENT AND INVESTMENT DECISIONS

People's daily activities are highly influenced by various environmental factors, and weather being such one kind of factors, which count as most important one among all (Lu and Chou, 2012). Our plans and behaviours change if the weather has significant changes. Throughout the evolution of mankind, people have built a certain level of genetic adaptability to environmental change, but once the level of weather changes exceeds our psychological resistance limit then people start showing some kind of reaction or even physical symptoms. According to Lu and Chou (2012) "Changes in weather will lead, both directly and indirectly, to complex psychological and physical responses".

In 1992 Roll noticed that, "Weather is a genuinely exogenous economic factor. It was a favorite example of an exogenous identifying variable in the early econometric literature… because weather is both exogenous and unambiguously…. weather data should be useful in assessing the information processing ability of financial market". Among the many weather variables, researchers have given their attention mainly to cloud cover, rain, temperature, air pollution, wind, humidity, barometric pressure and sunlight. In 1979 Cunningham showed that both in summer and winter, a clear day creates good mood and a cloudy day creates bad mood. According to Schwarz and Clore (1983) people gain more satisfaction on bright sunny days; on the other hand Symeonidis et al. (2010) suggested that cloud cover is always a natural factor, which influences people's sentiment.

After researching data based on England and Wales, Page et. al (2007) found that temperature has negative correlation with mood in the summer months. Some psychological researchers haven't found any correlation between mood and weather (Watson, 2000; Keller et al., 2005; Bauer et al., 2009). And some other researchers argue that changes in mood are caused not by weather but by biorhythmic disorders (Leger, 1994; Coren, 1996; Rosenthal, 1998).

Previous literatures have suggested that people's mood and weather have great influence on the decision-making process (Cao and Wei, 2005; Simonsohn, 2007). Isen (1993) said that when people are in good mood their cognitive processes are simple, for that reason they reach their decision quickly, on the other hand Hirshleifer and Shumway (2003) argue that, this cognitive process either reflects the cognitive loss associated with good mood, or effectively simplifies complicated information. Petersen (1937) argued that atmospheric disturbances have some influences on humans; people can overcome this type of disturbances if the magnitude is low, otherwise if the magnitude is high then there is a certain impact on people.

7.2.2. TEMPERATURE AND STOCK RETURNS

Prior literature indicates that in low temperature people have a tendency to be more aggressive and in high temperature people have a tendency to be aggressive and at the same time people could have hysteria and apathy (Cao and Wei, 2005). A research was conducted by Howarth and Hoffman in 1984 using 24 university students, who were monitored over an 11-day period, and they found that, the temperature between +8 ^{0} c to -28 ^{0} c has great influence on people's feelings, and they reported that these period of time people show more aggressive feelings than usual time and they also found that rising temperature lowered anxiety and skepticism mood scores. Connolly (2013) said that low temperature increases happiness and reduces tiredness and stress, raising net affect, on the other hand high temperature reduces happiness.

Denissen et al. (2008) found that higher temperature help people to up their low mood. Widrich (2013) found that people are happier in the high temperature. Klimstra et.al. (2011) said that mood improves with higher temperature. According to some psychologists cold weather commonly makes people impatient or upset (Chang et al. 2006).

According to Cao and Wei's (2002) investigation using data from eight stock exchanges on average low temperatures are associated with high returns and high temperatures are associated with low returns. Their argument was that lower temperature could lead to aggression, while higher temperature can lead to both apathy and aggression, and aggression could result in more risk-taking while apathy could impede risk-taking. In their extended paper Cao and Wei in 2005 examined the impact of ambient temperature alone on mood and behavior. They report that stock returns are negatively correlated with temperature, which means the lower the temperature, the higher the returns and vice versa. They also report that the relationship is slightly weaker in the summer than in the winter, because when the temperature is high apathy dominates aggression, and the results show lower returns but statistically significant, and overall negative correlation.

Keef and Roush (2002) reason that weather might well be multifaceted and they extended the prior research by adding more weather variables. After analyzing data from New Zealand all share index they uncover temperature has a small negative effect on stock returns. In 2005 Keef and Roush extended their research by examining the effect of New York's weather on the returns of the Dow Jones Industrial Average index and Standard and Poor's index during the period 1 January 1984 to 31 August 2002. They found that observed temperature does not exhibit any effect on stock returns but when they de-seasonalised the temperature then they found positive influence of cool days on stock market returns. Again in 2007 Keef and Roush analyzed the temperature effect on the stock market, and this time they used Australian stock indices and found that temperature has negative influence on the stock market.

Floros (2008) used a GARCH model to investigate if temperature influences stock returns. His dataset was based on five European countries. He found that in Austria, Belgium and France stock market returns were negatively correlated with the temperature, in the UK there are is no evidence of such an effect, and in Greece there is a positive but insignificant correlation between these two variables. Dowling and Lucey (2008) found that temperature has a positive correlation with stock returns. Extending Dowling and Lucey's (2008) research, 2009 Yoon and Kang (2009) also showed that extremely low temperature is positively correlated with stock returns.

Researchers haven't managed to reach a conclusion about the type of effect that temperature has on mood and mixed results are available in the literature. Some of the literature claims that higher temperature uplift people mood while some other studies claim that higher temperature makes people unhappy. In the same way some of the literature said that higher temperature are associated with lower stock returns and low temperature are associated with higher returns, and some of the literature said that higher temperature has a positive correlation with stock market returns. Still I can draw the conclusion that temperature has an effect on mood, though we cannot be sure about the direction (positive or negative) of the impact.

7.2.3. AIR POLLUTION AND STOCK RETURNS

The Air Quality Index (AQI), composed by the UK Department for Environment, Food and Rural Affairs, is an index reporting daily air quality and provides recommended actions and health advice. The index ranges from 1 to 10 and is divided into 4 different bands. Figure 6 shows the details of the 4 different bands and Figure 7 shows the UK Department for Environment, Food and Rural Affairs' recommended actions and health advices.

Index Bands

1	2	3		4	5	6		7	8	9		10
Low				Moderate				High				Very High

Figure 7: AQI bands

(Source: UK Department for Environment, Food and Rural Affairs, https://uk-air.defra.gov.uk/air-pollution/daqi)

The purpose of the AQI is to inform the public about the risks of air pollution and help researchers understand the link between air pollution and numerous health problems, including mental health and mood changes. UK AQI ranges from 1 to 10 and is divided into 4 bands. These four bands are low, moderate, high, and very high. Currently, air quality in the UK is relatively good, but air pollution is one of the major issues for developing and developed countries like the UK.

When people are in low mood they are more pessimistic (Li and Peng, 2016). According to Isen et.al. (1978) and Forgas and Bower (1987) individuals in good (bad) mood tend to find positive (negative) material more available, which is termed the mood congruency effect. People are more pessimistic when the air pollution rises and they use probability estimates more biased toward negative outcomes (Li and Peng, 2016). Medical studies suggest that an increase in air-pollution levels could raise the bodily levels of cortisol (a stress hormone) (Li and Peng, 2016). Cortisol has been proved to been associated with reduced sensation-seeking and risk-taking beahviour (Tomei et al. 2003; Nowakowicz-Debek,Saba, and Bis-Wwncel, 2004; Rosenblitt et al. 2001). Low spirits and depression induced by air pollution can also translate into a greater degree of risk aversion (Zuckerman1984, 1994; Carton et al. 1992, 1995). According to Lundberg (1996), environmental toxins can generate " symptoms compatible with anxiety and depression, among them cognitive and behavioral changes ".

Previous studies found that exposure to acute levels of ambient air pollution leads to heightened level of depression, anxiety, tension, helplessness and anger (Evans et al. 1987). High air pollution can lead to behvioural and physical changes (Cohen et al. 1986). Some other evidence about the impact of air pollution on mood is reported in studies dealing with the effect of environmental odors (Schiffiman el at. 1995). Air pollution has significant association with feelings of fatigue, low mood and exhaustion (Sagar et al., 2007). Air pollution represent " a major stressful stimulus to exposed persons and can lead to a variety of emotional, mental and physical changes not only by direct toxic effects ", for an indirect cognitive mediation can also play a role " in terms of a negative appraisal of pollutants " (Bullinger, 1990).

Prior research has shown that air pollution influences the stock market. Lepori (2016) used data for four industrial countries (Italy, the USA, Spain and Germany) from 1980 to till 2006 and found that air pollution is negatively correlated with stock returns. Lepori (2016) found that the relationship between local air pollution and stock returns was likely mediated by the behaviour of the trading floor community.

Recommended Actions and Health Advice

Air Pollution Banding	Value	Accompanying health messages for at-risk individuals	Accompanying health messages for the general population
Low	1-3	Enjoy your usual outdoor activities.	Enjoy your usual outdoor activities.
Moderate	4-6	Adults and children with lung problems and adults with heart problems, who experience symptoms, should consider reducing strenuous physical activity, particularly outdoors.	Enjoy your usual outdoor activities.
High	7-9	Adults and children with lung problems and adults with heart problems should reduce strenuous physical exertion, particularly outdoors, and particularly if they experience symptoms. People with asthma may find they need to use their reliever inhaler more often. Older people should also reduce physical exertion.	Anyone experiencing discomfort such as sore eyes, cough or sore throat should consider reducing activity, particularly outdoors.
Very High	10	Adults and children with lung problems and adults with heart problems, and old people, should avoid	Reduce physical exertion, particularly outdoors, especially if

		strenuous physical activity. People with asthma may find they need to use their reliever inhaler more often.	you experience symptoms such as cough or sore throat.

Figure 8: UK Department for Environment, Food and Rural Affairs, recommended actions and health advices.

(Source: UK Department for Environment, Food and Rural Affairs, https://uk-air.defra.gov.uk/air-pollution/daqi)

Levy and Yagil (2011) found a negative relation between daily stock returns and the air-quality index (AQI), using U.S. data from 1997 to 2007. In 2013, Levy and Yagil extended their research using data from Canada, the Netherlands, Hong Kong and Australia and found a similar kind of negative relationship between daily stock returns and AQI. Li and Peng (2016) also found a negative correlation between air pollution and stock returns like Lepori (2016) and Levy and Yagil (2011, 2013) when they conducted their research on Chinese data.

From previous literature we can see that people are more pessimistic when air pollution is high and some medical studies found that an increase in air-pollution levels could raise the bodily levels of cortisol. Previous studies also found that exposure to acute levels of ambient air pollution leads to heightened level of depression, anxiety, tension, helplessness and anger. The majority of previous researchers found negative correlation between air pollution and stock returns.

7.2.4. CLOUD, RAIN AND STOCK RETURNS

According to Saunders (1993) findings investors' mood is upbeat or optimistic in the sunny days and their mood is low or they are pessimistic on the cloudy (rainy) days. Hirshleifer and Shumway (2003) also agree with Saunders (1993) findings and they said sunlight has positive affects on mood and induces misattribution. People tend to rate their life satisfactions much higher on sunny days than on cloudy or raining days (Schwartsz and Clore, 1983).

Saunders (1993) used three global indices of the US market to investigate whether trader mood has any influence on the stock market. He used the percentage of cloud cover as his trader mood proxy, and he found that sunshine has positive impact on the stock market and cloud cover has a negative impact. Following Saunders's (1993) findings, Hirshleifer and Shumway (2003) conducted a research based on 26 countries and regions and obtained similar results, confirming that cloud cover has a negative influence on the stock market. Using a different methodology, Trombley (1997) replicated Saunders' (1993) work and found that cloud cover or rain was not correlated with stock returns and Kramer and Runde (1997) also found no correlation between cloud cover and stock returns. On the other hand, Dowling and Lucey (2005) concluded that rain has a minor but significant negative influence on stock market.

Using all Share indexes of the New Zealand Keef and Roush (2005, 2007) found that cloud cover is negatively correlated with stock returns. Goetzmann and Zhu (2005) also found a negative correlation between cloud cover and stock market returns. Shon and Zhou (2009) using bootstrap randomization procedures found that market reactions to earnings surprises are higher when earnings are announced on very sunny days (a proxy for positive investor sentiment) than a rainy days (a proxy for negative investor sentiment). In this chapter I use a model that is similar to theirs.

It is well established in literature that rainy or cloudy days make people more pessimistic and sunny days uplift people mood or make them more optimistic. On the other hand, from literature we can see that some researchers found cloud cover is negatively correlated with stock returns and some other researchers found there is no correlation between cloud cover (rain) with stock return.

7.3. TESTABLE HYPOTHESES

The hypotheses examined here are based on prior psychology, medicine and finance theories and literatures, especially dividend signaling hypothesis and investor sentiment hypothesis. Previous research was mainly interested in the relationship between investor mood and stock returns. In this thesis I extend previous research by combining the investor sentiment literature and the literature on the dividend-signaling hypothesis. My research question here is whether investor sentiment plays any role in the reaction of the stock market to dividend announcements. Following the existing literature, I construct three sentiment proxies, which are temperature, air pollution and rainfall, all measured in the city of London[21].

The reason to choose my first investor sentiment proxy temperature is that research in psychology has shown that temperature significantly affects mood, and mood changes in turn cause changes in investor optimism. A body of psychological literature shows that temperature is one of the important meteorological variables affecting people's mood, and the affected mood in turn regulates behavior. And it is also natural to conjecture that temperature variations would cause investors to alter their investment decision. I have chosen air pollution, as my second investor sentiment proxy because health related research documented that air pollution has

[21] The underlying assumption is that a sufficiently large number of traders in the FTSE 350's companies' stocks is located in London, and so changes in London weather may affect their sentiments and their trading decisions. Given the data that I have, this assumption is not empirically testable. Future research may look into this issue in greater detail.

negative mood effects. Experimental works in psychology relate bad mood to pessimism and increased risk aversion. While its health effects have been studied extensively, but its impact on stock market returns to dividend announcements has not been investigate yet. There are chances that rain has some kind of influence on investor mood, because people tent to rate their life satisfaction higher on sunny days than rainy days and according to previous study rain is associated with pessimism and depression. Previous research has been conducted on the mood effects of cloud cover or rain, but its impact on the reaction of stock returns to dividend announcements has not been investigate yet, due to that reason rain is my third investor sentiment proxy. I did not use Baker/Wurgler sentiment proxies for 2 reasons. (1) because they capture longer-term (i.e. monthly) shifts in investor sentiment; instead, I am interested in testing whether short-term (i.e. daily) fluctuations in investor sentiment (which may be caused by the weather, air pollution, etc) influence the reaction of stock prices to dividend announcements. (2) Baker and Wurgler's (2005) sentiment proxies are constructed based on observed stock market patterns (closed-end fund discount, share turnover, average first-day returns on IPOs, equity share in new issues, and dividend premium), so they are not purely exogenous. Instead, my sentiment measures based on the weather in London are purely exogenous.

Built on previous studies, I expect temperature to have an impact on mood and stock market returns, but I am not sure the direction of the impact (positive or negative). Based on these insights, I hypothesize that the stock markets react differently to dividend announcements depending on whether temperature is high or low. On the basis of this, my first null and alternative hypotheses are-

H_0: Investor sentiment (proxied by temperature) does not affect the reaction of the stock market to dividend increase (decrease) announcements.

H_{a1}: investor sentiment (proxied by temperature) affects the reaction of the stock market to dividend increase (decrease) announcements.

Previous researchers have found a negative correlation between air pollution and stock returns (Lepori, 2016; Levy and Yagil, 2011 and 2013 and Li and Peng, 2016). Previous research has also found that increase in air pollution levels lower people's mood and low mood is associated with investor pessimism (see section 9.2.3). Based on these insights, here I hypothesize that the stock market react less positively to dividend increases when air pollution level are high (and as a result investor sentiment is negative) and more negatively to dividend decreases when air pollution level are high. This leads to the following null and alternative hypotheses:

H_0: Investor sentiment (proxied by air pollution levels) does not affect the reaction of the stock market to dividend increases (decreases).

H_{a2}: Stock prices react less positively (more negatively) to dividend increases (decreases) when investor sentiment is negative (proxied by high air pollution levels).

People tend to rate their life satisfactions much higher on sunny days than on cloudy or rainy days (Schwartsz and Clore, 1983). Sunshine has positive impact on stock market and rain has negative impact on stock market. Investor's mood is upbeat in the sunny days and their mood is low (and level of pessimism high) on the rainy days. Based on these insights, I hypothesize that investors react less positively to dividend increases and more negatively to dividend decreases when it rains, because investor mood tends to be negative on rainy days. This leads to the following null and alternative hypotheses:

H_0: Investor sentiment (proxied by rainfall) does not affect the reaction of the stock market to dividend increases (decreases).

H_{a3}: Stock prices react less positively (more negatively) to dividend increases (decreases) when investor sentiment is negative (proxied by a positive amount of rainfall).

7.4. METHODOLOGY AND MODEL SPECIFICATIONS

To test the hypotheses discussed above I will use a standard event study methodology and regression analysis. According to the dividend signaling hypothesis dividend -increase (decrease) announcements have a positive (negative) effect on stock returns. My hypotheses extend the dividend-signaling hypothesis and examine how investor sentiment affects the relationship between dividend announcements and stock market returns. The event study methodology I use in this chapter are the same as in the previous chapter.

I have calculated two CAR for two of my event windows, those are (-1,+1) and (0, +1). In this chapter I will use two different types of linear models, both of my models are based on my chapter-6 model specifications. My number one model specification is a linear interaction model and number two-model specification is a linear binary model. In my interaction model there are two explanatory variables and both of them represent interaction effects. My first explanatory variable is the percentage change in dividends ($R\Delta DIV$), which is interacted with a dividend increase dummy (DPI), and the second explanatory variable is the percentage change in dividends, which interacted with a dividend decrease dummy (DPD). On the other hand in my binary model I will use only two dummy variables as my explanatory variables, which are DPI and DPD. The linear interaction model specification I use in this chapter is quite similar to the model employed by Shon and Zhou (2016).

For investor sentiment I have chosen three weather variables as sentiment proxies, which are rainfall, temperature, and air pollution, all measured in the city of London. Following the previous literature (Levy and Yagil, 2011 and 2013; Li and Peng, 2016; Dowling and Lucey, 2005) I have created a dummy variable for air pollution and rainfall. For rainfall, if it rains in the Heathrow airport area on day *t* then the rain dummy will take value 1, and 0 otherwise. The air pollution dummy takes value 1 on day *t* if London city's Air Quality Index (AQI) is above 3 and 0 otherwise. For the temperature variable I have followed Cao and Wei's (2002) method and I have used the average daily temperature in London as my investor mood proxy. In both models I use four control variables, which are Size, Reversal, Momentum and Dividend Yield. And I use CAR as my dependent variable. In both models I control for year fixed effects and either firms fixed effects or industry fixed effects. For the industry fixed effects I use Fama and French 17 industry classifications.

The two model specifications are given below with detailed explanations.

(a) Linear interaction model

(a)(i) Linear interaction model specifications for temperature

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * TEMP_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * TEMP_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it} \quad (24)$$

Where,

CAR_{it} = Cumulative abnormal returns.

$R\Delta DIV_{it} =$ Percentage change in dividend payment for firm *i*.

DPI_{it} = 1 if the dividend change is positive, and 0 otherwise.

DPD_{it} = 1 if the dividend change is negative, and 0 otherwise.

$TEMP_t$ = Average daily temperature in London on day *t*.

$SIZE_{it}$ = Firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement (in billions of British Pounds).

$REVERSAL_{it}$ = Reversal is measured using cumulative stock returns for firm *i* over previous month (in percentage).

$MOMENTUM_{it}$ = Momentum is the cumulative monthly stock returns from month t-12 to t-2.

$DIVIDEND_{YIELD_{it}}$ = Dividend Yield for firm i calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement.

DW = Day-of –the-week effect, where M_d, W_d , T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. Tuesday is the reference day.

μ_{it} = Error term.

$YEAR\ DUMMIES$ = Year fixed effect dummies beginning from July 1996 to December 2015, and the year 1996 is the reference year. (Temperature data are available from July 1996).

$FIXED\ EFFECT$ = Either industry fixed effects dummies or firm fixed effects dummies. The industry fixed effect dummies are based on Fama and French's 17 industry classifications. My reference industry is industry number one, which is the food industry. As for the firm fixed effects, there are 231 firms in my data sample. Firm 888 is my reference firm.

(a)(ii) Linear interaction model specifications for air pollution

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * AIR_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * AIR_t + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it} \quad (25)$$

Where,

AIR_t = 1 if London city's Air Quality Index (AQI) is above 3, and 0 otherwise.

$YEAR\ DUMMIES$ = Year fixed effect dummies beginning from 1990 to 2015 and the year 1990 is the reference year. (Air pollution data are available from January 1990).

(a)(iii) Linear interaction model specifications for rainfall

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * RAIN_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * RAIN_t + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it} \quad (26)$$

Where,

$RAIN_t$ = 1 If it is rains in the Heathrow airport area on day *t*, and 0 otherwise.

$YEAR\ DUMMIES$ = Year fixed effect dummies beginning from July 1996 to 2015 and year 1996 is the reference year. (Rain data are available from July 1996).

(b) Linear binary model

(b)(i) Linear binary model specifications for temperature

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * TEMP_t + \lambda_4 DPD_{it} * TEMP_{\ t} + \lambda_5\, SIZE_{\ it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it} \quad (27)$$

(b)(ii) Linear binary model specifications for air pollution

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * AIR_{it} + \lambda_4 DPD_{it} * AIR_{\ it} + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{\ it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it} \quad (28)$$

(b)(iii) Linear Binary model specifications for rainfall

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * RAIN_{it} + \lambda_4 DPD_{it} * RAIN_{it} + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it} \tag{29}$$

All the above models are estimated using pooled OLS regressions, as in Nissim and Ziv (2001). For statistical inference I will also show cluster-robust standard errors for both models, which generalize those proposed by White (1980) for independent heteroscedastic errors. I show clustered standard error to control for within-cluster error correlation, which can lead to misleadingly small standard errors, and consequently misleadingly narrow confidence intervals, large t-statistics and low p-values. Following Petersen's (2009) and Thompson's (2011) suggestions about estimating standard errors in finance panel data sets, I employ multi-way clustering: more specifically, standard errors are clustered by firm and date. I cluster the standard errors by firm because the error terms may be serially correlated, and I cluster the standard errors by date because the error terms may be correlated across firms at the same point in time.

7.5. DATA

This study is conducted using data on a sample of firms in the FTSE-350 index from 1990 to 2015. I collected the data from three different sources. Financial data were collected from Bloomberg. Air pollution data were collected from the

Department for Environment, Food & Rural Affairs[22]. Rainfall and temperature data were collected from Weather Forecast and Reports[23]. Selected firms are the current constituent list of the FTSE-350 (as of June 2016). To construct the sample of data I followed the same criteria as in the previous chapter. Descriptive statistics are given below.

7.5.1. DESCRIPTIVE STATISTICS

To test all three hypotheses in this chapter I use one event window, which is (-1,+1). The dividend announcement date is day 0, the day before the dividend announcement is day -1 and the day after the dividend announcement is day +1. The estimation window starts from t-200 to t-20, which means a total of 181 estimations days. I use three weather related investor sentiment proxies, which are temperature, air pollution, and rainfall. Table 24A reports some descriptive statistics about the three weather related investor sentiment variables on dividend announcement days.

TABLE 24A DETAILS OF FIRM DIVIDEND CHANGES OBSERVATIONS BY WEATHER RELATED INVESTOR SENTIMENT VARIABLES

Variables	**Number of Obs.**	**Dividend Increase**	**Dividend Decrease**	**Unchanged Dividend**
Temperature (From July 1996 to December 2015)	2,817	2,315	159	343
Air Pollution (From January 1990 to December 2015)	3,621	2,972	198	451
Rainfall (From July 1996 to December 2015)	2,817	2,315	159	343

[22] https://uk-air.defra.gov.uk/air-pollution/daqi
[23] https://www.wunderground.com/

Note: This table showing the details of firms dividend changes event window by weather related investor sentiment variables.

TABLE 25B DESCRIPTIVE STATISTICS OF WEATHER-RELATED INVESTOR SENTIMENT VARIABLES

Variables	N	Mean	Std. Dve.	Mini	Maxi	5%	25%	75%	95%	Skewness	Kurtosis
Temperature	2,817	21.302	10.618	1	35	8	11	33	35	0.042	1.282
Air Pollution	3,621	0.331	0.471	0	1	0	0	1	1	0.718	1.515
Rain	2,817	0.548	0.498	0	1	0	0	1	1	-0.195	1.038

Note: This table showing the descriptive statistics of weather related investor sentiment variables.

Table 24B shows that there is quite a lot of variation in daily temperature and air pollution in London, which allows the econometrician to identify the effect of interest. As for rain, there is less variability, as it often rains in London (55% of the days in the sample); given that there is not much variation in the rain variable, it is more difficult to estimate the effect of interest with enough precision.

Table 25 provides some descriptive statistics for the whole data sample. It has 3 panels and it provides details statistics on the base of my three weather related investor sentiment proxies, which are temperature, air pollution and rainfall. Each panel gives information about mean, standard deviation, minimum value, maximum value, percentile value, skewness and kurtosis value for dividend changes, size, reversal, momentum, dividend yield and cumulative abnormal returns.

In Table 25 $R\Delta DIV$ refers to the percentage change in dividends and I follow Benartzi et al.'s (1997) formula to calculate $R\Delta DIV$ as in my previous empirical chapters,

$$R\Delta DIV = \frac{DIV_0 - DIV_{-1}}{DIV_{-1}} \tag{30}$$

Where DIV_0 represent the dividend paid at base year or year 0 and DIV_{-1} is the dividend paid the previous year. From Table 25 we can see that panel A and Panel C shows same mean, standard deviation even percentile values. Both panels also show same skewness and kurtosis values. Only panel C, which is showing air pollution values are different than other two panels. In panel B reversal and dividend yield has little higher kurtosis value than panel A and panel C.

TABLE 26 DESCRIPTIVE STATISTICS FOR DIVIDEND EVENT OBSERVATIONS BASED ON INVESTOR SENTIMENT

Panel A: Temperature

Variables	N	Mean	Std.Div.	Mini	Max	5%	25%	75%	95%	skewness	Kurtosis
RΔDIV (%)	2,817	9.911	13.118	-50.00	50.00	-2.876	4.118	15.385	32.353	-0.736	7.918
Size (£ billion)	2,697	7.259	1.405	0.386	12.061	5.268	6.266	8.154	9.836	0.356	3.303
Reversal (%)	2,817	0.056	0.426	-4.039	2.318	-0.638	-0.152	0.297	0.683	-0.635	9.271
Momentum (%)	2,817	0.267	1.519	-7.935	6.279	-2.386	-0.542	1.187	2.483	-0.636	5.043
Divi. Yield (%)	2,817	2.017	1.276	0.004	12.761	0.035	1.246	2.644	4.166	1.473	9.738
CAR (%)	2,817	1.209	5.993	-40.881	51.255	-7.456	-1.840	4.285	10.455	-0.126	10.261

Panel B: Air pollution

Variables	N	Mean	Std.Div.	Mini	Max	5%	25%	75%	95%	skewness	Kurtosis
RΔDIV (%)	3,621	9.787	13.101	-50.00	50.00	-2.522	4.098	15.347	31.034	-0.820	8.135
Size (£ billion	3,409	7.080	1.453	0.386	12.061	4.891	6.078	8.014	9.708	0.253	3.201
Reversal (%)	3,621	0.055	0.435	-4.039	7.490	-0.618	-0.157	0.281	0.693	0.869	29.924
Momentum (%)	3,618	0.303	1.503	-9.598	6.279	-2.354	-0.507	1.232	2.509	-0.631	5.282
Divi.Yield (%)	3,621	2.035	1.328	0.004	17.248	0.004	1.268	2.639	4.211	2.086	16.467
CAR (%)	3,621	1.256	5.945	-40.881	51.255	-7.294	-1.732	4.224	10.469	-0.034	9.873

Panel C: Rainfall

Variables	N	Mean	Std.Div.	Mini	Max	5%	25%	75%	95%	skewness	Kurtosis
R∆DIV (%)	2,817	9.911	13.118	-50.00	50.00	-2.876	4.118	15.385	32.353	-0.736	7.918
Size (£ billion)	2,697	7.259	1.405	0.386	12.061	5.268	6.266	8.154	9.836	0.356	3.303
Reversal (%)	2,817	0.056	0.426	-4.039	2.318	-0.638	-0.152	0.297	0.683	-0.635	9.271
Momentum (%)	2,817	0.267	1.519	-7.935	6.279	-2.386	-0.542	1.187	2.483	-0.636	5.043
Divi. Yield (%)	2,817	2.017	1.276	0.004	12.761	0.035	1.246	2.644	4.166	1.473	9.738
CAR (%)	2,817	1.209	5.993	-40.881	51.255	-7.456	-1.840	4.285	10.455	-0.126	10.261

Note: This table reports the firm's characteristic for the sample firms. $R\Delta DIV$ is the annual changes of the dividend payment in percentage terms. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stoke returns over previous months, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. And finally CAR is representing Cumulative Abnormal Return, estimated using the abnormal returns around the dividend announcement date.

Table 26 represent pair wise correlation matrix for all explanatory variables and dependent variable. All three panels in Table 26 shows that only Dividend Yield has negative correlation with dividend changes, Size, Reversal and Momentum, and CAR has negative correlation with Size, Reversal and Momentum. Sentiment variable temperature has positive correlation with dividend changes, reversal and with CAR. Sentiment dummy variable air pollution has negative correlation with reversal, momentum, dividend yield and CAR, and other sentiment dummy variable rainfall is negatively correlated with dividend changes, dividend yield and CAR.

TABLE 27 CORRELATION MATRIX FOR THREE INVESTOR SENTIMENTS

Panel A: Temperature

Variables	*RΔDIV*	*Size*	*Reversal*	*Momentum*	*Divi. Yield*	*CAR*	*Temperature*
RΔDIV	1.0000						
Size	0.0633	1.0000					
Reversal	0.0360	0.0088	1.0000				
Momentum	0.2339	0.0986	-0.0393	1.0000			
Divi. Yield	-0.2190	-0.2075	-0.1522	-0.3527	1.0000		
CAR	0.1093	-0.1311	-0.0647	-0.0353	0.436	1.0000	
Temperature	0.0399	-0.0130	0.0168	-0.0273	-0.0527	0.0260	1.0000

Panel B: Air pollution

Variables	*RΔDIV*	*Size*	*Reversal*	*Momentum*	*Divi. Yield*	*CAR*	*Air pollution*
RΔDIV	1.0000						
Size	0.0483	1.0000					
Reversal	0.0286	0.0079	1.0000				
Momentum	0.2407	0.0684	-0.0402	1.0000			
Divi. Yield	-0.2221	-0.1686	-0.1379	-0.3569	1.0000		
CAR	0.0973	-0.1306	-0.0632	-0.0344	0.0642	1.0000	
Air pollution	0.0283	0.0010	-0.0561	-0.0229	-0.0059	-0.0166	1.0000

Panel C: Rainfall

Variables	$R\Delta DIV$	Size	Reversal	Momentum	Divi. Yield	CAR	Rainfall
$R\Delta DIV$	1.0000						
Size	0.0633	1.0000					
Reversal	0.0360	0.0088	1.0000				
Momentum	0.2339	0.0986	-0.0393	1.0000			
Divi. Yield	-0.2190	-0.2075	-0.1522	-0.3527	1.0000		
CAR	0.1093	-0.1311	-0.0647	-0.0353	-0.0436	1.0000	
Rainfall	-0.0036	0.0124	0.0001	0.0341	-0.0132	-0.0052	1.0000

Note: The table present here represents the correlation matrix of the variables used to hypotheses. Correlation matrix is explained using three different investor sentiments. $R\Delta DIV$ is the annual changes of the dividend payment in percentage terms. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stoke returns over previous months, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. And finally CAR is representing Cumulative Abnormal Return, estimated using the abnormal returns around the dividend announcement date.

7.6. EMPIRICAL RESULTS

7.6.1 EXPECTED SIGNS

Table 27 shows the expected signs of all variables and the reasons behind those expected sings.

TABLE 28 EXPECTED SIGNS

Variables	Coefficient	Expected sign	Comments
Constant	λ_0	+	According to Kalay and Loewenstein (1985) investor requires higher rates of returns to hold stocks around their dividend announcements as compensation for the increased risk per unit of time in this period. The explanation given by Cohen et al. (2007) about the abnormal returns is that - “it is compensation for risk incurred when investors are hold securities during a period when valuation relevant information is expected to be released. Suppose mean-variance pricing, investors require higher announcement returns when a newsworthy announcement is expected and the associated risk is non-diversifiable”.
$R\Delta IVI * DPI$	λ_1 (Equation-	+	The greater the increase in dividend, the greater the increase in stock returns.

	24-26)		
$R\Delta IVI * DPD$	λ_2(Equation-24-26)	+	The greater the decrease in dividend, the greater the decrease in stock returns.
$R\Delta DIV_{it} * DPI_{it} * TEMP_t$	λ_3(Equation-24)	+/-	Stock prices react less or more positively to dividend increase announcements when temperature is high (and as a result, investor sentiment is either negative or positive).
$R\Delta DIV_{it} * DPD_{it} * TEMP_t$	λ_4(Equation-24)	+/-	Stock prices react less or more negatively to dividend increase announcements when temperature is high (and as a result, investor sentiment is either negative or positive).
$R\Delta DIV_{it} * DPI_{it} * AIR_t$	λ_3(Equation-25)	-	Stock prices react less positively to dividend increases when investor sentiment is negative (proxied by high air pollution levels). When air pollution levels are high investor sentiment is negative.
$R\Delta DIV_{it} * DPD_{it} * AIR_t$	λ_4(Equation-25)	+	Stock prices react more negatively to dividend decreases when investor sentiment is negative (proxied by high air pollution levels). When air pollution levels are high investor sentiment is negative.
$R\Delta DIV_{it} * DPI_{it} * RAIN_t$	λ_3(Equation-26)	-	Stock prices react less positively to dividend increases when investor sentiment is negative (proxied by a positive amount of rainfall). When it rains, investor sentiment is negative.
$R\Delta DIV_{it} * DPD_{it} * RAIN_t$	λ_4(Equation-26)	+	Stock prices react more negatively to dividend decreases when investor sentiment is negative (proxied by a positive amount of rainfall). When it rains, investor sentiment is negative.
DPI	λ_1(Equation-27-29)	+	Positive dividend changes have a positive effect on stock returns.
DPD	λ_2(Equation-27-29)	-	Negative dividend changes have a negative effect on stock returns.
$DPI_{it} * TEMP_t$	λ_3(Equation-27)	+/-	Stock prices react less or more positively to dividend increase announcements when temperature is high (and as a result, investor sentiment is either negative or positive).
$DPD_{it} * TEMP_t$	λ_4(Equation-27)	+/-	Stock prices react less or more negatively to dividend increase announcements when temperature is high (and as a result, investor sentiment is either negative or positive).
$DPI_{it} * AIR_t$	λ_3(Equation-28)	-	Reaction of the stock market is less positive to positive dividend changes announcements when investor sentiment is negative (proxied by high air pollution levels). When air pollution levels are high investor sentiment is negative.
$DPD_{it} * AIR_t$	λ_4(Equation-28)	-	Reaction of the stock market is more negative to negative dividend changes announcements when investor sentiment is negative (proxied by high air pollution levels). When air pollution levels are high investor sentiment is negative.
$DPI_{it} * RAIN_t$	λ_3(Equation-29)	-	Reaction of the stock market is less positive to positive dividend changes announcements when investor sentiment is negative (proxied by a positive amount of rainfall). When it rains, investor sentiment is negative.
$DPD_{it} * RAIN_t$	λ_4(Equation-29)	-	Reaction of the stock market is more negative to negative dividend changes announcements when investor sentiment is negative (proxied by a positive amount of rainfall). When it rains, investor sentiment is negative.
SIZE	λ_5	-	"Small size effect" where small firms earn higher abnormal returns than large firm (Fuller, 2003 and Dasilas and Leventis, 2011).
REVERSAL	λ_6	+/-	De Bondt and Thaler (1985) argue that investors overreact to both positive and negative information, pushing the prices away from their fundamental values, and over the next two to three years, prices revert back to their fundamental values generating a reversal in stock returns. Based on that reversal could be positive or negative, empirical work based on CAR and reversal suggest that reversal is negative indicating less favorable reactions for firms with recent stock price increases (Autore and Jiang,

			2017)
MOMENTUM	λ_7	+/-	Stocks with high (low) unconditional expected rates of return in adjacent time periods are expected to have high (low) realized rates of returns in both periods. Hence, momentum strategies will yield negative average returns even if the expected returns on stocks are in constant over time (Lo and MacKinlay, 1990 and Jegadeesh and Titman, 1999). Based on that reversal could be positive or negative, empirical work based on CAR and reversal suggests that reversal is negative indicating less favorable reactions for firms with recent stock price increases (Autore and Jiang, 2017).
$DIVIDEND_{YIELD}$	λ_8	+	Dividend yield is the main driver of abnormal returns on dividend announcement dates (Dasilas and Leventis, 2011).

Note: Expected signs for interaction and binary model specification variables.

7.6.2. POSITIVE INTERCEPT

If the market is efficient then security prices should reflect changes in dividends. The empirical evidence in this chapter indicates that the mean realized returns around the dividend announcements period are higher than 'normal' and statistically significant. The systematic risk during the event period is found to be larger than that estimated in the non-event period (Kalay and Loewenstein, 1985). My results show that standardized mean excess returns are significantly positive in the event period.

The timing of the next dividend announcement can be predicted by market with certainty. As we know that dividend announcements are repetitive and generally made in the same calendar time. So, if the required rate of the returns around the dividend announcement is identical to that in any other random day, one should not be able to make excess returns by trading around these announcements. According to dividend signaling theory, dividend announcements convey positive (negative) new information. So it means if the market is efficient then the security prices should reflect these changes.

The unconditional expected rate of return during the event period should be higher than normal. A larger required rate of return during the event period is consistent with the theory that the relevant risk per unit of time during the event is higher (Kalay and Loewenstein, 1985). Therefore the reason for positive intercept in all of my model specifications is that investor requires higher rates of returns to hold stocks around their dividend announcements as compensation for the increased risk per unit of time in this period. Some previous literature documents significant positive abnormal returns around predicted news announcements period (Penman, 1984; Chari et al. 1988; Ball and Kothari, 1991)[24]. The explanation given by Cohen et al. (2007) about the abnormal returns is that - "it is compensation for risk incurred when investors are hold securities during a period when valuation relevant information is expected to be released. Suppose mean-variance pricing, investors require higher announcement returns when a newsworthy announcement is expected and the associated risk is non-diversifiable".

7.6.3. LINEAR INTERACTION MODEL

Based on medical, psychological, financial and dividend-signalling theory literature I have made my models. In this section I will use interacted linear model, which is based on my chapter 6's interaction linear model, or in other words I can say that I have augmented my chapter 6's interaction linear model with investor sentiment proxies. Where my key explanatory variables are interacted with dividend changes

[24] A few empirical studies fail to show the evidence of announcement-day premium (Peterson, 1990; Brown and Kim, 1993). Whereas majority of the evidence supports the presence of higher returns on predictable disclosure events indicating that investors require an announcement-day premium.

percentage. This model is based on dividend-signalling hypothesis, and the investor sentiment hypothesis.

To test all three hypotheses mentioned in the hypothesis section I use three-investor sentiment proxies, which are temperature, air pollution and rain in London. To test all three hypotheses I calculate CAR using a 3-days window, i.e. CAR(-1,+1). I have created three tables, each of the table represent one of my investor sentiment proxy. Table 28 represents temperature, Table 29 represents air pollution and Table 30 represents rainfall. In each of these three tables have four different model variations. Model 1 results in all three tables are presented without day-of-the-week effects, year fixed effects, industry fixed effects and clustered standard errors; model 2 results are presented with year fixed effects, industry fixed effects and clustered standard errors but without day-of-the-week effect; model 3 results are with day-of-the-week effects, year fixed effects, industry fixed effects and clustered standard errors and model 4 results are with day-of-the-week effects, year fixed effects, firms fixed effects and clustered standard errors.

Table 28 represents investor sentiment proxy temperature. In Table 28 coefficient λ_1 and coefficient λ_2 results are consistent with the dividend-signalling theory. The average stock return is 0.01619%. Coefficient λ_3 is economically insignificant, as the value of coefficient λ_3 is approximately 7 times less than the average stock market return. Coefficient λ_3 is also statistically insignificant in all four models. But coefficient λ_4 is statistically significant at 1% level in model 1, at 10% level in model 2 and 3, and on the other hand in model 4 coefficient λ_4 is statistically insignificant. Coefficient λ_4 is economically insignificant in all four models. These results suggest that dividend decrease announcements have a less negative effect on stock returns when temperature is high. Computing the partial effect of a dividend decrease on CAR all else constant:

TABLE 29 REGRESSION ANALYSIS OF TEMPERATURE AS INVESTOR SENTIMENT ON DIVIDEND ANNOUNCEMENT DATES USING INTERACTION SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * TEMP_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * TEMP_t + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		Model-1	Model-2	Model-3	Model-4
Constant (λ_0)	Point Estimate	0.04644[a]	0.04795[a]	0.04715[a]	0.07920[a]
	t-statistics	6.51	4.22	4.07	3.37
	Standard Error	0.00714	0.01137	0.01159	0.02349
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.03399[c]	0.03747[c]	0.03822[c]	0.04431[c]
	t-statistics	1.69	1.75	1.78	1.65
	Standard Error	0.02009	0.02139	0.02148	0.02683
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.16563[a]	0.17035[b]	0.17156[b]	0.17381[b]
	t-statistics	4.56	2.45	2.48	2.55
	Standard Error	0.03635	0.06939	0.06929	0.06813
$R\Delta DIV * DPI * TEMP$ (λ_3)	Point Estimate	0.00095	0.00102	0.00107	0.00094
	t-statistics	1.33	1.41	1.47	0.98
	Standard Error	0.00071	0.00072	0.00072	0.00095
$R\Delta DIV * DPD * TEMP$ (λ_4)	Point Estimate	-0.00445[a]	-0.00474[c]	-0.00481[c]	-0.00454
	t-statistics	-2.83	-1.77	-1.79	-1.59
	Standard Error	0.00157	0.00268	0.00268	0.00286
$SIZE$ (λ_5)	Point Estimate	-0.00552[a]	-0.00485[a]	-0.00503[a]	-0.01412[a]
	t-statistics	-6.64	-5.07	-5.17	-4.06
	Standard Error	0.00083	0.00096	0.00097	0.00348
$REVERSAL$ (λ_6)	Point Estimate	-0.95118[a]	-1.06754[a]	-1.06929[a]	-1.07816[b]
	t-statistics	-3.52	-2.65	-2.66	-2.47
	Standard Error	0.27023	0.40263	0.40162	0.43589
$MOMENTUM$ (λ_7)	Point Estimate	-0.18679[b]	-0.23942[c]	-0.24405[c]	-0.25029[c]
	t-statistics	-2.30	-1.90	-1.94	-1.94
	Standard Error	0.08129	0.12570	0.12556	0.12909
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.08716	0.08361	0.06799	0.00075
	t-statistics	0.87	0.62	0.51	0.00
	Standard Error	0.10058	0.13500	0.13412	0.30489
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		4.26%	5.45%	5.58%	14.83%
N		2,697	2,697	2,697	2,697

Note: In here the dependent variable is CAR (-1,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. *TEMP* is average daily temperature. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where M_d, W_d , T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \lambda_2 DPD_{it} + \lambda_4 DPD_{it} * TEMP_t \quad (31)$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * TEMP_t$$

$= \widehat{\lambda_2} + \widehat{\lambda_4} * \overline{TEMP}$ [$\overline{TEMP}$ =Average daily temperature in London between June 1996 and December 2015]

$$= \widehat{\lambda_2} + \widehat{\lambda_4} * 21.302$$

hence, for mode 1

= 0.16563 + (-0.00445) * 21.302

= 0.07084

for model 2

= 0.17035 + (-0.00474) * 21.302

= 0.06938

for model 3

=0.17156 + (-0.00481) * 21.302

= 0.06910

and, for model 4

=0.17381 + (-0.00454) * 21.302

= 0.07709

After conducting the joint significant test using Table 28 I can see that the firm fixed effect is significant, which means my preferred model is model 4, even though I will consider my other three models as well. Equation 31 suggests that a 10% decreases in dividends decrease stock returns by 0.7709% (according to model 4) if it happens when temperature is at its average value (i.e. 21.3 degrees Celsius). On the other hand a 10% decrease in dividends decreases stock returns by 1.7381% (according to model 4) if it happen when the temperature is equal to 0 degrees Celsius. This suggests that the higher is the temperature in London (and allegedly the better investor mood), the smaller is the negative effect of dividend –decrease announcements on stock returns. We observe similar kind of results in coefficient λ_4 in other models.

These results suggest that stock prices react less negatively to dividend decrease when investor mood is positive (proxied by high temperature). On the basis of these results, there is marginal evidence to reject the null hypothesis in favour of the alternative hypothesis, even though my preferred model (model 4) is statistically insignificant. Therefore, we can tell that high temperature does not affect the reaction of stock prices to dividend increase announcements, but stock prices react less negatively to dividend decreases when investor mood is positive (proxied by high temperature).

Table 28 shows that λ_0 is economically significant in all four models and also statistically significant in all four models at 1% level. Table 28 also shows that λ_0 is positive in all three models. The reason behind the positive intercept is given in section 9.6.2. Control variable size, reversal and momentum are statistically significant in all four models, on the other hand dividend yield is statistically insignificant, but all control variables signs are consistent with previous literature in all four models.

Table 29 represents investor sentiment proxy air pollution. Table 29 shows that the point estimates of coefficient $\lambda_1$are 5.249%, 5.933%, 6.035% and 7.179%

respectively in model 1, 2, 3 and 4. The point estimates of coefficient λ_2 in model 1 is 2.704%, in model 2 is 2.799%, in model 3 is 2.866% and in model 4 is 3.383%. Coefficient λ_2 is statistically insignificant, which does not support the dividend signaling theory. On the other hand, coefficient λ_3 is economically and statistically insignificant in all four models. Coefficient λ_3 shows inconsistent sign with my hypothesis, the reason behind this inconsistent sign may be due to sampling variability.

But coefficient $\lambda_4$is statistically significant in all four models and the sign is consistent with my hypothesis. Coefficient λ_4 is statistically significant at 1% level in model 1 and at 5% level in model 2, 3 and 4. Coefficient λ_4 is economically significant in all four models (The average stock return is 0.01619%). This means air pollution affects the reaction of stock market returns to dividend decrease announcements. After running a joint significant test of coefficient λ_2 and coefficient λ_4, my results show that they are jointly statistically significant at the 5% level, which means that both dividend-decrease announcements have a negative impact on stock returns and the negative impact is stronger when investor mood is low (i.e. air pollution is high). As such, the results of the joint significance test support the dividend-signaling theory. To get the total effect of a dividend decrease we need to consider both coefficient λ_2 and coefficient λ_4. Computing the partial effect of a dividend decrease on CAR all else constant:

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \lambda_2 DPD_{it} + \lambda_4 DPD_{it} * AIR_t \tag{32}$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * AIR_t$$

$$= \widehat{\lambda_2} + \widehat{\lambda_4} * 1$$ [1 if London city's Air Quality Index (AQI) is above 3]

hence, for model 1

= 0.02704 + 0.14351 * 1

= 0.17055

for model 2

=0.02799 + 0.13774 * 1

=0.16573

for model 3

=0.02866 + 0.13538 * 1

= 0.16404

and, for model 4

=0.03383 + 0.12826 * 1

= 0.16209

TABLE 30 REGRESSION ANALYSIS OF AIR POLLUTION AS INVESTOR SENTIMENT ON DIVIDEND ANNOUNCEMENT DATES USING INTERACTION SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * AIR_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * AIR_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.04069[a]	0.03779[b]	0.03601[b]	0.05963[a]
	t-statistics	6.87	2.11	2.01	3.00
	Standard Error (μ_{it})	0.00592	0.01789	0.01790	0.01988
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.05249[a]	0.05933[a]	0.06035[a]	0.07179[a]
	t-statistics	4.37	4.65	4.76	4.82
	Standard Error (μ_{it})	0.01199	0.01276	0.01267	0.01489
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.02704	0.02799	0.02866	0.03383
	t-statistics	1.49	0.97	1.00	1.06
	Standard Error (μ_{it})	0.01819	0.02871	0.02856	0.03179
$R\Delta DIV * DPI * AIR$ (λ_3)	Point Estimate	0.00424	0.00482	0.00636	0.00272
	t-statistics	0.30	0.34	0.45	0.17
	Standard Error (μ_{it})	0.01425	0.01432	0.01423	0.01585
$R\Delta DIV * DPD * AIR$ (λ_4)	Point Estimate	0.14351[a]	0.13774[b]	0.13538[b]	0.12826[b]
	t-statistics	4.19	2.17	2.14	2.09
	Standard Error (μ_{it})	0.03424	0.06342	0.06325	0.06127
$SIZE$ (λ_5)	Point Estimate	-0.00515[a]	-0.00468[a]	-0.00495[a]	-0.01339[a]
	t-statistics	-7.33	-4.95	-5.23	-4.91
	Standard Error (μ_{it})	0.00070	0.00095	0.00095	0.00273
$REVERSAL$ (λ_6)	Point Estimate	-0.86233[a]	-1.00199[a]	-0.99344[a]	-1.06084[a]
	t-statistics	-3.59	-2.77	-2.75	-2.80

	Standard Error (μ_{it})	0.24029	0.36226	0.36078	0.37894
$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.16722^{b}	-0.20682^{c}	-0.21132^{c}	-0.18907^{c}
	t-statistics	-2.29	-1.88	-1.92	-1.67
	Standard Error (μ_{it})	0.07312	0.11005	0.11006	0.11330
$DIVIDEND_{YIELD}\ (\lambda_8)$	Point Estimate	0.21313^{b}	0.17554	0.15008	0.12923
	t-statistics	2.43	1.52	1.29	0.55
	Standard Error (μ_{it})	0.08784	0.11575	0.11655	0.23579
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Fixed Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.97%	5.48%	5.73%	13.43%
N		3,407	3,407	3,407	3,407

Note: In here the depended variable is CAR (-1,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. *AIR* is if London city air pollution above the Air Quality Index (AQI) level 3 then it takes value 1 otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using the values of stoke returns one month before the dividend announcement month, it also repressing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where $M_d, W_d\ , T_d\ and\ F_d$ are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

Joint significant test results suggest that the firm fixed effect is significant in Table 29, which means my preferred model is model 4, even though I will consider my other three models as well. From equation 32 we can see that a 10% decrease in dividends decrease stock returns by 1.6209% (according to model 4) if it happen when investor sentiment is negative (proxied by high air pollution levels). On the other hand a 10% decrease in dividends decrease stock returns by 0.3383% (according to model 4) if it happen when investor sentiment is positive i.e. low air pollution levels. We observe similar kind of results in other models in coefficient λ_4.

These results suggest that stock prices react more negatively to dividend decrease announcements when investor sentiment is negative (proxied by high air pollution levels). On the basis of these results I can reject the null hypothesis in favour of the alternative hypothesis, and we can conclude that high air pollution level does not affect the reaction of the stock prices to dividend increase announcements but stock prices react more negatively to dividend decrease announcements when investor sentiment is negative (proxied by high air pollution levels).

Table 29 shows that λ_0 is economically significant in all four models and statistically significant at 1% level in model 1 and 4, and at 5% level in model 2 and 3. Table 29 also shows that λ_0 is positive in all four models. Control variable size, reversal and momentum are statistically significant in all four models; on the other hand dividend yield is only significant in model 1 at 5%. And all control variables signs are consistent with previous literature.

Table 30 represents the investor sentiment proxy rainfall. If we look at Table 30 then we can see that the results of coefficient λ_1 and coefficient λ_2 are consistent with the dividend-signalling theory. On the other hand, coefficient λ_3 and coefficient λ_4 are economically significant but statistically insignificant in all four models. Coefficient λ_4 signs also shows inconsistent sign with the dividend-signalling theory and investor sentiment hypothesis, the reason behind this inconsistent sign may be due to sampling variability. On the basis of these results I cannot reject the null hypothesis, which means there is no evidence to argue that investor sentiment (proxied by rainfall) affects the reaction of the stock market to dividend increase (decrease) announcements. Coefficient λ_0 is economically significant in all four models and statistically significant at 1% level in all four models. Except dividend yield rest of the three control variables are statistically significant.

TABLE 31 REGRESSION ANALYSIS OF RAINFALL AS INVESTOR SENTIMENT ON DIVIDEND ANNOUNCEMENT DATES USING INTERACTION SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * RAIN_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * RAIN_t + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.04770[a]	0.04345[a]	0.04313[a]	0.09398[a]
	t-statistics	6.68	3.00	2.97	4.00
	Standard Error (μ_{it})	0.00714	0.01448	0.01453	0.02349
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.05857[a]	0.06355[a]	0.06544[a]	0.06743[a]
	t-statistics	4.07	4.08	4.21	3.84
	Standard Error (μ_{it})	0.01438	0.01558	0.01554	0.01756
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.09543[a]	0.09477[c]	0.09370[c]	0.09808[b]
	t-statistics	3.93	1.92	1.92	1.97
	Standard Error (μ_{it})	0.02430	0.04936	0.04887	0.04966
$R\Delta DIV * DPI * RAIN$ (λ_3)	Point Estimate	-0.00749	-0.00803	-0.00861	-0.00669
	t-statistics	-0.49	-0.56	-0.59	-0.41
	Standard Error (μ_{it})	0.01521	0.01440	0.01454	0.01624
$R\Delta DIV * DPD * RAIN$ (λ_4)	Point Estimate	-0.04025	-0.03989	-0.03815	-0.02933
	t-statistics	-1.18	-0.67	-0.65	-0.49
	Standard Error (μ_{it})	0.03409	0.05964	0.05899	0.05989
$SIZE$ (λ_5)	Point Estimate	-0.00564[a]	-0.00504[a]	-0.00522[a]	-0.01427[a]
	t-statistics	-6.78	-5.19	-5.30	-4.18
	Standard Error (μ_{it})	0.00083	0.00097	0.00098	0.00341
$REVERSAL$ (λ_6)	Point Estimate	-0.93873[a]	-1.04910[a]	-1.05033[a]	-1.08909[b]
	t-statistics	-3.47	-2.57	-2.58	-2.48
	Standard Error (μ_{it})	0.27066	0.40876	0.40778	0.43935
$MOMENTUM$ (λ_7)	Point Estimate	-0.19492[b]	-0.24366[c]	-0.24795[b]	-0.25417[b]
	t-statistics	-2.40	-1.93	-1.96	-1.99
	Standard Error (μ_{it})	0.08137	0.12633	0.12621	0.12764
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.069950	0.05786	0.04358	-0.01292
	t-statistics	0.70	0.43	0.33	-0.04
	Standard Error (μ_{it})	0.10062	0.13310	0.13268	0.29563
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.97%	5.12%	5.23%	14.55%
N		2,697	2,697	2,697	2,697

Note: In here the depended variable is CAR (-1,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. $RAIN$ = If there is rain in London then rain will take value 1 otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using the values of stoke returns one month before the dividend announcement month, it also repressing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where $M_d, T_d, W_d, T_d\ and\ F_d$ are the dummy variables for Monday, Tuesday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

7.6.4. LINEAR BINARY MODEL

In this section I will use linear binary model, which is based on my empirical chapter 6's linear binary model. This model is based on dividend-signalling theory and investor sentiment hypothesis. The binary model only concentrates on the direction of the dividend change and ignores the size of the dividend change to find out whether dividend change direction has any effect on stock returns. By concentrating dividend change direction, the binary model mitigates the effect of outliers.

Table 31 represents the investor sentiment proxy temperature. In Table 31 coefficient λ_1 and coefficient λ_2 are shows consistent results with the dividend-signalling theory. On the other hand coefficient λ_3 is economically and statistically insignificant, but coefficient λ_4 is statistically significant at 1% level in model 1, at 5% level in model 2 and 3 and at 10% in model 4. The results shows in these four models are incremental effect of a dividend increase (decrease) when temperature is high, to obtain the total effect of a dividend decrease we have to consider both coefficient λ_2 and coefficient λ_4. Computing the partial effect of a dividend decrease on CAR all else constant:

$$\left(\frac{\partial CAR_{it}}{\partial DPD_{it}}\middle| DPD_{it} = 1\right) = \lambda_2 + \lambda_4 * TEMP_t \qquad (33)$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta DPD_{it}}\middle| DPD_{it}\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * TEMP_t$$

$= \widehat{\lambda_2} + \widehat{\lambda_4} * \overline{TEMP_t}$ [$\overline{TEMP}$ =Average daily temperature in London between June 1996 and December 2015]

$= \widehat{\lambda_2} + \widehat{\lambda_4} * 21.302$

hence, for model 1

= -0.04587 + 0.00147 * 21.302

= -0.01456

for model 2

= -0.04641 + 0.00150 * 21.302

= -0. 01446

TABLE 32 REGRESSION ANALYSIS OF TEMPERATURE AS INVESTOR SENTIMENT ON DIVIDEND ANNOUNCEMENT DATES USING BINARY SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * TEMP_t + \lambda_4 DPD_{it} * TEMP_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model -4**
Constant (λ_0)	Point Estimate	0.04406[a]	0.04609[a]	0.04609[a]	0.07088[a]
	t-statistics	5.90	3.93	3.85	2.98
	Standard Error (μ_{it})	0.00747	0.01174	0.01198	0.02377
DPI (λ_1)	Point Estimate	0.01127[b]	0.01095[b]	0.01142[b]	0.01359[b]
	t-statistics	2.53	2.37	2.47	2.30
	Standard Error (μ_{it})	0.00446	0.00463	0.00462	0.00589
DPD (λ_2)	Point Estimate	-0.04587[a]	-0.04641[a]	-0.04652[a]	-0.05178[a]
	t-statistics	-4.12	-2.75	-2.74	-2.81
	Standard Error (μ_{it})	0.01113	0.01689	0.01696	0.01840
$DPI * TEMP$ (λ_3)	Point Estimate	0.00012	0.00014	0.00015	0.00006
	t-statistics	1.03	1.16	1.25	0.38
	Standard Error (μ_{it})	0.00012	0.00012	0.00012	0.00017
$DPD * TEMP$ (λ_4)	Point Estimate	0.00147[a]	0.00150[b]	0.00153[b]	0.00164[c]
	t-statistics	3.31	2.08	2.10	1.91
	Standard Error (μ_{it})	0.00044	0.00072	0.00073	0.00086
$SIZE$ (λ_5)	Point Estimate	-0.00586[a]	-0.00533[a]	-0.00558[a]	-0.01371[a]
	t-statistics	-7.03	-5.31	-5.51	-3.98
	Standard Error (μ_{it})	0.00083	0.00100	0.00101	0.00344
$REVERSAL$ (λ_6)	Point Estimate	-0.92801[a]	-1.02267[a]	-1.02093[a]	-1.03089[b]
	t-statistics	-3.43	-2.59	-2.59	-2.37
	Standard Error (μ_{it})	0.27047	0.39555	0.39451	0.43466
$MOMENTUM$ (λ_7)	Point Estimate	-0.16908[b]	-0.20902[c]	-0.21321[c]	-0.20919
	t-statistics	-2.08	-1.69	-1.73	-1.63
	Standard Error (μ_{it})	0.08111	0.12362	0.12316	0.12822
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.05157	0.04165	0.02581	0.00286
	t-statistics	0.52	0.31	0.19	0.01
	Standard Error (μ_{it})	0.09988	0.13388	0.13319	0.29534
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		4.13%	5.17%	5.31%	14.61%
N		2,697	2,697	2,697	2,697

Note: In here the depended variable is CAR (-1,+1). The dummy variables are DPI and DPD. If the dividend change is positive then DPI=1, otherwise 0, and if the dividend change is negative then DPD =1, otherwise 0. *TEMP* is average daily temperature. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using the values of stoke returns one month before the dividend announcement month, it also repressing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where M_d, W_d , T_d *and* F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

for model 3

$$= -0.04652 + 0.00153 * 21.302$$

$$= -0.01393$$

and , for model 4

$$= -0.05178 + 0.00164 * 21.302$$

$$= -0.01684$$

Joint significant test results suggest that the firm fixed effect is significant in Table 31, which means my preferred model is model 4, even though I will consider my other three models as well. Results from equation 33 suggests that when temperature is at its average value (21.3 degrees Celsius) dividend decrease announcements are accompanied by a drop in stock market returns of -1.684% (model 4), whereas when the low temperature is low (0 degrees Celsius) dividend decrease announcements lead to a drop in stock market returns of -5.178% (model 4). Other three models also show similar kind of results. According to these results we can tell that stock prices react less negatively to dividend decrease announcements when the temperature is high (and allegedly investor sentiment is positive). On the basis of these results I reject the null hypothesis in favour of the alternative hypothesis and the results suggests that stock prices does not react to dividend increase announcement when temperature is high but stock prices react less negatively to dividend decreases when investor mood is positive (proxied by high temperature). The higher is the temperature, the smaller is the negative reaction of the stock market to dividend decrease announcements. Coefficient λ_0 is statistically significant and shows positive sign; the reason behind the positive intercept is given in section 7.6.2. Except dividend yield all other three-control variables are statistically significant and consistent with the previous literature.

Table 32 representing the investor sentiment proxy air pollution. Coefficient λ_2 is statistically insignificant, which does not support the dividend signaling theory. In Table 32 coefficient λ_3 is economically and statistically insignificant but the signs are consistent with the dividend-signalling theory and investor sentiment hypothesis. On the other hand coefficient λ_4 is statistically significant at 1% in model 1 and at 10% in model 2 and 3, but model 4 is statistically not different from zero. Coefficient λ_4 is economically significant as well in all four models. These results suggest that dividend decrease announcements have a strong negative effect on stock returns when air pollution is high (i.e. investor sentiment is negative). Computing the partial effect of a dividend decrease on CAR all else constant:

$$\left(\frac{\partial CAR_{it}}{\partial DPD_{it}}\middle|DPD_{it} = 1\right) = \lambda_2 + \lambda_4 * AIR_t \quad (34)$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta DPD_{it}}\middle|DPD_{it} = 1\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * AIR_t$$

$= \widehat{\lambda_2} + \widehat{\lambda_4} * 1$ [1 if London city's Air Quality Index (AQI) is above 3]

hence, for model 1

= -0.00325 + (-0.03078) * 1

= -0.03403

for model 2

= -0.00413 + (-0.02881) * 1

= -0.03294

TABLE 33 REGRESSION ANALYSIS OF AIR POLLUTION AS INVESTOR SENTIMENT ON DIVIDEND ANNOUNCEMENT DATES USING BINARY SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * AIR_t + \lambda_4 DPD_{it} * AIR_{\ t} + \lambda_5\ SIZE_{it} + \lambda_6\ REVERSAL_{\ it} + \lambda_7\ MOMENTUM_{it} + \lambda_8\ DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03943[a]	0.04007[b]	0.03854[b]	0.06380[a]
	t-statistics	6.29	2.21	2.11	3.34
	Standard Error (μ_{it})	0.00627	0.01815	0.01824	0.01910
DPI (λ_1)	Point Estimate	0.01228[a]	0.01229[a]	0.01293[a]	0.01322[a]
	t-statistics	3.67	3.68	3.87	3.11
	Standard Error (μ_{it})	0.00335	0.00334	0.00334	0.00424
DPD (λ_2)	Point Estimate	-0.00325	-0.00413	-0.00371	-0.00550
	t-statistics	-0.54	-0.60	-0.54	-0.66
	Standard Error (μ_{it})	0.00598	0.00693	0.00693	0.00834
$DPI * AIR$ (λ_3)	Point Estimate	-0.00073	-0.00068	-0.00047	-0.00025
	t-statistics	-0.31	-0.30	-0.21	-0.09
	Standard Error (μ_{it})	0.00235	0.00227	0.00225	0.00275
$DPD * AIR$ (λ_4)	Point Estimate	-0.03078[a]	-0.02881[c]	-0.02842[c]	-0.02911
	t-statistics	-3.23	-1.69	-1.66	-1.59
	Standard Error (μ_{it})	0.00954	0.01700	0.01708	0.01831
$SIZE$ (λ_5)	Point Estimate	-0.00545[a]	-0.00513[a]	-0.00542[a]	-0.01317[a]
	t-statistics	-7.70	-5.27	-5.60	-4.83
	Standard Error (μ_{it})	0.00071	0.00097	0.00097	0.00273
$REVERSAL$ (λ_6)	Point Estimate	-0.88276[a]	-0.99638[a]	-0.98795[a]	-1.05796[a]
	t-statistics	-3.66	-2.75	-2.74	-2.76
	Standard Error (μ_{it})	0.24116	0.36212	0.36057	0.038295
$MOMENTUM$ (λ_7)	Point Estimate	-0.14213[c]	-0.16250	-0.16647	-0.13049
	t-statistics	-1.95	-1.47	-1.52	-1.13
	Standard Error (μ_{it})	0.07294	0.11023	0.10985	0.11541
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.17429[b]	0.12637	0.10213	0.10311
	t-statistics	1.99	1.09	0.87	0.45
	Standard Error (μ_{it})	0.08762	0.11637	0.11685	0.23022
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.64%	5.29%	5.00%	12.63%
N		3,407	3,407	3,407	3,047

Note: In here the depended variable is CAR (-1,+1). The dummy variables are DPI and DPD. If the dividend change is positive then DPI=1, otherwise 0, and if the dividend change is negative then DPD =1, otherwise 0. *AIR* is if London city air pollution above Air Quality Index (AQI) level 3 then it takes value 1 otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using the values of stoke returns one month before the dividend announcement month, it also repressing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where $M_d, W_d\ , T_d\ and\ F_d$ are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

for model 3

$$= -0.00371 + (-0.02842) * 1$$

$$= -0.03213$$

and, for model 4

$$=-0.00550 + (-0.02911) * 1$$

$$= -0.03461$$

Joint significant test results suggest that the firm fixed effect is significant in Table 32, which means my preferred model is model 4, even though I will consider my other three models as well. These results are suggests that when investor sentiment is negative (air pollution levels are high) across firms decreasing dividends stock market returns is -3.461% lower (model 4), but when air pollution level is low on average across firms decreasing dividends stock market returns only -0.550% lower (model 4). We observer similar kind of result in model 1 and 2 but model 4 is not different from zero. These results suggest that there is marginal evidence that stock prices react more negatively to dividend decreases when the air pollution level is high (and allegedly investor sentiment is negative).

On the basis of these results there is marginal evidence to reject the null hypothesis in favour of the alternative hypothesis and the results suggest that stock prices do not react any differently to dividend increase announcements when air pollution level is high but stock prices react more negatively to dividend decreases when investor mood is negative (proxied by high air pollution). Coefficient λ_0 is statistically significant and shows positive sign (see section 7.6.2). Control variable size and reversal are statistically significant in all models models, but momentum and dividend yield are statistically significant only in model 1.

Now if we look at Table 33 then we can see that coefficient λ_1, coefficient λ_2 and coefficient λ_3 signs are consistent with the dividend-signalling theory and with my hypothesis, but coefficient λ_4 shows the inconsistent sign with the dividend-signalling theory and my hypothesis. The reason behind this inconsistent sign may be due to sampling variablity. If we look at the coefficient λ_1 and coefficient λ_2 then we can see that coefficient λ_1 is economically and statistically significant in all four models, but coefficient λ_2 only statistically significant in model 1. On the other hand coefficient λ_3 and coefficient λ_4 are economically and statistically insignificant. Coefficient λ_0 is statistically significant and shows positive sign. Except dividend yield all other three-control variables are statically significant. On the basis of these results I cannot reject the null hypothesis, which means there is no evidence to argue that investor sentiment (proxied by rainfall) affects the reaction of the stock market to dividend increase (decrease) announcements.

TABLE 34 REGRESSION ANALYSIS OF RAINFALL AS INVESTOR SENTIMENT ON DIVIDEND ANNOUNCEMENT DATES USING BINARY SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * RAIN_{it} + \lambda_4 DPD_{it} * RAIN_{it} + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.04520[a]	0.04028[a]	0.04062[a]	0.08411[a]
	t-statistics	6.04	2.71	2.72	3.84
	Standard Error (μ_{it})	0.00747	0.01488	0.01496	0.02189
DPI (λ_1)	Point Estimate	0.01459[a]	0.01506[a]	0.01587[a]	0.01594[a]
	t-statistics	3.71	3.60	3.81	3.06
	Standard Error (μ_{it})	0.00394	0.00418	0.00417	0.00521
DPD (λ_2)	Point Estimate	-0.01631[b]	-0.01629	-0.01552	-0.01806
	t-statistics	-2.13	-1.57	-1.51	-1.50
	Standard Error (μ_{it})	0.00767	0.01039	0.01025	0.01206
$DPI * RAIN$ (λ_3)	Point Estimate	-0.00143	-0.00174	-0.00193	-0.00197
	t-statistics	-0.56	-0.72	-0.78	-0.67

	Standard Error (μ_{it})	0.00253	0.00241	0.00246	0.00294
$DPD * RAIN\ (\lambda_4)$	Point Estimate	0.00336	0.00361	0.00299	0.00151
	t-statistics	0.35	0.25	0.21	0.10
	Standard Error (μ_{it})	0.00959	0.01458	0.01436	0.01596
$SIZE\ (\lambda_5)$	Point Estimate	-0.00593[a]	-0.00549[a]	-0.00573[a]	-0.01359[a]
	t-statistics	-7.10	-5.37	-5.54	-4.01
	Standard Error (μ_{it})	0.00083	0.00102	0.00103	0.00339
$REVARSAL\ (\lambda_6)$	Point Estimate	-0.95159[a]	-1.03800[a]	-1.0365[a]	-1.07112[b]
	t-statistics	-3.51	-2.58	-2.58	-2.44
	Standard Error (μ_{it})	0.27097	0.40223	0.40116	0.43868
$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.17848[b]	-0.21551[c]	-0.21946[c]	-0.21581[c]
	t-statistics	-2.20	-1.74	-1.78	-1.70
	Standard Error (μ_{it})	0.08127	0.12401	0.12356	0.12722
$DIVIDEND_{YIELD}\ (\lambda_8)$	Point Estimate	0.02713	0.00941	-0.00550	-0.00763
	t-statistics	0.27	0.07	-0.04	-0.03
	Standard Error (μ_{it})	0.09982	0.13433	0.13389	0.28656
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
FIRM Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.72%	4.74%	4.87%	14.20%
N		2,697	2,697	2,697	2,697

Note: In here the depended variable is CAR (-1,+1). The dummy variables are DPI and DPD. If the dividend change is positive then DPI=1, otherwise 0, and if the dividend change is negative then DPD =1, otherwise 0. *RAIN* = If there is rain in London area then rain will take value 1 otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using the values of stoke returns one month before the dividend announcement month, it also repressing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where $M_d,\ W_d\ ,T_d\ and\ F_d$ are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

7.7. ROBUSTNESS TEST

An event study attempts to measure the valuation effects of a corporate event, by examining the response of the stock market price around the event. In the previous section I used 3 days event window i.e. (-1,+1), and in this section I will use 2 days event window i.e. (0,+1) to do a robustness test. These two days event window is dividend announcements day t_0 and one day after the dividend announcement day t_1.

One of the underlying assumptions of the event window is that the market processes information about the event in an unbiased manner. Thus, we should be able to see the effect of the dividend announcement on stock market prices, how quickly market can incorporate information and whether this information has any direct effect on stock prices. According to Efficient Market Hypothesis (EMH) from the market should react efficiently. Due to that reason in this section I will examine whether there are any empirical evidence that 2 days event window results are different than 3 days event window results. Except for CAR all other variables are the same as in the previous section.

If we analysis the results of this section then we can see that, even though I use different event window to do the robustness test but I have found similar kind of result like previous section in both model specifications for all three investor sentiment proxies (see appendix-1). So we can tell that the results are robust.

7.8. DISCUSSION

In Table 28 and 31 the coefficient λ_3 is statistically and economically insignificant, whereas the coefficient λ_4 is statistically significant in first three models but in model 4 it is not different from zero. Both coefficient signs are consistent with the dividend-signalling theory and investor sentiment hypothesis. And both Table 28 and Table 30 in my empirical result section suggests that dividend decrease have a smaller negative effect than usual on stock returns when the temperature in London is high and as a result investor sentiment is likely positive. So my results are consistent with the dividend-signalling theory and investor sentiment hypothesis when temperature is used as the investor sentiment proxy.

If we look at Table 29 and Table 32 we can see that coefficient λ_3 is statistically and economically insignificant in both model specifications and coefficient λ_3 shows inconsistent sign with the dividend-signalling theory and investor sentiment hypothesis in Table 29, but coefficient λ_4 is statistically and economically significant and shows consistent sign with the dividend-signalling theory and investor sentiment hypothesis. The results support the alternative hypothesis and suggest that the negative impact of dividend decrease announcements on returns is bigger than usual when the air pollution level is high and as a result investor's sentiment is negative.

Finally I have used rainfall as my third investor sentiment proxy, and we can see in Table 30 and Table 33 that both coefficient λ_3 and λ_4 are statistically and economically insignificant and the sign of coefficient λ_4 is inconsistent with the dividend signaling theory and investor sentiment hypothesis. On the basis of these results I cannot reject the null hypothesis, which means that there is not enough evidence to argue that investor sentiment (proxied by rainfall) does not affect the reaction of the stock market to dividend increase (decrease) announcements.

After using the 3-day event window period and 3 investor sentiment proxies to analysis whether investor sentiment plays any role in the response of stock prices to dividend announcements, my results are in favour of my alternative hypotheses and reject the null hypotheses. This means my empirical results suggest that there is at least marginal evidence that investor sentiment plays a role in the response of stock prices to dividend announcements. But to check whether these results are robust or not I have conducted a robustness tests.

When I have conducted the robustness test using 2-day event window period CAR (0,+1), I have found similar kind of results, which suggests that the findings are not driven by my choice of the event window. This study has a number of limitations, which are (1) in this study I used only four control variables, but in the future researchers can try to use more and different types of control variables, (2) my sample has a small number of dividend decrease observations, which means small statistical power to detect an effect, (3) future research can be done using more investor sentiment proxies i.e. wind, sunshine, snow.

7.9. CONCLUSION

It is true that all human activities to some extent are affected by the atmospheric environment, and indeed, weather plays a crucial role to affect the sentiment and decision-making processes of the people. From previous literature we can learn that some environmental stimuli in the city that hosts the stock exchange affect the behaviour of that particular stock market's returns. The present investigation has focused on whether investor sentiment plays a role in the response of stock prices to dividend announcements. No previous research has investigated this question before. Here I used three weather variables as investor sentiment proxies, which are temperature, air pollution and rainfall in London. My results show that there is at least marginal evidence that investment sentiment plays a role in the reaction of the stock market to dividend announcements.

If we look at investor sentiment proxy temperature then we can observe that coefficient λ_3 is statistically not significant in all the tables, while coefficient λ_4 is statistically significant in all models in linear binary model specification; except for model 4, the other three models are statistically significant in the linear interaction model specification, but both coefficiens signs are consistent with the dividend signaling theory and investor sentiment hypothesis. We can see that my results are in favour of the alternative hypothesis and reject the null hypothesis due to that reason there is at least marginal evidence to conclude that dividend decrease announcements have a smaller negative effect than usual on stock returns when the temperature is high and as a result investor sentiment is positive.

When I used air pollution as investor proxy then the results showed that the negative impact of dividend decrease announcement on returns is bigger than usual when air pollution levels are high and as a result investor sentiment is negative. Coefficient λ_3 is statistically and economically insignificant in both tables (Table 29 and 32), and coefficient λ_4 is statistically significant in all models in the linear interaction model specification; except for model 4, the other three models are statistically significant in the linear binary model specification

With regards to the sentiment proxy rainfall coefficient λ_3 and coefficient λ_4 are statistically insignificant in both tables (Table 30 and 33 and coefficient λ_4 shows inconsistent sign with the dividend signaling theory and investor sentiment hypothesis in both tables (Table 30 and 33). So investor sentiment (proxied by rainfall) does not seem to affect the reaction of the stock market to dividend increase (decrease) announcements. The results concerning two of the three-investor sentiment proxies are consistent with the interpretation that investor sentiment plays a role in the response of stock prices to dividend announcements. It may be the case that no evidence was found when using the sentiment proxy rainfall because, in the UK, rainfall does not significantly affect investor sentiment. In the UK, people may be so used to the rain that a rainy day has no relevant impact on their moods. The typical take away of this kind of behavioural finance studies is that, once investors become aware of the cognitive and emotional biases that affect their decisions, they can make "better" decisions. So, in the case of my study, if we can teach investors that their response to dividend announcements is being influenced by "irrelevant factors" (temperature, air pollution, rain etc), then they should be able to make better investment decisions.

8 CALENDAR ANOMALIES AND THE EFFECT OF DIVIDEND ANNOUNCEMENTS ON STOCK RETURNS: A STUDY ON UK DATA

8.1. INTRODUCTION

This chapter investigates a number of stock market anomalies that have been found in the previous literature to have significant impact on stock returns. These stock market anomalies are called calendar anomalies and were first introduced by Wachtel (1942). Some of the well-known calendar anomalies include the Monday effect, Halloween effect (Sell in May and go away), Turn-of-the-month (here on TOM) effect, and January effect, which are the anomalies studies in this chapter. According to Urquhart and McGroarty (2014) these anomalies are inconsistent with the EMH, because according to the EMH at any given time prices fully reflect all available information on a particular stock market. Also (weak form) EMH suggest that no investors can gain an advantage in predicting the return on a stock using market related information. And there is a lot of evidence against the EMH in the real world of investment (Cho el at. 2007).

The main aim of this chapter is to answer the question of whether calendar anomalies play any role in the relationship between dividend announcements and stock returns. To give this question an answer I will extend my chapter 6's findings, where I found that dividend-increase (decrease) announcements have a positive (negative) effect on stock returns, which is consistent with the dividend-signalling theory. The study reported in this chapter is mainly exploratory in nature. I do not try to explain why some calendar anomalies affect how the stock market responds to dividend announcements. I simply try to uncover evidence that it does react differently due to some calendar effects. In this chapter I extend my research by examining the role of four calendar anomalies (Monday effect, Halloween effect, TOM effect, and January effect). Following the existing literature I use four of the most popular calendar anomalies. To conduct this research I am going to use two model specifications, similar to the ones employed in the previous chapters. The key innovation is that in this chapter the calendar anomalies are interacted with the two existing model specifications from chapter 6.

The seasonality of stock markets has a long history despite academic research being dominated by the efficient market theory as surveyed by Fama (1970, 1991). The Monday effect is one of the most widely pronounced stock market anomalies (Bakar et al. 2014). The logic behind the Monday effect is that Monday returns are negative or significantly lower than those of the other days of the week. French (1980) documented early evidence of such a pattern in the US market during the 1950s and 1970s. Monday effect is also observed in international markets, as evidenced in Jaffe and Westerfield (1985); Condoyanni et al. (1987); Tong (2000) and Steeley (2001).

According to the Easterday et al. (2016), the January effect anomaly is associated with accounting earnings and expectations about future earnings, in a manner both economically rational and consistent with accounting theory. A capital market phenomenon is that returns are on average higher in January than in the other months of the year (Easterday et al., 2016). Previous studies suggest that the January effect is disappearing (Gu, 2003; He & He, 2011), some other studies indicate that the January effect continues to appear in the modern US markets (Anderson et al., 2007; Brown & Luo, 2006; Ciccone, 2011; Ziemba, 2011) although it does not happen in every year (Easterday et al., 2016).

Another calendar anomaly is Halloween effect or “Sell in May and go away” effect, which was first introduced by Bouman and Jacobsen (2002). Their study was inspired by an old saying, “Sell in May and go away”. The main massage of this saying is that stock returns are lower from May to October than other months of the year. Till today no one knows exactly how old this saying is, but Jacobsen and Zhang (2010) found a written reference in the *Financial times* from 1935. In this chapter I will also discuss another calendar anomaly, which is the turn-of-the-month (TOM). TOM effect was first reported by Ariel (1987), and it is still at the forefront of the seasonal anomalies literature. TOM effect is defined as the tendency of stock returns to be higher during a period encompassing the end of each month and the beginning of the new month.

Previous researchers have tried to understand the relationship between calendar anomalies and stock market returns using different calendar or seasonal anomalies. However, a question that has not been addresses yet is whether calendar anomalies play any role in the relationship between dividend announcements and stock market returns. In this chapter I try to answer this question. To the best of my knowledge, no previous studies have considered this question before. To answer this question I have selected four calendar anomalies, which are the TOM effect, Halloween effect, Monday effect and January effect.

In this chapter I use FTSE-350 (LSE) companies to test some novel hypotheses related to this question. Empirically, I use one partially novel model specification (binary model), which is based on chapter 6’s model specifications. I call my first model linear interaction model and my second model linear binary model. To do the hypotheses test I will use event window (-1,+1) and to do the robustness test I will use event window (0,+1). My research question is inspired by previous work on the dividend-signalling theory and calendar or seasonal anomalies hypotheses. My main object of investigation is the dividend-signalling theory.

My results suggest that calendar or seasonal anomalies play an important role in the reaction of the stock market to dividend announcements. The stock market reacts less negatively to dividend-decrease announcements during the November to April period than during the May to October period (Halloween effect) according to the interaction model specification, but when we use binary model then the stock market is estimated to react less negatively to dividend-decrease announcements during the November to April period than during the May to October period. The stock market reacts more negatively to dividend-decrease announcements if they occur at the TOM, when we use interaction model specifications. When I use the interaction model specification then we can see that the stock market reacts less positively to dividend increase announcements and stock market reacts less negatively to dividend decrease announcements if they occur in January. On the other hand when I used linear binary model specification I haven't found any significantly different result about the stock market reaction to dividend increase (decrease) announcements on Mondays. Taken together, these results are consistent with the dividend-signalling theory and the calendar anomalies literature.

This work contributes to the literature in several ways. Firstly, no previous researchers have tried to answer the question of whether calendar or seasonal anomalies play any role in the reaction of the stock market to dividend announcements. Secondly, I employ one partially novel model specification based on chapter 6 (binary model). Thirdly, I employ a larger data set compared to similar studies in this area. Fourth, my findings provide an original contribution to the two strands of the literature on the dividend-signalling theory and calendar or seasonal effects.

The rest of the chapter is organized as follows. The next section discusses the calendar anomalies while section 3 presents the testable hypotheses and section 4 discusses methodology. Section 5 presents the data while section 6 reports the empirical results. Section 7 presents a robustness test. Section 8 presents the discussion and section 9 provides conclusions.

8.2. LITERATURE REVIEW

8.2.1. HALLOWEEN EFFECT

The Halloween effect was first documented by Bouman and Jacoben (2002), who found that the old market adage of "sell in May and go away but buy back on St Leger Day" was successful for 36 out of the 37 equity markets analyzed. Bouman and Jacoben (2002) examined different reasons to find an explanation for the anomaly, such as risk, cross correlation between markets, the January effects, data mining, shifts in interest rates, as well as shifts in trading volume and the existence of a seasonal factor in news provision. According to Bouman and Jacoben (2002) none of these seemed to provide an explanation.

Maberly and Pierce (2004) re-examined the Bouman and Jacoben (2002) Halloween effect for the US stock market for the period between April 1982 and April 2003, and they found that Bouman and Jacoben (2002) documentation of a significant Halloween effect for the US market appears to be driven by two outliers, one of the outliers is the "crash" in the world equity market in October 1987 and other one is the collapse of the Long-term Capital Management hedge fund in August 1998.

After adjusting the outliers Maberly and Pierce (2004) found that the Halloween effect disappeared in the US market. But Maberly and Pierce (2004) work was criticized by Witte (2010), who argued that, Maberly and Pierce (2004) identified the two outliers without formalizing criteria and dealt with them in an unsatisfactory way. Witte (2010) found that his robust regression analysis suggests that outliers do not drive the results of Bouman and Jacoben (2002).

Maberly and Pierce (2005) using Japanese data found that the Halloween effect is concentrated in the period prior to the introduction of Nikkei 225 index futures in September 1986. They also found that Halloween effect disappears in the Japanese markets after the internationalization in the mid-1980s. Ditchtl and Drobetz (2015) confirmed the existence of a Halloween anomaly in their regression analysis, when they use the maximum history of available index date, but when they account for the availability of adequate investment instruments and the publications date of the Bouman and Jacoben (2002) study, Ditchtl and Drobetz (2015) found that the Halloween effect became weaker and in some markets even disappeared.

Previous researchers haven't managed to reach any conclusion whether Halloween affect stock market returns or not. Previous studies show some mixed results. Some previous studies claim that Halloween has strong effect on stock market returns and on the other hand, few studies claim there are weaker or no Halloween effect on the stock market returns. Some previous studies claim after controlling the outliers there are no Halloween effect but another study claim there are still Halloween effect after controlling the outliers. So till now Halloween effect is a puzzle for the researchers.

8.2.2. TOM EFFECT

Previous studies have shown that returns are higher during the first few trading days of each month (sharma and Narayan, 2014). This type of behaviour is consistent with the TOM effect (see, for instance, Lakonishok and Smidt, 1988; McConnell and Xu, 2008; Holden et al, 2005). Ariel (1987) first found the TOM effect in the US stock market. Ariel (1987) used equally-weighted and value-weighted daily returns from the NYSE during the period 1963 to 1981, and he found that mean daily stock returns are positive at the beginning of the month and continuing through the first half of the month. But returns after this point are predominantly negative. Lakonishok and Smidt (1988) examined the DJIA from 1897 to 1986 and found that the rate of returns are higher in the last trading day of the month and first three trading days of the month. Later on McConnell and Xu (2008) extend Lakonishok and Smidt (1988) work using data from 1897 to 2005 and they also found TOM effect in 31 of the 35 countries they examined.

Recently Sharma and Narayan (2014) examine the TOM effect on 560 firms listed on the NYSE and they found evidence that the TOM affects returns and returns volatility of firms. They also found that the effects are different for different firms, firm size and sectors, suggesting that TOM has a heterogeneous effect on firm returns and firm return volatility. Dzhabarov and Ziemba (2010) examine TOM effect using daily returns for the Russell 2000 and S&P 500 futures market and through subperiod analysis find that the TOM effect still exists. Atanasova and Hudson (2010) also find evidence of the TOM effect on the stock market returns for the FT-30 using -1 and +3 days for the period July 1935 to March 2009. Liu (2013) found TOM effect in the broad US equity market from January 2001 to December 2011.

Previous researchers have found significant TOM effect on stock returns. Prior research shows that first few days of each month returns are higher compare to other days of the month. According to some researchers the length of TOM is 4-5 days and some others 20 days. Previous research also shows that TOM effect is different for different size and different sector firms.

8.2.3. JANUARY EFFECT

The presence of the January effects has been repeatedly debated in finance literature since Rozeff and Kinney (1976) first documented this. The January effects states that returns are higher in January than in other months of the year. According to Klock and Bacon (2014) investors obtain abnormally large returns on small cap stocks at the turn of the calendar year, in this process investors buy stock in a small or underperforming company at the end of the year and then sells the stock when the prices rises in January. Rozeff and Kinney (1976) use the NYSE for the period 1904 to 1974 and find that the average return for the month of January was 3.48% and 0.42% for the other months.

Kim (1983) uses the NYSE data starting from 1963 to 1979 and found that approximately 50% of the average size of the risk-premium of small firms relative to larger firms is due to January abnormal returns. He also uncovered that 50% of the January premium is due to abnormal returns during the first week of the year. Roll (1983) and Reinganum (1983) support Kim (1983) findings for the small firms, especially small firms with low share prices. On the other hand, according to Kohers and Kohli (1991) January effect is not related to the small firms. Lakonishok and Smidt (1988) find no evidence of January effect when they use the DJIA market data.

Some other studies also suggest that January effect is disappearing (Gu, 2003; He & He, 2011; Hensel & Ziemba, 2000). Kato and Schallheim (1985) use data from Tokyo Stock Exchange to examine excess return. They found excess returns in the Tokyo Stock Exchange and a strong relationship between return and size.

According to Easterday and Sen (2016) January effect is correlated with accounting earnings and expectations about future earnings. They extend the work of Henker and Debapriya (2012), who argue against "irrational noise trader" explanation of the January effect. Tax management is the most usual explanation for the January effect: investors usually take advantage of capital gain losses at year end for the tax purposes, which create temporary downward mispricing resulting larger January returns when prices rebound after turn of the year (Branch, 1977; Brown et al., 2010; Dalton, 1993; Phua et al., 2010; Sikes, 2014). Sun and Tong (2010) results suggest that in January volatility is not higher than other months of the year and the higher January returns reflect greater compensation for risk.

There are some mixed findings available in the literature about the January effect. Some researchers said there is still January effect in the market; on the other hand some other researchers argued that January effect is disappearing. There are some arguments in the previous studies about the relationship between small firms and January effect; couple of previous studies suggests that January effect is related to the small firms but one study provide evidence against this findings. Previous studies also claim that tax management is the most common explanation for the January effect.

8.2.4. MONDAY EFFECT

A number of studies documents that weekday returns vary with the day of the week (day-of-the-week-effect). One of the most pronounced day-of-the-week effects is the Monday effect. The Monday effect refers to the fact that asset returns are lower than usual on Mondays. First market practitioners and then academics documented a Monday effect. Maberly (1995) found that practitioners were familiar with Monday effect as early as 1920s, with the first documented findings by Kelly (1930) who showed that Monday is the worse day to buy stocks from a three-year statistical study. Negative Monday returns have been found to be robust over time and different markets (see Jaffe and Westerfield, 1985; Keim and Stambaugh, 1984). French (1980) found early evidence of unusual price patterns in the weekends in the US market during the 1950s and to 1970s. After him numerous studies confirmed the Monday effect using various time periods and different stock returns indexes.

Cross (1973) was the first academic who documented a Monday effect using S&P 500 data from 1953 to 1970. Over this period, the index advanced on 62% of the Fridays and the mean return was +0.12%, on the other hand the index advanced on just 39.5% of the Mondays and the mean return was -0.18%. Cross (1973) also documented that Monday returns were dependent on previous Friday returns. French (1980) documented day-of-the-week evidence in the US stock market, including negative and statistically significant Monday returns, when he used the S&P 500 from 1953 to 1977. Gibbons and Hess (1981) also found similar results when they used the S&P 500 and CRSP value and equally-weighted index from NYSE and AMEX securities from1962 to 1978. Lakonishok and Smidt (1988) found negative Monday returns for their entire sample period (1897-1986), and they also reported that all but two of their subsamples were statistically significant. Rogalski (1984) found that the average negative Monday return occurs during the nontrading period from Friday's close to Monday's open. Later Damodaran (1989) showed that firms usually report bad news on Fridays and this late announcement of bad news might cause the negative Monday returns.

A number of previous studies found that the Monday effect is diminished and in some cases even reversed over time. Connolly (1989) documented that Monday returns were statistically significant before 1974, but were not statistically significant after 1974, but they remained negative. These results were confirmed by Chang et al.(1993). On the other hand, Kamara (1997) documented that the Monday effect has diminished significantly after introduction of the S&P 500 futures contract in 1982. Wang et al. (1997) suggest that negative Monday returns occur during the last two weeks of the month and they also show that the mean returns of the first three weeks is not statistically different from zero. Bakar et al. (2014) documented that Monday effect disappears after controlling for investor mood when they used daily mood data from Facebook across 20 international markets. Brusa and Pu (2000) found that Monday returns for the large US stocks were positive and largest of any day of the week during 1990. Mehdian and Perry (2001) documented this 'reversal' in returns for large US stocks from November 1987 to August 1998, but they did find negative Monday returns for small stocks.

Previous studies claim that Monday returns are statistically different from zero. On the other hand, a few studies claim that the Monday effect has diminished, although they found negative returns. Some previous studies suggest that negative Monday returns happen because firms tend to report bad news on Fridays and that late bad news has effect on Monday returns. One study claims that the Monday effect occurs primarily in the last two weeks of the month and the first three weeks' Monday returns are not statistically different from zero. Another study suggests that the Monday effect disappears after controlling for investor mood.

8.3. TESTABLE HYPOTHESES

The hypotheses examined here are based on prior finance theories and literatures, especially dividend signaling theory and calendar anomalies. Previous research was mainly interested in the relationship between calendar anomalies and stock returns. In this thesis I extend previous literature by combining the calendar anomalies literature and the literature on the dividend-signalling hypothesis.

My research question here is whether calendar anomalies play any role in the reaction of the stock market to dividend announcements. Following the existing literature I use four of the most popular calendar anomalies, which are the Halloween effect, TOM effect, January effect and Monday effect.

According to prior research the Halloween effect has a strong influence on stock returns (Bouman and Jacoben, 2002; Witte, 2010). On the other hand some other studies suggest that the Halloween effect is disappearing (Maberly and Pierce, 2004 & 2005) or getting weaker (Ditchtl and Drobetz, 2015). Based on these insights, I hypothesize that the reaction of the stock market to dividend increase (decrease) announcements is different during the Halloween period (November-April) than during other periods of the year (May-October). On the basis of this, my null and alternative hypotheses are:

H_0: The Halloween effect does not affect the reaction of the stock market to dividend announcements.

H_{a1}: The reaction of the stock market to dividend increase (decrease) announcements is different during the Halloween period (November-April) than during the rest of the year (May-October).

Previous studies have shown that returns are higher during the first few trading days of each month and the last trading day of the month (sharma and Narayan, 2014; Lakonishok and Smidt, 1988; McConnell and Xu, 2008; Holden et al, 2005). Sharma and Narayan (2014) found that the TOM affects returns and returns volatility of firms. They also found that the effects are different for different firms, firm size and sectors. Atanasova and Hudson (2010) also find evidence of the TOM effect on the stock market returns for the FT-30 using -1 and +3 days for the period July 1935 to March 2009. Based on these insights, I hypothesize that the reaction of the stock market to dividend increase (decrease) announcements is different during the TOM period (-1,+3) than during other periods of the month. This leads to the following null and alternative hypotheses:

H_0: The TOM effect does not affect the reaction of the stock market to dividend announcements.

H_{a2}: The reaction of the stock market to dividend increase (decrease) announcements is different at the turn of the month (-1,+3) than during the rest of the month.

The January effect states that returns are higher in January than in other months of the year. Rozeff and Kinney (1976) found that the average return for the month of

January was 3.48% and 0.42% for the other months. According to Kohers and Kohli (1991) the January effect is not related to the small firms anomaly. Lakonishok and Smidt (1988) suggest that the January effect is disappearing. Some other studies also suggest that the January effect is disappearing (Gu, 2003; He & He, 2011; Hensel & Ziemba, 2000). Tax management is the most usual explanation for the January effect. Sun and Tong (2010) documented that in January volatility is not higher than other months of the year. Based on these insights, I hypothesize that the reaction of the stock market to dividend increase (decrease) announcements is different in January than on other months of the year. This leads to the following null and alternative hypotheses:

H_0: The January effect does not affect the reaction of the stock market to dividend announcements.

H_{a3}: The reaction of the stock market to dividend increase (decrease) announcements is different in January than in the other months of the year.

A number of previous studies document that weekday returns vary with the day of the week (day-of-the-week-effect). The Monday effect is one of the most pronounced day-of-the-week effects. The Monday effect refers to the fact that asset returns are lower than usual on Mondays. Some previous studies suggest that Mondays have statistically significant negative returns. On the other hand some other studies argue that the size of the Monday effect has been decreasing, although they found negative returns (see section 8.2.4). Based on these insights, I hypothesize that the reaction of the stock market to dividend increase (decrease) announcements is different on Monday than on other days of the week. On the basis of this, my null and alternative hypotheses are:

H_0: The Monday effect does not affect the reaction of the stock market to dividend announcements.

H_{a4}: The reaction of the stock market to dividend announcements is different on Mondays than during the rest of the week.

8.4. METHODOLOGY AND MODEL SPECIFICATIONS

To test the hypotheses discussed above I will use a standard event study methodology and regression analysis. According to the dividend-signalling theory dividend -increase (decrease) announcements have a positive (negative) effect on stock market returns. In this chapter I am extending the dividend-signalling theory and examining how calendar anomalies affect the relationship between dividend announcements and stock market returns. The event study methodology I use in this chapter is the same as in the previous chapters.

For my two event windows I have calculated two CAR's, which are (-1,+1) and (0,+1). To conduct the hypotheses tests I will use two different linear model specifications, both of which are based on chapter 6. My number one model specification is a linear interaction model and number two-model specification is a linear binary model. In my linear interaction model I have two explanatory variables and both of them represent interaction effects. My first explanatory variable in the linear interaction model is the percentage change in dividends ($R\Delta DIV$), which is interacted with a dividend increase dummy (DPI), and the second explanatory variable is the percentage change in dividends, which is interacted with a dividend decrease dummy (DPD). On the other hand in my linear binary model I will use only two dummy variables as my explanatory variables, which are DPI and DPD.

With regards to calendar effects I have chosen four of the most popular calendar anomalies, which are the Halloween effect, TOM effect, January effect and Monday effect, and for all four of these calendar anomalies I have created four different dummy variables. For Halloween I have followed Bouman and Jacoben (2002), where the Halloween dummy takes value 1 if *t* belongs to the period between November and April and 0 otherwise. For the TOM effect, the TOM variable takes value 1 from the last trading day of given month through the third trading day of the next month (-1 to +3) (Atanasova and Hudson, 2010) and 0 otherwise. For the January effect, the January dummy takes value 1 if t belongs to the month of January and 0 otherwise. Similarly, for the Monday effect the Monday dummy takes value 1 on Mondays and 0 otherwise. In both models I use four control variables in the empirical results section and robustness test, which are Size, Reversal, Momentum and Dividend Yield. CAR is my dependent variable. In both models I control for year fixed effects and either industry fixed effects or firm fixed effects. For the industry fixed effects I use Fama and French 17 industry classifications.

The two model specifications are given below with detailed explanations.

(a) Linear interaction model

(a)(i) Linear interaction model specifications for Halloween effect

$$\begin{aligned} CAR_{it} \; = \; & \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} \\ & * HALL_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * HALL_t + \lambda_5 \, SIZE_{it} \\ & + \lambda_6 \, REVERSAL_{it} + \lambda_7 \, MOMENTUM_{it} + \lambda_8 \, DIVIDEND_{YIELD_{it}} \\ & + \vartheta_1 DW \; Effect + \vartheta_2 YEAR \; DUMMIES + \vartheta_3 FIXED \; EFFECT \\ & + \mu_{it} \qquad (35) \end{aligned}$$

Where,

CAR_{it} = Cumulative abnormal returns.

$R\Delta DIV_{it}$ = Percentage change in dividend payment for firm *i*.

DPI_{it} = 1 if the dividend change is positive, and 0 otherwise.

DPD_{it} = 1 if the dividend change is negative, and 0 otherwise.

$HALL_t$ =1 if *t* belongs to the period between November and April, and 0 otherwise.

$SIZE_{it}$ = Firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement (in billions of British Pounds).

$REVERSAL_{it}$ = Reversal is measured using cumulative stock returns over previous month (in percentage).

$MOMENTUM_{it}$ = Momentum is the cumulative monthly stock returns from month t-12 to t-2.

$DIVIDEND_{YIELD_{it}}$ = Dividend Yield for firm i calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement.

DW = Day-of –the-week effect, where M_d, W_d , T_d *and* F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. Tuesday is the reference day.

μ_{it} = Error term.

$YEAR\ DUMMIES$ = Year fixed effect dummies beginning from 1990 to 2015, and the year 1990 is the reference year.

$FIXED\ EFFECTS$ = Either industry fixed effects dummies or firm fixed effects dummies. The industry fixed effect dummies are based on Fama and French's 17 industry classifications. My reference industry is industry number one, which is the food industry. As for the firm fixed effects, there are 231 firms in my data sample. Firm 888 is my reference firm.

(a)(ii) Linear interaction model specifications for TOM effect

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * TOM_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * TOM_{\ t} + \lambda_5\ SIZE_{it} + \lambda_6\ REVERSAL_{it} + \lambda_7\ MOMENTUM_{it} + \lambda_8\ DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECS + \mu_{it} \quad (36)$$

Where,

TOM_t = 1 if t belongs to the TOM interval, i.e. from the last trading day of a given month through the third trading day of the next month [-1,+3], and 0 otherwise.

(a)(iii) Linear interaction model specifications for January effect

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * Jan_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * Jan_t + \lambda_5\ SIZE_{it} + \lambda_6\ REVERSAL_{it} + \lambda_7\ MOMENTUM_{it} + \lambda_8\ DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMYIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it} \quad (37)$$

Where,

Jan_t = 1 If t belongs to the month of January, and 0 otherwise.

(a)(iv) Linear interaction model specifications for Monday effect

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * Mon_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * Mon + \lambda_5 \, SIZE_{it} + \lambda_6 \, REVERSAL_{it} + \lambda_7 \, MOMENTUM_{it} + \lambda_8 \, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW \, Effect + \vartheta_2 YEAR \, DUMMIES + \vartheta_3 FIXED \, EFFECTS + \mu_{it} \tag{38}$$

Where,

Mon_t = 1 on Mondays, and 0 otherwise.

(b) Linear binary model

(b)(i) Linear binary model specifications for Halloween effect

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * HALL_t + \lambda_4 DPD_{it} * HALL_{\ t} + \lambda_5 \, SIZE_{\ it} + \lambda_6 \, REVERSAL_{it} + \lambda_7 \, MOMENTUM_{it} + \lambda_8 \, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW \, Effect + \vartheta_2 YEAR \, DUMMIES + \vartheta_3 FIXED \, EFFECTS + \mu_{it} \tag{39}$$

(b)(ii) Linear binary model specifications for TOM effect

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * TOM_t + \lambda_4 DPD_{it} * TOM_{\ t} + \lambda_5 \, SIZE_{it} + \lambda_6 \, REVERSAL_{\ it} + \lambda_7 \, MOMENTUM_{it} + \lambda_8 \, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW \, Effect + \vartheta_2 YEAR \, DUMMIES + \vartheta_3 FIXED \, EFFECTS + \mu_{it} \tag{40}$$

(b)(iii) Linear Binary model specifications for January effect

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * Jan_t + \lambda_4 DPD_{it} * Jan_{\ t} + \lambda_5 \, SIZE_{it} + \lambda_6 \, REVERSAL_{\ it} + \lambda_7 \, MOMENTUM_{it} + \lambda_8 \, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW \, Effect + \vartheta_2 YEAR \, DUMMIES + \vartheta_3 FIXED \, EFFECTS + +\mu_{it} \tag{41}$$

(b)(iv) Linear Binary model specifications for Monday effect

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * Mon_t + \lambda_4 DPD_{it} * Mon_{\ t} + \lambda_5 \, SIZE_{it} + \lambda_6 \, REVERSAL_{\ it} + \lambda_7 \, MOMENTUM_{it} + \lambda_8 \, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW \, Effect + \vartheta_2 YEAR \, DUMMIES + \vartheta_3 FIXED \, EFFECTS + \mu_{it} \tag{42}$$

All the above models are estimated using pooled OLS regressions, as in Nissim and Ziv (2001). For statistical inference I will also show cluster-robust standard errors for both models, which generalize those proposed by White (1980) for independent heteroscedastic errors. I show clustered standard error to control for within-cluster error correlation, which can lead to misleadingly small standard errors, and consequently misleadingly narrow confidence intervals, large t-statistics and low p-values. Following Petersen's (2009) and Thompson's (2011) suggestions about estimating standard errors in finance panel data sets, I employ multi-way clustering: more specifically, standard errors are clustered by firm and date. I cluster the standard errors by firm because the error terms may be serially correlated, and I cluster the standard errors by date because the error terms may be correlated across firms at the same point in time.

8.5. DATA

This study is conducted using data on a sample of firms in the FTSE-350 index from 1990 to 2015. Selected firms are the current constituents of the FTSE-350 index (as of June 2016). I have collected all the data from Bloomberg from June 2016 to August 2016. To construct the sample of data I followed the same criteria as in the previous chapter. Descriptive statistics are given below.

8.5.1. DESCRIPTIVE STATISTICS

I will use one event window (-1,+1) to test all four hypotheses. The dividend announcement date is day 0, the day before the dividend announcement is day -1 and the day after the dividend announcement is day +1. The estimation window goes from t-200 to t-20, which means a total of 181 estimation days. I shall examine four calendar anomalies, which are the Halloween effect, TOM effect, January effect and Monday effect. Table 34 reports some descriptive statistics about the four calendar anomalies variables on dividend announcement days.

TABLE 35 DETAILS OF FIRM DIVIDEND CHANGES OBSERVATIONS BY CALENDAR ANOAMLIES

Variables	Number of Obs.	Dividend Increase	Dividend Decrease	Unchanged Dividend
Halloween	2,335	1,908	138	289
TOM	438	367	23	48
January	61	50	4	7
Monday	476	419	25	32

Note: This table showing the details of firms dividend changes event window by calendar anomalies variables.

From Table 34 we can see that Halloween has the highest number of observations (2,335) with 1,908 dividend increase observations, 138 dividend decrease observations and 289 unchanged dividends. And January has the lowest number of observations (61) with 50 dividend increase, 4 dividend decrease and 7 unchanged dividends.

TABLE 36 DESCRIPTIVE STATISTICS FOR DIVIDEND EVENT OBSERVATIONS

Variables	N	Mean	Std.Div.	Mini	Max	5%	25%	75%	95%	skewness	Kurtosis
RΔDIV (%)	3,621	9.787	13.101	-50.00	50.00	-2.522	4.098	15.347	31.034	-0.820	8.135
Size (£ billion	3,409	7.080	1.453	0.386	12.061	4.891	6.078	8.014	9.708	0.253	3.201
Reversal (%)	3,621	0.055	0.435	-4.039	7.490	-0.618	-0.157	0.281	0.693	0.869	29.924
Momentum (%)	3,618	0.303	1.503	-9.598	6.279	-2.354	-0.507	1.232	2.509	-0.631	5.282
Divi.Yield (%)	3,621	2.035	1.328	0.004	17.248	0.004	1.268	2.639	4.211	2.086	16.467
CAR (-1,+1) (%)	3,621	1.256	5.945	-40.881	51.255	-7.294	-1.732	4.224	10.469	-0.034	9.873
CAR(0,+1) (%)	3,621	1.083	5.689	-42.146	56.583	-7.044	-1.701	3.964	9.709	-0.081	11.542

Note: This table reports the firm's characteristic for the sample firms. $R\Delta DIV$ is the annual changes of the dividend payment in percentage terms. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2.

Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. And finally CAR is representing Cumulative Abnormal Return, estimated using the abnormal returns around the dividend announcement date.

From Table 35 we can see that size variable has 3,409 observations and dividend yield variable has 3,618 observations, while the number of observations concerning dividend changes, reversal, momentum and CAR is 3,621. All six variables show positive mean values. Percentage dividend changes, momentum and CAR show negative skewness values, but all six variables have a positive kurtosis.

TABLE 37 CORRELATION MATRIX FOR FOUR CALENDAR ANOMALIES

Panel-A: Halloween effect

Variables	*RΔDIV*	*Size*	*Reversal*	*Momentum*	*Divi. Yield*	*CAR*	*Halloween*
RΔDIV	1.0000						
Size	0.0483	1.0000					
Reversal	0.0286	0.0079	1.0000				
Momentum	0.2407	0.0684	-0.0402	1.0000			
Divi. Yield	-0.2221	-0.1686	-0.1379	-0.3569	1.0000		
CAR	0.0973	-0.1306	-0.0632	-0.0344	0.0642	1.0000	
Halloween effect	-0.0037	0.0005	0.0595	0.0053	-0.0759	0.0377	1.0000

Panel-B: TOM effect

Variables	*RΔDIV*	*Size*	*Reversal*	*Momentum*	*Divi. Yield*	*CAR*	*TOM*
RΔDIV	1.0000						
Size	0.0483	1.0000					
Reversal	0.0286	0.0079	1.0000				
Momentum	0.2407	0.0684	-0.0402	1.0000			
Divi. Yield	-0.2221	-0.1686	-0.1379	-0.3569	1.0000		
CAR	0.0973	-0.1306	-0.0632	-0.0344	0.0642	1.0000	
TOM effect	0.0023	0.0375	0.0154	0.0302	0.0260	0.0022	1.0000

Panel-C: January effect

Variables	*RΔDIV*	*Size*	*Reversal*	*Momentum*	*Divi. Yield*	*CAR*	*January*
RΔDIV	1.0000						
Size	0.0483	1.0000					

Reversal	0.0286	0.0079	1.0000				
Momentum	0.2407	0.0684	-0.0402	1.0000			
Divi. Yield	-0.2221	-0.1686	-0.1379	-0.3569	1.0000		
CAR	0.0973	-0.1306	-0.0632	-0.0344	0.0642	1.0000	
January effect	-0.0041	0.0499	0.0146	-0.0105	-0.0382	-0.0229	1.0000

Panel-D: Monday effect

Variables	***$R\Delta DIV$***	***Size***	***Reversal***	***Momentum***	***Divi. Yield***	***CAR***	***Monday***
$R\Delta DIV$	1.0000						
Size	0.0483	1.0000					
Reversal	0.0286	0.0079	1.0000				
Momentum	0.2407	0.0684	-0.0402	1.0000			
Divi. Yield	-0.2221	-0.1686	-0.1379	-0.3569	1.0000		
CAR	0.0973	-0.1306	-0.0632	-0.0344	0.0642	1.0000	
Monday effect	0.0406	-0.0932	0.0210	0.0397	-0.0894	-0.0216	1.0000

Note: This table reports the firm's characteristic for the sample firms. $R\Delta DIV$ is the annual changes of the dividend payment in percentage terms. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. And finally CAR is representing Cumulative Abnormal Return, estimated using the abnormal returns around the dividend announcement date.

Table 36 represents a pair wise correlation matrix for all explanatory variables and dependent variable. In all four panels in Table 36 only dividend yield has negative correlation with the dividend changes, size, reversal and momentum. TOM effect has positive correlation with all other variables. On the other hand, Halloween effect has negative correlation with the dividend changes and dividend yield and January effect has positive correlation with size and reversal. The Monday effect has negative correlation with size, dividend yield and CAR.

8.6. EMPIRICAL RESULTS

8.6.1. EXPECTED SIGNS

This section presents the expected signs of the explanatory variables included in my regression models.

TABLE 38 EXPECTED SIGNS

Variables	Coefficient	Expected sign	Comments
Constant	λ_0	+	According to Kalay and Loewenstein (1985) investor requires higher rates of returns to hold stocks around their dividend announcements as compensation for the increased risk per unit of time in this period. The explanation given by Cohen et al. (2007) about the abnormal returns is that - "it is compensation for risk incurred when investors are hold securities during a period when valuation relevant information is expected to be released. Suppose mean-variance pricing, investors require higher announcement returns when a newsworthy announcement is expected and the associated risk is non-diversifiable".
$R\Delta IVI * DPI$	λ_1 (Equation 35-38)	+	The greater the increase in dividend, the greater the increase in stock returns.
$R\Delta IVI * DPD$	λ_2 (Equation 35-38)	+	The greater the decrease in dividend, the greater the decrease in stock returns.
$R\Delta DIV_{it} * DPI_{it} * HELL_t$	λ_3(Equation 35)	+/-	Stock prices react either more or less positively to dividend increase announcements during Halloween period (November –April) than other period of the year (May-October). Ditchtl and Drobetz (2015) found the existence of a Halloween effect in their regression analysis when they use the maximum history of available index date, but when they account for the availability of adequate investment instruments and the publications date of the Bouman and Jacoben (2002) study, Ditchtl and Drobetz (2015) found that the Halloween effect became weaker and in some markets even disappeared.
$R\Delta DIV_{it} * DPD_{it} * HELL_t$	λ_4 (Equation 35)	+/-	Stock prices react either more or less negatively to dividend decrease announcements during Halloween period (November –April) than other period of the year (May-October). Ditchtl and Drobetz (2015) found the existence of a Halloween effect in their regression analysis when they use the maximum history of available index date, but when they account for the availability of adequate investment instruments and the publications date of the Bouman and Jacoben (2002) study, Ditchtl and Drobetz (2015) found that the Halloween effect became weaker and in some markets even disappeared.
$R\Delta DIV_{it} * DPI_{it} * TOM_t$	λ_3 (Equation 36)	+/ -	Stock prices react either more or less positively to dividend increase announcements during TOM period (-1,+3) than other period of the month. Sharma and Narayan (2014) found that the TOM affects returns and returns volatility of firms. They also found that the effects are different for different firms, firm size and sectors.
$R\Delta DIV_{it} * DPD_{it} * TOM_t$	λ_4 (Equation 36)	+/-	Stock prices react either more or less negatively to dividend decrease announcements during TOM period (-1,+3) than other period of the month. Sharma and Narayan (2014) found that the TOM affects returns and returns volatility of firms. They also found that the effects are different for different

			firms, firm size and sectors.
$R\Delta DIV_{it} * DPI_{it} * Jan_t$	λ_3 (Equation 37)	+/-	Stock prices react either more or less positively to dividend increase announcements during January than other month of the year. Because the January effects states that returns are higher in January than in other months of the year. According to Klock and Bacon (2014) investors obtain abnormally large returns on small cap stocks at the turn of the calendar year, in this process investors buy stock in a small or underperforming company at the end of the year and then sells the stock when the prices rises in January.
$R\Delta DIV_{it} * DPD_{it} * Jan_t$	λ_4(Equation 37)	+/-	Stock prices react either more or less negatively to dividend decrease announcements during January than other month of the year. Because the January effects states that returns are higher in January than in other months of the year. According to Klock and Bacon (2014) investors obtain abnormally large returns on small cap stocks at the turn of the calendar year, in this process investors buy stock in a small or underperforming company at the end of the year and then sells the stock when the prices rises in January.
$R\Delta DIV_{it} * DPI_{it} * Mon_t$	λ_3 (Equation 38)	+/-	Stock prices react either more or less positively to dividend increase announcements during Mondays than other days of the week. Monday effect is when market observes the asset returns are negative in the Mondays. Kelly (1930) shows that Monday return is the worse day to buy stocks from a three-year statistical study. So previous studies found Monday effect is diminishing.
$R\Delta DIV_{it} * DPD_{it} * Mon_t$	λ_4 (Equation 38)	+/-	Stock prices react either more or less negatively to dividend decrease announcements during Mondays than other days of the week. Monday effect is when market observes the asset returns are negative in the Mondays. Kelly (1930) shows that Monday return is the worse day to buy stocks from a three-year statistical study. So previous studies found Monday effect is diminishing.
DPI	λ_1 (Equation 39-42)	+	Positive dividend changes have a positive effect on stock returns.
DPD	λ_2(Equation 39-42)	-	Negative dividend changes have a negative effect on stock returns.
$DPI_{it} * HELL_t$	λ_3(Equation 39)	+/-	Reaction of the stock market is either more or less positive to dividend increase announcements during Halloween period (November –April) than other period of the year (May-October). Ditchtl and Drobetz (2015) found the existence of a Halloween effect in their regression analysis when they use the maximum history of available index date, but when they account for the availability of adequate investment instruments and the publications date of the Bouman and Jacoben (2002) study, Ditchtl and Drobetz (2015) found that the Halloween effect became weaker and in some markets even disappeared.
$DPD_{it} * HELL_t$	λ_4(Equation 39)	+/-	Reaction of the stock market is either more or less negative to dividend decrease announcements during Halloween period (November –April) than other period of the year (May-October). Ditchtl and Drobetz (2015) found the existence of a Halloween effect in their regression analysis when they use the maximum history of available index date, but when they account for the availability of adequate investment instruments and the publications date of the Bouman and Jacoben (2002) study, Ditchtl and Drobetz (2015) found that the Halloween effect became weaker and in some markets even disappeared.
$DPI_{it} * TOM_t$	λ_3 (Equation 40)	+/-	Reaction of the stock market is either more or less positive to dividend increase announcements during TOM period (-1,+3) than other period of the month. Sharma and Narayan (2014) found that the TOM affects returns and returns volatility of firms. They also found that the effects are different for different firms, firm size and sectors.
$DPD_{it} * TOM_t$	λ_4 (Equation	+/-	Reaction of the stock market is either more or less negative

	40)		to dividend decrease announcements during TOM period (-1,+3) than other period of the month. Sharma and Narayan (2014) found that the TOM affects returns and returns volatility of firms. They also found that the effects are different for different firms, firm size and sectors.
$DPI_{it} * Jan_t$	λ_3(Equation 41)	+/-	Reaction of the stock market is either more or less positive to dividend increase announcements during January than other months of the year. Because the January effects states that returns are higher in January than in other months of the year. According to Klock and Bacon (2014) investors obtain abnormally large returns on small cap stocks at the turn of the calendar year, in this process investors buy stock in a small or underperforming company at the end of the year and then sells the stock when the prices rises in January.
$DPD_{it} * Jan_t$	λ_4 (Equation 41)	+/-	Reaction of the stock market is either more or less negative to dividend decrease announcements during January than other months of the year. Because the January effects states that returns are higher in January than in other months of the year. According to Klock and Bacon (2014) investors obtain abnormally large returns on small cap stocks at the turn of the calendar year, in this process investors buy stock in a small or underperforming company at the end of the year and then sells the stock when the prices rises in January.
$DPI_{it} * Mon_t$	λ_3(Equation 42)	+/-	Reaction of the stock market is either more or less positive to dividend increase announcements during Mondays than other days of the Week. Monday effect is when market observes the asset returns are negative in the Mondays. Kelly (1930) shows that Monday return is the worse day to buy stocks from a three-year statistical study. So previous studies found Monday effect is diminishing.
$DPD_{it} * Mon_t$	λ_4(Equation 42)	+/-	Reaction of the stock market is either more or less negative to dividend decrease announcements during Mondays than other days of the Week. Monday effect is when market observes the asset returns are negative in the Mondays. Kelly (1930) shows that Monday return is the worse day to buy stocks from a three-year statistical study. So previous studies found Monday effect is diminishing.
SIZE	λ_5	-	"Small size effect" where small firms earn higher abnormal returns than large firm (Fuller, 2003 and Dasilas and Leventis, 2011).
REVERSAL	λ_6	+/-	De Bondt and Thaler (1985) argue that investors overreact to both positive and negative information, pushing the prices away from their fundamental values, and over the next two to three years, prices revert back to their fundamental values generating a reversal in stock returns. Based on that reversal could be positive or negative, empirical work based on CAR and reversal suggests that reversal is negative indicating less favorable reactions for firms with recent stock price increases (Autore and Jiang, 2017).
MOMENTUM	λ_7	+/-	Stocks with high (low) unconditional expected rates of return in adjacent time periods are expected to have high (low) realized rates of returns in both periods. Hence, momentum strategies will yield negative average returns even if the expected returns on stocks are in constant over time (Lo and MacKinlay, 1990 and Jegadeesh and Titman, 1999). Based on that reversal could be positive or negative, empirical work based on CAR and reversal suggests that reversal is negative indicating less favorable reactions for firms with recent stock price increases (Autore and Jiang, 2017).
$DIVIDEND_{YIELD}$	λ_8	+	Dividend yield is the main driver of abnormal returns on dividend announcement dates (Dasilas and Leventis, 2011).

Note: Expected signs for interaction and binary model specification variables.

8.6.2. POSITIVE INTERCEPT

If the market is efficient then security prices should reflect changes in dividends. The empirical evidence in this chapter indicates that the mean realized returns around the dividend announcements period are higher than 'normal' and statistically significant. The systematic risk during the event period is found to be larger than that estimated in the non-event period (Kalay and Loewenstein, 1985). My results show that standardized mean excess returns are significantly positive in the event period.

The timing of the next dividend announcement can be predicted by the market with certainty. As we know that dividend announcements are repetitive and generally made in the same calendar time. So, if the required rate of the returns around the dividend announcement is identical to that in any other random day, one should not be able to make excess returns by trading around these announcements. According to dividend signaling theory, dividend announcements convey positive (negative) new information. So it means if the market is efficient then the security prices should reflect these changes.

The unconditional expected rate of return during the event period should be higher than normal. A larger required rate of return during the event period is consistent with the theory that the relevant risk per unit of time during the event is higher (Kalay and Loewenstein, 1985). Therefore the reason for positive intercept in all of my model specifications is that investor requires higher rates of return to hold stocks around their dividend announcements as compensation for the increased risk per unit of time in this period. Some previous literature documents significant positive abnormal returns around predicted news announcements period (Penman, 1984; Chari et al. 1988; Ball and Kothari, 1991)[25]. The explanation given by Cohen et al. (2007) about the abnormal returns is that - "it is compensation for risk incurred when investors are to hold securities during a period when valuation relevant information is expected to be released. Suppose mean-variance pricing, investors require higher announcement returns when a newsworthy announcement is expected and the associated risk is non-diversifiable".

8.6.3. LINEAR INTERACTION MODEL

I have set up my models based on the calendar anomalies literature and the dividend-signalling theory. In this section I have augmented my empirical chapter 6's linear interaction model with calendar anomalies. In the linear interaction model my key explanatory variables are interacted with the dividend changes percentage.

Four of my hypotheses are based on calendar anomalies, which are the Halloween effect, TOM effect, January effect and Monday effect. To test all four hypotheses I calculate CAR using 3-days window, i.e. CAR (-1, +1). For four of my calendar anomalies I have created four different tables. Table 39 represents the Halloween effect, Table 40 represents the TOM effect, Table 41 represents the January effect and finally Table 42 represents the Monday effect. In each of these four tables I consider four different model variations. In Model 1 there are no day-of-the-week effects, year fixed effects, industry fixed effects, firm fixed effects and clustered standard errors; Model 2 contains year fixed effects, industry fixed effects and clustered standard errors but no day-of-the-week effects and firm fixed effects. Model

[25] A few empirical studies fail to show the evidence of announcement-day premium (Peterson, 1990; Brown and Kim, 1993). Whereas majority of the evidence supports the presence of higher returns on predictable disclosure events indicating that investors require an announcement-day premium.

3 contains day-of-the-week effects, year fixed effects, industry fixed effects and clustered standard errors but no firm fixed effects; model 4 contains day-of-the-week effects, year fixed effects, firm fixed effects and clustered standard errors but no industry fixed effects.

Table 38 examines the Halloween effect. The average stock return is 0.01619%. If we look at Table 38 then we can see that coefficient λ_1 and coefficient λ_2 both are economically significant and statistically significant at the 1% level in all four models, which is consistent with the dividend-signalling theory. On the other hand, coefficient λ_3 is economically significant and shows a positive sign in model 1, 2 and 3 but in model 4 coefficient λ_3 is economically insignificant and shows a negative sign, which may due to sampling variability. But coefficient λ_3 is statistically not different from zero in all four models. These results indicate that there is no evidence that the reaction of the stock market to dividend-increase announcements is different during the November-April period (Halloween effect) than during the May-October.

Table 38 shows that the point estimates of coefficient λ_4 are -17.103%, -17.257%, -17.361% and -17.603% in model 1, 2, 3 and 4 respectively (the standard errors are 0.03188, 0.06207, 0.06143 and 0.06249 in model 1, 2, 3 and 4 respectively). Coefficient λ_4 is statistically significant at the 1% level in all four models and shows a negative sign. At the same time coefficient λ_4 is economically highly significant as the point estimate is approximately 22 times higher than the average stock return; this may be due to the fact that only 60 dividend decrease announcements out of the 198 dividend decrease announcements in my sample fall in the November-April period. These results suggest that the stock market reacts less strongly (i.e. less negatively) to dividend-decrease announcements during the

November to April period than during the rest of the year. Below I have computed the partial effect of a dividend-decrease announcement, conditional on the fact that it happens in the November-April period.

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \lambda_2 DPD_{it} + \lambda_4 DPD_{it} * HALL_t \tag{43}$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * HALL$$

$$= \widehat{\lambda_2} + \widehat{\lambda_4} * 1 \text{ [if November to April =1]}$$

hence, for model 1

= 0.17767+ (-0.17103) *1

= 0.00664

for model 2

= 0.17812 + (-0.17257) *1

= 0.00555

for model 3,

= 0.17887 + (-0.17361) *1

= 0.00526

and, for model 4,

=0.18399 + (-0.17603) *1

=0.00796

Joint significant test results suggest that the firm fixed effects are significant in Table 38, which means my preferred model is model 4, even though I will consider my other three models as well. Now if we look at the values after combining coefficient λ_2 and coefficient λ_4 from Table 39 we can see that a 10% decrease in dividends decreases stock returns by 0.0796% (according to model 4) if it happens in the November-April period; on the other hand, a 10% decrease in dividends decreases stock returns by 1.8399% (model 4) if it happens in the May-October period. We can see similar results in the other models. These results indicate that the stock market reacts less negatively to dividend-decrease announcements during the November-April period than during other periods of the year. These results are consistent with the dividend-signalling theory and the Halloween effect literature. On the basis of these results I can reject the null hypothesis in favour of the alternative hypothesis. My findings suggest that the Halloween effect does not affect the reaction of stock returns to dividend increase announcements, but stock market seems to react less negatively to dividend-decrease announcements during the November-April period than during other periods of the year.

TABLE 39 REGRESSION ANALYSIS OF HALLOWEEN EFFECT AS CALENDAR ANOMALY ON DIVIDEND ANNOUNCEMENT DATES USING INTERACTION SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * HALL_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * HALL_t + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.04025[a]	0.03079[a]	0.03003[a]	0.05650[a]
	t-statistics	6.81	2.94	2.85	2.86
	Standard Error	0.00591	0.01047	0.01052	0.01974
$R\Delta DIV * DPI\ (\lambda_1)$	Point Estimate	0.04721[a]	0.05425[a]	0.05519[a]	0.07422[a]
	t-statistics	3.29	3.66	3.80	3.17
	Standard Error	0.01436	0.01483	0.01453	0.02343
$R\Delta DIV * DPD\ (\lambda_2)$	Point Estimate	0.17767[a]	0.17812[a]	0.17887[a]	0.18399[a]
	t-statistics	6.76	3.07	3.12	3.17
	Standard Error	0.02629	0.05794	0.05742	0.05799
$R\Delta DIV * DPI * HALL\ (\lambda_3)$	Point Estimate	0.01119	0.01174	0.01272	-0.00105
	t-statistics	0.79	0.81	0.88	-0.04
	Standard Error	0.01421	0.01456	0.01440	0.02733
$R\Delta DIV * DPD * HALL\ (\lambda_4)$	Point Estimate	-0.17103[a]	-0.17257[a]	-0.17361[a]	-0.17603[a]
	t-statistics	-5.36	-2.78	-2.83	-2.82
	Standard Error	0.03188	0.06207	0.06143	0.06249
$SIZE\ (\lambda_5)$	Point Estimate	-0.00517[a]	-0.00476[a]	-0.00504[a]	-0.01385[a]
	t-statistics	-7.37	-5.02	-5.32	-5.03
	Standard Error	0.00070	0.00095	0.00095	0.00275
$REVERSAL\ (\lambda_6)$	Point Estimate	-0.86096[a]	-0.99408[a]	0.98879[a]	-1.03281[a]
	t-statistics	-3.59	-2.72	-2.72	-2.70
	Standard Error	0.23981	0.36515	0.36355	0.38728
$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.15221[b]	-0.19526[c]	-0.19978[c]	-0.17529

	t-statistics	-2.08	-1.75	-1.79	-1.53
	Standard Error	0.07302	0.11143	0.11134	0.11462
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.23474[a]	0.19636[c]	0.17001	0.13278
	t-statistics	2.67	1.69	1.45	0.56
	Standard Error	0.08779	0.11634	0.11688	0.23775
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		4.53%	5.85%	6.13%	13.83%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (-1,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. *HALL* equal to 1 if *t* belongs to month November to April, and 0 otherwise. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of–the-week effect, where M_d, W_d , T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

Table 38 shows that λ_0 is economically significant in all four models and also statistically significant in all four models at the 1% level. Table 38 also shows that λ_0 is positive in all four models (see section 8.6.2). Control variables size and reversal are statistically significant in all four models, but the control variable momentum is statistically significant in the first three models and dividend yield is statistically significant at the 1% level in model 1, at 10% in model 2 and statistically not significant in model 3 and 4.

Table 39 examines the TOM effect. Table 39 shows that the coefficient λ_1 is economically significant (the average daily stock returns is 0.01619%) in all four models and statistically significant at the 1% level in all four models. Coefficient λ_2 is economically significant in all four models and statistically significant at 1% level in model 1 and at 5% level in the other models. These results are consistent with the dividend-signalling theory, which argues that dividend increase (decrease) announcements have a positive (negative) effect on stock returns. Coefficient λ_3 is economically significant in model 1, 2 and 4 but insignificant in model 3 and statistically not different from zero. Coefficient λ_3 shows a negative sign in all four models. This suggests there is no evidence that the reaction of the stock market to dividend-increase announcements during the TOM [-1,+3] period is different than during the rest of the month.

Coefficient λ_4 is statistically significant at 5% level in all four models and shows a negative sign. Coefficient λ_4 is economically significant as well. The reason behind this economically significant results may be because only 23 dividend decrease announcements out of the 198 dividend decrease announcements in my sample occur during the TOM period [-1,+3]. Computing the partial effect of a dividend decrease on CAR, all else constant:

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}\middle|DPD_{it}=1\right) = \lambda_2 DPD_{it} + \lambda_4 DPD_{it} * TOM_t \tag{44}$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}\middle|DPD_{it}=1\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * TOM_t$$

$$= \widehat{\lambda_2} + \widehat{\lambda_4} * 1 \text{ [if TOM=1]}$$

hence, for model 1

= 0.07754 + (-0.10479) * 1

= - 0.02725

for model 2

= 0.07624 + (-0.09843) * 1

= - 0.02219

for model 3

= 0.07626 + (-0.09831) * 1

= -0.02205

and, for model 4

=0.08014 + (-0.09994) * 1

=-0.01980

TABLE 40 REGRESSION ANALYSIS OF TOM EFFECT AS CALENDAR ANOMALY ON DIVIDEND ANNOUNCEMENT DATES USING INTERACTION SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * TOM_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * TOM_t + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ Effects + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.04139[a]	0.03869[b]	0.03654[b]	0.06697[a]
	t-statistics	6.97	2.16	2.04	3.29
	Standard Error	0.00594	0.01793	0.01795	0.02038
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.05542[a]	0.06243[a]	0.06380[a]	0.07583[a]
	t-statistics	4.92	5.08	5.21	5.18
	Standard Error	0.01127	0.01229	0.01225	0.01463
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.07754[a]	0.07624[b]	0.07626[b]	0.08014[b]
	t-statistics	4.61	2.54	2.56	2.56
	Standard Error	0.01681	0.03004	0.02983	0.03129
$R\Delta DIV * DPI * TOM$ (λ_3)	Point Estimate	-0.01034	-0.00926	-0.00713	-0.02038
	t-statistics	-0.50	-0.48	-0.37	-0.97
	Standard Error	0.02051	0.01934	0.01924	0.02099
$R\Delta DIV * DPD * TOM$ (λ_4)	Point Estimate	-0.10479[b]	-0.09843[b]	-0.09831[b]	-0.09994[b]
	t-statistics	-2.25	-2.31	-2.33	-2.38
	Standard Error	0.04663	0.04260	0.04214	0.04195
$SIZE$ (λ_5)	Point Estimate	-0.00524[a]	-0.00479[a]	-0.00505[a]	-0.01345[a]
	t-statistics	-7.43	-5.05	-5.33	-4.93
	Standard Error	0.00071	0.00095	0.00095	0.00273
$REVERSAL$ (λ_6)	Point Estimate	-0.85323[a]	-0.98655[a]	-0.98109[a]	-1.05006[a]
	t-statistics	-3.55	-2.70	-2.70	-2.76
	Standard Error	0.24045	0.36541	0.36391	0.38107
$MOMENTUM$ (λ_7)	Point Estimate	-0.17005[b]	-0.20931[c]	-0.21476[c]	-0.19160[c]
	t-statistics	-2.32	-1.87	-1.91	-1.67
	Standard Error	0.07332	0.11219	0.11215	0.11497
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.20792[b]	0.17	0.14333	0.12204
	t-statistics	2.36	1.47	1.24	0.52
	Standard Error	0.08807	0.11528	0.11591	0.23490
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.85%	5.16%	5.42%	13.21%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (-1,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. 1 if t belongs to the TOM interval of [-1,+3], and 0 otherwise. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of–the-week effect, where M_d, W_d, T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

Joint significant test results suggest that the firm fixed effects are significant in Table 39, which means my preferred model is model 4, even though I will consider my other three models as well. After combining coefficient λ_2 and coefficient λ_4 Table 39 shows that a 10% dividend decrease actually increases stock returns by 0.1980% in model 4 if it occurs at the turn of the month, whereas it decreases stock returns by 0.8014% (model 4) if it occurs during the rest of the month. Other models show similar results. This means that the stock market reacts less negatively (actually positively) to dividend-decrease announcements if they occur at the turn of the month than if they occur during the rest of the month. On the basis of these results I can reject the null hypothesis in favour of the alternative hypothesis, which means the TOM effect does not affect the reaction of stock returns to dividend increase announcements but there is evidence that the stock market reacts less negatively (actually positively) to dividend-decrease announcements if they occur at the turn of the month than if they occur during the rest of the month.

Table 39 shows that λ_0 is economically significant in all four models and also statistically significant at 1% level in model 1 and 4, and at 5% level in model 2 and 3. Table 40 also shows that λ_0 is positive in all four models (see section 8.6.2). Control variables size and reversal are statistically significant at 1% in all three models. Momentum is statistically significant at 5% in model 1 and at 10% in model

2, 3 and 4. On other hand the dividend yield is statistically significant at 5% level in model 1only.

Table 40 refers to the January effect. The results for coefficient λ_1 and coefficient λ_2 are consistent with the dividend-signalling theory. Coefficient λ_3 is economically significant at all four models (the point estimates are -7.718%, -6.203%, -6.387% and -7.138% in model 1, 2, 3 and 4 respectively). Coefficient λ_3 is statistically not significant in model 1 but statistically significant at 5% level in model 2 and 3, and at 10% level in model 4. These coefficients indicate that the January effect has a significant influence on the relationship between dividend-increase announcements and stock returns. Below I am computing the partial effect of a dividend -increase announcement occurring in January.

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}\middle| DPI_{it} = 1\right) = \lambda_1 DPI_{it} + \lambda_3 DPI_{it} * Jan_t \quad (45)$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}\middle| DPI_{it} = 1\right) = \widehat{\lambda_1} + \widehat{\lambda_3} * Jan_t$$

$$= \widehat{\lambda_1} + \widehat{\lambda_3} * 1 \text{ [If January=1]}$$

hence, for model 1

=0.05511 + (-0.07718) * 1

= -0.02207

for mode 2

=0.06249 + (-0.06203) * 1

=0.00046

for model 3

= 0.06410 + (-0.06387) * 1

= 0.00023

and, for model 4

=0.07372 + (-0.07138) * 1

=0.00234

Joint significant test results suggest that the firm fixed effects are significant in Table 39, which means my preferred model is model 4, even though I will consider my other three models as well. Equation 45 indicates that a 10% dividend increase increases stock returns by 0.7372% in model 4 if it occurs in the February-December period, whereas it increases stock returns by only 0.0234% if it occurs in January. In summary, these results indicate that the stock market reacts less strongly (i.e. less positively) to dividend-increase announcements if they occur in January than if they occur during the rest of the year.

Table 40 shows that coefficient λ_4 is statistically significant at 1% in model 1 and 4 and at 5% in model 2 and 3. Coefficient λ_4 is economically highly significant (the average stock return is 0.01619%), however in my sample I have only 4 dividend decrease announcements occurring in January. Below I compute the partial effect of a dividend-decrease announcement occurring in January.

TABLE 41 REGRESSION ANALYSIS OF JANUARY EFFECT AS CALENDAR ANOMALY ON DIVIDEND ANNOUNCEMENT DATES USING INTERACTION SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * Jan_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * Jan_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ Effects + \mu_{it}$$

Variables		Model-1	Model-2	Model-3	Model-4
Constant (λ_0)	Point Estimate	0.04074[a]	0.03029[a]	0.02926[a]	0.06559[a]
	t-statistics	6.87	2.87	2.75	3.30
	Standard Error	0.00593	0.01056	0.01063	0.01987
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.05511[a]	0.06249[a]	0.06410[a]	0.07372[a]
	t-statistics	5.01	5.25	5.40	5.19
	Standard Error	0.01101	0.01190	0.01187	0.01422
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.05605[a]	0.05559[a]	0.05564[b]	0.05842[b]
	t-statistics	3.50	2.10	2.12	2.08
	Standard Error	0.01600	0.02644	0.02627	0.02814
$R\Delta DIV * DPI * Jan$ (λ_3)	Point Estimate	-0.07718	-0.06203[b]	-0.06387[b]	-0.07138[c]
	t-statistics	-1.45	-2.30	-2.16	-1.67
	Standard Error	0.05323	0.02691	0.02954	0.04277
$R\Delta DIV * DPD * Jan$ (λ_4)	Point Estimate	0.32329[a]	0.32183[b]	0.32007[b]	0.34234[a]
	t-statistics	3.47	2.38	2.49	2.65

	Standard Error	0.09304	0.13504	0.12875	0.12906
$SIZE\ (\lambda_5)$	Point Estimate	-0.00512[a]	-0.00469[a]	-0.00496[a]	-0.01327[a]
	t-statistics	-7.27	-4.95	-5.24	-4.90
	Standard Error	0.00070	0.00095	0.00095	0.00271
$REVERSAL\ (\lambda_6)$	Point Estimate	-0.89443[a]	-1.02699[a]	-1.01949[a]	-1.10494[a]
	t-statistics	-3.72	-2.88	-2.86	-2.96
	Standard Error	0.24037	0.35704	0.35585	0.37282
$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.16842[b]	-0.20668[c]	-0.21142[c]	-0.18945[c]
	t-statistics	-2.30	-1.84	-1.89	-1.65
	Standard Error	0.07315	0.11208	0.11197	0.11466
$DIVIDEND_{YIELD}\ (\lambda_8)$	Point Estimate	0.19991[b]	0.17300	0.14595	0.12299
	t-statistics	2.27	1.51	1.26	0.52
	Standard Error	0.08798	0.11478	0.11538	0.23522
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		4.10%	5.38%	5.64%	13.43%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (-1,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. *Jan* takes value 1 if t belongs to month of January, and 0 otherwise. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of–the-week effect, where $M_d, W_d, T_d\ and\ F_d$ are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \lambda_2 DPD_{it} + \lambda_4 DPD_{it} * Jan_t \quad (46)$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * Jan_t$$

$$= \widehat{\lambda_2} + \widehat{\lambda_4} * 1 \text{ [if January=1]}$$

hence, for model 1

=0.05605 + 0.32329 * 1

=0.37934

for model 2

=0.05559 + 0.32183 * 1

= 0.37742

for model 3

= 0.05564 + 0.32007 * 1

=0.37571

and, for model 4

= 0.05842 + 0.34234 * 1

=0.40076

Joint significant test results suggest that the firm fixed effects are statistically significant in Table 40, which means my preferred model is model 4, even though I will consider my other three models as well. Equation 46 indicates that a 10% dividend decrease reduce stock returns by 4.0076% in model 4 if it happens in January, whereas a 10% dividend decrease reduces stock returns by only 0.5842% if it happens in other months of the year. The other three models also show similar results. These results indicate that the stock market reacts more strongly (i.e. more negatively) to dividend-decrease announcements if they occur in January than if they occur during the rest of the year. However, my sample contains only 4 dividend decrease announcements occurring in January; for this reason, this result is very weak.

On the basis of the results from equations 45 and 46 I reject the null hypothesis in favour of alternative hypothesis that the stock market reacts less positively to dividend-increase announcements if it occurs in January than if it occurs during the rest of the year and the stock market reacts more negatively to dividend-decrease announcements if it occurs in January than if it occurs during the rest of the year.

Table 40 shows that λ_0 is economically and statistically significant at 1% level in all four models. Table 41 also shows that λ_0 is positive in all three models (see section 8.6.2). In Table 41 control variables size and reversal are statistically significant at 1% level in all four models. Momentum is statistically significant at 5%

level in model 1 and at 10% level in model 2, 3 and 4. On the other hand the dividend yield is statistically significant at 10% level only in model 1.

Table 41 concerns the Monday effect. Coefficient λ_1 is economically significant and statistically significant at 1% level in all four models. Coefficient λ_2 is economically significant in all three models and statistically significant at 1% level in model 1 and at 5% level in the rest of the models. This result is consistent with the dividend-signalling hypothesis. On the other hand coefficient λ_3 is statistically significant at 10% level in model 1 and 2, but in model 3 and 4 it is insignificant. Coefficient λ_3 is economically significant in all four models. These results suggest that there is only weak evidence that the reaction of the stock market to dividend-increase announcements is different on Mondays than on other days of the week. Below I compute the partial effect of a dividend-increase announcement occurring on Monday.

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}\middle| DPI_{it} = 1\right) = \lambda_1 DPI_{it} + \lambda_3 DPI_{it} * Mon_t \tag{47}$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}\middle| DPI_{it} = 1\right) = \widehat{\lambda_1} + \widehat{\lambda_3} * Mon_t$$

$$= \widehat{\lambda_1} + \widehat{\lambda_3} * 1 \text{ [If Monday=1]}$$

hence, for model 1

= 0.05795 + (-0.03251) * 1

= 0.02544

for model 2

= 0.06419 + (-0.02665) * 1

= 0.03754

From equation 47 we can see that on Mondays a 10% dividend-increase announcement increases stock returns by only 0.3754% (model 2), whereas it increases stock returns by 0.6419% if it occurs on other days of the week. Similar results apply to model 1, but in model 3 and 4 the coefficient λ_3 is not different from zero. After analyzing these results we can say that there is only weak evidence that the stock market reacts less strongly (i.e. less positively) to dividend-increase announcements if they occur on Mondays than on other days of the week.

Table 41 shows that coefficient λ_4 is economically significant in all three models (the point estimates are 8.668% in model 1, 8.912% in model 2, 8.447% in model 3 and 5.954% in model 4). In my data sample, only 25 dividends decrease announcements out of 198 dividends decrease announcements occur on Mondays. Coefficient λ_4 is statistically significant only in model 1. These results suggest that there is only weak evidence that the reaction of the stock market to dividend-decrease announcements is different on Mondays than on other days of the week. Below I compute the partial effect of a dividend-decrease announcement, conditional on the fact that it happens on Monday.

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \lambda_2 DPD_{it} + \lambda_4 DPD_{it} * Mon_t \qquad (48)$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * Mon_t$$

$$= \widehat{\lambda_2} + \widehat{\lambda_4} * 1 \text{ [If Monday =1]}$$

hence, for model 1

= 0.05570 + 0.08668 * 1

=0.14238

Equation 48 shows that on Mondays a 10% dividend-decrease announcement decreases stock returns by 1.4238% (model 1), whereas it decreases stock returns by 0.5570% if it occurs on other days of the week. This means there is at least some evidence that the stock market reacts more strongly (i.e. more negatively) to dividend-decrease announcements on Mondays than on the other days of the week.

On the basis of these results I can only marginally reject the null hypothesis in favour of alternative hypothesis that the stock market reacts less positively to dividend-increase announcements if they occur on Mondays than on other days of the week and the stock market reacts more negatively to dividend-decrease announcements on Mondays than on the other days of the week.

Table 41 shows that λ_0 is economically significant in all four models and statistically significant at 1% level in model 1 and 4, and at 5% level in model 2 and 3. Table 42 also shows that λ_0 is positive in all three models (see section 8.6.2). In Table 42 control variables size and reversal are statistically significant at 1% in all four models. Momentum is statistically significant at 5% level in model 1 and at 10% in model 2 and 3. The control variable dividend yield is only statistically significant in model 1 at 5% level.

TABLE 42 REGRESSION ANALYSIS OF MONDAY EFFECT AS CALENDAR ANOMALY ON DIVIDEND ANNOUNCEMENT DATES USING INTERACTION SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * Mon_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * Mon_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ Effects + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.04253[a]	0.03896[b]	0.03622[b]	0.06733[a]
	t-statistics	7.11	2.16	2.01	3.11
	Standard Error	0.00598	0.01801	0.01803	0.02164
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.05795[a]	0.06419[a]	0.06489[a]	0.07455[a]
	t-statistics	5.15	5.31	5.24	5.03
	Standard Error	0.01125	0.01209	0.01237	0.01482
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.05570[a]	0.05498[b]	0.05537[b]	0.06175[b]
	t-statistics	3.34	2.15	2.17	2.34
	Standard Error	0.01667	0.02563	0.02550	0.02643
$R\Delta DIV * DPI * Mon$ (λ_3)	Point Estimate	-0.03251[c]	-0.02665[c]	-0.02099	-0.01576
	t-statistics	-1.68	-1.65	-0.77	-0.51
	Standard Error	0.01936	0.01612	0.02719	0.03109
$R\Delta DIV * DPD * Mon$ (λ_4)	Point Estimate	0.08668[c]	0.08912	0.08447	0.05954
	t-statistics	1.80	0.75	0.68	0.45
	Standard Error	0.04822	0.11926	0.12339	0.13238
$SIZE$ (λ_5)	Point Estimate	-0.00536[a]	-0.00489[a]	-0.00505[a]	-0.01337[a]
	t-statistics	-7.56	-5.13	-5.32	-4.90
	Standard Error	0.00071	0.00095	0.00095	0.00273
$REVERSAL$ (λ_6)	Point Estimate	-0.85904[a]	-0.98829[a]	-0.98558[a]	-1.05651[a]
	t-statistics	-3.58	-2.71	-2.72	-2.76
	Standard Error	0.24023	0.36458	0.36252	0.38273

$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.16482[b]	-0.20383[c]	-0.20926[c]	-0.18754
	t-statistics	-2.25	-1.80	-1.85	-1.62
	Standard Error	0.07324	0.11299	0.11290	0.11594
$DIVIDEND_{YIELD}\ (\lambda_8)$	Point Estimate	0.19939[b]	0.16405	0.14709	0.12648
	t-statistics	2.26	1.42	1.27	0.54
	Standard Error	0.08823	0.11539	0.11565	0.23510
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.87%	5.17%	5.37%	13.11%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (-1,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. *Mon* takes value 1 if t belongs Monday, and 0 otherwise. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of–the-week effect, where M_d, W_d, T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

8.6.4. LINEAR BINARY MODEL

In this section I will use the linear binary model, which is based on my empirical chapter 6's linear binary model. This model is based on the dividend-signalling theory and calendar anomaly literature. This linear binary model only concentrates on direction of the dividend changes and ignores the size of the dividend changes to find out whether the direction of a dividend change has any effect on stock returns.

Table 42 concerns the Halloween effect. The point estimates of coefficient λ_1 are 0.973%, 0.947%, 0.989% and 0.965% in model 1, model 2, model 3 and model 4 respectively. Coefficient λ_1 is economically significant in all four models as the mean daily stock return is 0.01619% and statistically significant at 1% in model 1 and 3 and at 5% in model 2, but in model 4 it is statistically insignificant. Coefficient λ_2 is economically significant and statistically significant at 1% in all four models. These results support the dividend-signalling theory.

Coefficient λ_3 is economically significant in all four models. Coefficient λ_3 is statistically significant at 10% level in model 1 and at 5% level in model 2 and 3, but statistically insignificant in model 4. After running a joint significant test of coefficient λ_1 and coefficient λ_3 in model 4 my results shows that they are jointly statistically significant at the 5% level. The variables DPI and DPI*HALL are highly correlated, and that is why they turn out to be individually statistically insignificant but jointly statistically significant. These results suggest that there is at least marginal evidence that dividend-increase announcements cause a larger increase in stock returns when they occur in the November-April period than during the rest of the year. Below I compute the partial effect of a dividend-increase announcement, conditional on the fact that it happens in the November-April period.

$$\left(\frac{\partial CAR_{it}}{\partial DPI_{it}}\middle| DPI_{it} = 1\right) = \lambda_1 + \lambda_3 * HALL_t \tag{49}$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta DPI_{it}}\middle| DPI_{it} = 1\right) = \widehat{\lambda_1} + \widehat{\lambda_3} * HALL_t$$

$$= \widehat{\lambda_1} + \widehat{\lambda_3} * 1 \text{ [if month November to April = 1]}$$

hence, for model 1,

=0.00973 + 0.00385 * 1

= 0.01358

for model 2,

= 0.00947 + 0.00438 * 1

= 0.01385

for model 3,

= 0.00989 + 0.00492 * 1

= 0.01481

and, for model 4,

= 0.00965 + 0.00564 * 1

= 0.01529

Joint significant test results suggest that the firm fixed effects are significant in Table 42, which means my preferred model is model 4, even though I will consider my other three models as well. Equation 49 indicates that during the months of November to April, across firms increasing dividends, stock market returns are 1.529% higher (model 4), whereas, during the months of May to October, on average, across firms increasing dividends stock market returns are only 0.529% higher than for firms leaving dividends unchanged. Similar results apply to model 1 and 2, and in model 3. These results provide marginal evidence that dividend-increase announcements cause a larger increase in stock returns when they occur in the November-April period than during the rest of the year.

From Table 42 we can also see that Coefficient λ_4 is economically significant and statistically significant at 1% level in all four models. These results indicate that dividend-decrease announcements cause a smaller decrease (actually an increase) in stock returns when they occur in the November-April period than during the rest of the year. Below I compute the partial effect of a dividend-increase announcement, conditional on the fact that it happens in the November-April period.

$$\left(\frac{\partial CAR_{it}}{\partial DPD_{it}}\middle| DPD_{it} = 1\right) = \lambda_2 + \lambda_4 * HALL_t \quad (50)$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta DPD_{it}}\middle| DPD_{it} = 1\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * HALL_t$$

$$= \widehat{\lambda_2} + \widehat{\lambda_4} * 1 \text{ [if November to April =1]}$$

hence, for model 1,

= (-0.04632) + 0.04858 * 1

=0.00226

for model 2,

= (-0.04710) + 0.04917 * 1

= 0.00207

for model 3,

= (-0.04689) + 0.04967 * 1

= 0.00278

TABLE 43 REGRESSION ANALYSIS OF HALLOWEEN EFFECT AS CALENDAR ANOMALY ON DIVIDEND ANNOUNCEMENT DATES USING BINARY SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * HALL_t + \lambda_4 DPD_{it} * HALL_t + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\, Effect + \vartheta_2 YEAR\, DUMMIES + \vartheta_3 FIXED\, Effects + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03845[a]	0.03137[a]	0.03117[a]	0.05949[a]
	t-statistics	6.14	2.97	2.94	3.03
	Standard Error	0.00626	0.01056	0.01059	0.01961
DPI (λ_1)	Point Estimate	0.00973[a]	0.00947[b]	0.00989[a]	0.00965
	t-statistics	2.74	2.52	2.63	1.59
	Standard Error	0.00355	0.00376	0.00376	0.00608
DPD (λ_2)	Point Estimate	-0.04632[a]	-0.04710[a]	-0.04689[a]	-0.05365[a]
	t-statistics	-5.44	-3.36	-3.38	-3.64
	Standard Error	0.00851	0.01403	0.01389	0.01473
$DPI * HALL$ (λ_3)	Point Estimate	0.00385[c]	0.00438[b]	0.00492[b]	0.00564
	t-statistics	1.66	1.96	2.16	0.88
	Standard Error	0.00232	0.00223	0.00228	0.00644
$DPD * HALL$ (λ_4)	Point Estimate	0.04858[a]	0.04917[a]	0.04967[a]	0.05661[a]
	t-statistics	5.10	3.24	3.30	3.44
	Standard Error	0.00953	0.01517	0.01505	0.01648
$SIZE$ (λ_5)	Point Estimate	-0.00545[a]	-0.00517[a]	-0.00550[a]	-0.01366[a]
	t-statistics	-7.71	-5.33	-5.69	-4.97
	Standard Error	0.00071	0.00097	0.00097	0.00275
$REVERSAL$ (λ_6)	Point Estimate	-0.85324[a]	-0.97094[a]	-0.96735[a]	-1.00273[a]
	t-statistics	-3.55	-2.71	-2.72	-2.64
	Standard Error	0.24039	0.35805	0.35628	0.38026
$MOMENTUM$ (λ_7)	Point Estimate	-0.12310[c]	-0.15066	-0.15429	-0.11778
	t-statistics	-1.69	-1.36	-1.40	-1.01
	Standard Error	0.07275	0.11077	0.11032	0.11626
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.20959[b]	0.16218	0.13806	0.10166
	t-statistics	2.39	1.38	1.17	0.44

	Standard Error	0.08771	0.11732	0.11756	0.23107
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		4.15%	5.31%	5.61%	13.17%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (-1,+1). The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. $HALL$ equal to 1 if t belongs to month November to April, and 0 otherwise Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of–the-week effect, where M_d, W_d , T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

and, for model 4,

$$=(-0.05365) + 0.05661 * 1$$

$$=0.00296$$

From equation 50 we can see that during the months of November to April, on average, across firms reducing dividends stock market returns actually increase by 0.296% (model 4), whereas during the other months of the year stock returns decrease by 5.365% in model 4. The other three models also show similar results. These results indicate that dividend-decrease announcements cause a smaller decrease (actually, an increase) in stock returns when they occur in the November-April period than during the rest of the year.

On the basis of these results I can reject the null hypothesis in favour of the alternative hypothesis that the stock market reacts more positively to dividend-increase announcements during the November-April period than during the rest of the year, and the stock market reacts less negatively to dividend-decrease announcements during the November-April period than during the rest of the year.

Table 42 shows that λ_0 is economically significant and statistically significant at 1% level in all four models (see section 8.6.2). Table 43 also shows that λ_0 is positive in all four models. Table 43 also shows that control variables size and reversal are statistically significant at 1% level in all four models. On the other hand, the control variable momentum is only statistically significant in model 1 at 10% level and dividend yield is also statistically significant in model 1 only at 5% level.

Table 43 concerns the TOM effect. Coefficient λ_1 and coefficient λ_2 are consistent with the TOM effect results in the linear interaction model. On the other hand coefficient λ_3 and coefficient λ_4 are neither economically nor statistically significant. These results indicate that there is no evidence that the stock market reacts differently to dividend announcements during the TOM [-1,+3] period than during the rest of the month.

TABLE 44 REGRESSION ANALYSIS OF TOM EFFECT AS CALENDAR ANOMALY ON DIVIDEND ANNOUNCEMENT DATES USING BINARY SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * TOM_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * TOM_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FIXED\ Effects + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03959[a]	0.04023[b]	0.03859[b]	0.06787[a]
	t-statistics	6.29	2.22	2.12	3.47
	Standard Error	0.00629	0.01809	0.01818	0.01957
$DPI\ (\lambda_1)$	Point Estimate	0.01185[a]	0.01193[a]	0.01258[a]	0.01298[a]
	t-statistics	3.62	3.44	3.63	3.04
	Standard Error	0.00328	0.00347	0.00347	0.00427
$DPD\ (\lambda_2)$	Point Estimate	-0.01329[b]	-0.01345[b]	-0.01285[c]	-0.01497[c]
	t-statistics	-2.40	-2.02	-1.95	-1.89
	Standard Error	0.00553	0.00664	0.00659	0.00792
$DPI * TOM\ (\lambda_3)$	Point Estimate	0.00078	0.00087	0.00144	0.00028
	t-statistics	0.23	0.30	0.48	0.07
	Standard Error	0.00338	0.00293	0.00301	0.00374
$DPD * TOM\ (\lambda_4)$	Point Estimate	0.00802	0.00697	0.00643	0.00574
	t-statistics	0.60	0.41	0.38	0.30
	Standard Error	0.01343	0.01688	0.01687	0.01901
$SIZE\ (\lambda_5)$	Point Estimate	-0.00545[a]	-0.00512[a]	-0.00543[a]	-0.01309[a]

	t-statistics	-7.68	-5.29	-5.63	-4.84
	Standard Error	0.00071	0.00097	0.00096	0.00270
$REVERSAL\ (\lambda_6)$	Point Estimate	-0.86347[a]	-0.97499[a]	-0.96869[a]	-1.03909[a]
	t-statistics	-3.58	-2.70	-2.70	-2.72
	Standard Error	0.24091	0.36066	0.35903	0.38203
$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.13931[c]	-0.16041	-0.16482	-0.12869
	t-statistics	-1.91	-1.44	-1.48	-1.11
	Standard Error	0.07309	0.11141	0.11100	0.11616
$DIVIDEND_{YIELD}\ (\lambda_8)$	Point Estimate	0.16942[c]	0.12177	0.09661	0.09699
	t-statistics	1.93	1.05	0.83	0.42
	Standard Error	0.08783	0.11586	0.11636	0.22957
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.35%	4.51%	4.77%	12.40%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (-1,+1). The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. 1 if t belongs to the TOM interval of [-1,+3], and 0 otherwise. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of–the-week effect, where M_d, W_d , T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

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Table 43 shows that λ_0 is economically significant and statistically significant at 1% level in model 1 and 4, and at 5% in model 2 and 3 (see section 8.6.2). Table 43 also shows that λ_0 is positive in all four models. Table 44 shows that control variables size and reversal are statistically significant at 1% level in all four models. Control variable momentum is only statistically significant in model 1 at 10% level. On the other hand control variable dividend yield is also only statistically significant in model 1 at 10% level.

Table 44 concerns the January effect. The coefficient λ_1 is economically significant as the mean daily stock return is 0.01619%. Coefficient λ_1 is statistically significant at 1% level in all four models. Coefficient λ_2 is also economically significant in all four models and statistically significant at 5% level in model 1 and at

10% level in model 2, 3 and 4. Coefficient λ_3 is economically significant in all four models but statistically not different than zero. This result is not consistent with linear interaction model's January effect results for Coefficient λ_3. The results suggest that there is no evidence that the stock market reacts differently to dividend-increase announcements in January than during the rest of the year.

Coefficient λ_4 is economically significant (the point estimates are -7.849%, -7.712%, -7.642% and 8.245% in model 1, 2, 3 and 4 respectively), but my sample contains only 4 dividend decrease announcements out of 198 dividend decrease announcements occurring in January. Coefficient λ_4 is statistically significant at 1% level in all four models. Below I compute the partial effect of a dividend-decrease announcement occurring in January.

$$\left(\frac{\partial CAR_{it}}{\partial R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \lambda_2 DPD_{it} + \lambda_4 DPD_{it} * Jan_t \quad (51)$$

$$=> \left(\frac{\Delta CAR_{it}}{\Delta R\Delta DIV_{it}}\middle| DPD_{it} = 1\right) = \widehat{\lambda_2} + \widehat{\lambda_4} * Jan_t$$

$$= \widehat{\lambda_2} + \widehat{\lambda_4} * 1 \text{ [If January =1]}$$

hence, for model 1

=-0.01074 + (-0.07849) * 1

=-0.08923

For model 2,

= -0.01102 + (-0.07712) * 1

=-0.08814

for model 3,

=-0.01050 + (-0.07642) * 1

=-0.08692

TABLE 45 REGRESSION ANALYSIS OF JANUARY EFFECT AS CALENDAR ANOMALY ON DIVIDEND ANNOUNCEMENT DATES USING BINARY SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * Jan_t + \lambda_4 DPD_{it} * Jan_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMIES + \vartheta_3 FEffects + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Mean	0.03944[a]	0.02998[a]	0.02912[a]	0.06753[a]
	t-statistics	6.28	2.81	2.71	3.47
	Standard Error	0.00627	0.01068	0.01075	0.01949
DPI (λ_1)	Point Estimate	0.01197[a]	0.01219[a]	0.01289[a]	0.01303[a]
	t-statistics	3.68	3.60	3.81	3.10
	Standard Error	0.00325	0.00338	0.00338	0.00421
DPD (λ_2)	Point Estimate	-0.01074[b]	-0.01102[c]	-0.01050[c]	-0.01261[c]
	t-statistics	-2.02	-1.79	-1.72	-1.65
	Standard Error	0.00532	0.00615	0.00612	0.00766
$DPI * Jan$ (λ_3)	Point Estimate	-0.01002	-0.00759	-0.00797	-0.00640
	t-statistics	-1.01	-1.03	-1.00	-0.66
	Standard Error	0.00989	0.00736	0.00797	0.00971
$DPD * Jan$ (λ_4)	Point Estimate	-0.07849[a]	-0.07712[a]	-0.07642[a]	-0.08245[a]
	t-statistics	-2.63	-2.92	-3.15	-3.49
	Standard Error	0.02982	0.02643	0.02429	0.02359
$SIZE$ (λ_5)	Point Estimate	-0.00539[a]	-0.00511[a]	-0.00540[a]	-0.01314[a]
	t-statistics	-7.60	-5.26	-5.59	-4.84
	Standard Error	0.00071	0.00097	0.00097	0.00271
$REVERSAL$ (λ_6)	Point Estimate	-0.87773[a]	-0.98773[a]	-0.97991[a]	-1.05849[a]
	t-statistics	-3.64	-2.78	-2.77	-2.81
	Standard Error	0.24085	0.35494	0.35376	0.37619
$MOMENTUM$ (λ_7)	Point Estimate	-0.14207[c]	-0.16274	-0.16678	-0.13096
	t-statistics	-1.95	-1.47	-1.51	-1.13
	Standard Error	0.07295	0.11101	0.11058	0.11576
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.16018[c]	0.12274	0.09732	0.09187
	t-statistics	1.83	1.06	0.84	0.40
	Standard Error	0.08774	0.11549	0.11600	0.22940
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.57%	4.68%	4.94%	12.58%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (-1,+1). The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. *Jan* takes value 1 if t belongs to month of January, and 0 otherwise. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of–the-week effect, where M_d, W_d , T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

and, for model 4,

$$=-0.01261 + (-0.08245) * 1$$

$$=-0.09506$$

Joint significant test results suggest that the firm fixed effects are significant in Table 44, which means my preferred model is model 4, even though I will consider my other three models as well. Equation 51 implies that in January , on average, across firms reducing dividends stock market returns decrease by -9.506% (model 4), whereas during other months on average stock returns decrease by -1.261%. So these results suggest that the stock market reacts more negatively to dividend-decrease announcements when they occur in January than during the rest of the year.

On the basis of these results I can reject the null hypothesis in favour of the alternative hypothesis that the January effect does not affect the reaction of the stock market to dividend increase announcements, but the stock market reacts more negatively to dividend-decrease announcements when they occur in January than during the rest of the year. This result is weak because it is based on only 4 dividend decrease observations occurring in January.

Table 44 shows that λ_0 is economically significant and statistically significant at 1% level in all four models (see section 8.6.2). Table 44 also shows that λ_0 is positive in all four models. Table 45 also shows that control variables size and reversal are statistically significant at 1% level in all four models. And other two-control variables momentum and dividend yield are statistically significant at 10% level only in model 1.

Table 45 concerns the Monday effect. Coefficient λ_1 in Table 45 is economically significant in all three models and statistically significant at 1% level in all four models. Coefficient λ_2 is economically significant in all three models and statistically significant at 5% level in model 1 and at 10% level in model 2, 3 and 4. These results are consistent with the linear interaction model and the dividend-signalling theory. Coefficient λ_3 is economically insignificant and statistically not different from zero.

TABLE 46 REGRESSION ANALYSIS OF MONDAY EFFECT AS CALENDAR ANOMALY ON DIVIDEND ANNOUNCEMENT DATES USING BINARY SPECIFICATION

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * Mon_t + \lambda_4 DPD_{it} * Mon_t + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\, Effect + \vartheta_2 YEAR\, DUMMIES + \vartheta_3 FIXED\, Effects + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.04075[a]	0.04054[b]	0.03877[b]	0.06813[a]
	t-statistics	6.44	2.24	2.14	3.52
	Standard Error	0.00633	0.01808	0.01815	0.01938
DPI (λ_1)	Point Estimate	0.01265[a]	0.01263[a]	0.01212[a]	0.01243[a]
	t-statistics	3.85	3.70	3.45	2.86
	Standard Error	0.00328	0.00341	0.00351	0.00435
DPD (λ_2)	Point Estimate	-0.01097[b]	-0.01113[c]	-0.01173[c]	-0.01464[c]
	t-statistics	-1.98	-1.68	-1.77	-1.83
	Standard Error	0.00554	0.00661	0.00662	0.00799
$DPI * Mon$ (λ_3)	Point Estimate	-0.00509	-0.00419	0.00782	0.00710
	t-statistics	-1.60	-1.54	0.59	0.51
	Standard Error	0.00319	0.00272	0.01314	0.01400
$DPD * Mon$ (λ_4)	Point Estimate	-0.01081	-0.01164	-0.00053	0.00543
	t-statistics	-0.84	-0.55	0.02	0.22
	Standard Error	0.01292	0.02125	0.02309	0.02473
$SIZE$ (λ_5)	Point Estimate	-0.00558[a]	-0.00523[a]	-0.00538[a]	-0.01304[a]
	t-statistics	-7.82	-5.38	-5.55	-4.82
	Standard Error	0.00071	0.00097	0.00097	0.00271
$REVERSAL$ (λ_6)	Point Estimate	-0.85729[a]	-0.96787[a]	-0.96759[a]	-1.04105[a]
	t-statistics	-3.56	-2.68	-2.70	-2.72
	Standard Error	0.24077	0.36113	0.35864	0.38217
$MOMENTUM$ (λ_7)	Point Estimate	-0.13763[c]	-0.15874	-0.16171	-0.12704
	t-statistics	-1.89	-1.42	-1.46	-1.09
	Standard Error	0.07297	0.11159	0.11092	0.11644
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.15936[c]	0.11499	0.09915	0.09574
	t-statistics	1.81	0.99	0.85	0.42
	Standard Error	0.08798	0.11619	0.11624	0.22969
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.43%	4.57%	4.77%	12.40%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (-1,+1). The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. *Mon* takes value 1 if t belongs to Monday, and 0 otherwise. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of–the-week effect, where M_d, W_d , T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

On the other hand, coefficient λ_4 only in models 1 and 2 is economically significant and in model 3 and 4 it is economically insignificant, and at the same time in all four models it is statistically not significant. On the basis of these results we cannot reject the null hypothesis, which means there is no evidence that stock market reacts differently to dividend announcements on Mondays than on other days of the week.

Table 45 shows that λ_0 is economically significant and statistically significant at 1% level in model 1 and 4, and at 5% level in model 2 and 3 (se section 8.6.2). Table 46 also shows that λ_0 is positive in all four models. Table 45 shows that control variables size and reversal are statistically significant at 1% level in all four models. And control variables momentum and dividend yield are statistically significant at 10% level only in model 1.

8.7. ROBUSTNESS TEST

An event study attempts to measure the valuation effects of a corporate event by examining the response of the stock market price around the event. In the previous section I used a 3-day event window i.e. (-1,+1), and in this section I will use a 2-day event window i.e. (0,+1) to do a robustness test. These two-day event window contains the dividend announcements day t_0 and one day after the dividend announcement day t_1.

One of the underlying assumptions of the event window is that the market processes information about the event in an unbiased manner. Thus, we should be able to see the effect of the dividend announcement on stock market prices depending on how quickly market can incorporate information and whether this information has any direct effect on stock prices. According to Efficient Market Hypothesis (EMH) the market should react efficiently. Due to that reason in this section I will examine whether there are is any empirical evidence that the results based on a 2-day event window are different than the results based on a 3-day event window. Except for CAR all other variables are the same as in the previous section.

If we analyse the results of this section then we can see that, though I used a different event window to do the robustness test, the results are similar to the previous section in both specifications for all four calendar anomalies (see appendix-2). This suggests that the results are robust.

8.8. DISCUSSION

I have found different Halloween effect results in two of my different model specifications. My linear interact model specification revealed that there is no evidence that the stock market reacts differently to dividend-increase announcements during the November-April period than during the May-October period. On the other hand, according to Table 39 the stock market reacts less strongly (i.e. less negatively) to dividend-decrease announcements during the November-April period than during other periods of the year. The linear binary model specification showed that the stock market reacts more positively to dividend-increase announcements during the November-April period than during the rest of the year, and the stock market reacts less negatively to dividend-decrease announcements during the November-April period than during the rest of the year.

My linear interaction model specification for the TOM effect strongly supports that the stock market reacts less negatively (actually, positively) to dividend-decrease announcements if they occur at the turn of the month than if they occur during the rest of the month. But TOM effect does not affect the reaction of stock returns to dividend increase announcements. These results support the dividend-signalling theory and previous literature. On the other hand my linear binary model specifications indicate that there is no evidence that the stock market reacts differently to dividend increase (decrease) announcements if they occur at the turn of the month than if they occur during the rest of the month. This means I cannot reject the null hypothesis in the case of the linear binary model.

When I used the linear interaction model specifications for the January effect I found strong evidence in favour of alternative hypothesis. This means the stock market reacts less positively to dividend-increase announcements if they occur in January than if they occur during the rest of the year, and the stock market reacts more negatively to dividend-decrease announcements if they occur in January than if they occur during the rest of the year. On the other hand, when I used the linear binary model I found slightly different results than for the linear interaction model specifications, but still there was enough evidence to reject the null hypothesis in favour of alternative hypothesis. My linear binary model specification suggests that the January effect does not affect the reaction of the stock returns to dividend increase announcements, but the stock market reacts more negatively to dividend-decrease announcements when they occur in January than during the rest of the year. Both the linear interaction model and linear binary model's results are consistent with the dividend-signalling theory, but somewhat inconsistent with the previous January effect literature. Overall, the results are weak, because they are based on only 4 dividend decrease observations occurring in January.

Lastly, I examined the Monday effect, where I found some mixed results. Linear interaction model specification revealed that only in model 1 and model 2 stock market reacts less strongly (i.e. less positively) to dividend-increase announcements on Mondays than on other days of the week. On the other hand in the case of dividend decrease announcements, only model 1 is statistically significant, which means the stock market reacts more strongly (i.e. more negatively) to dividend-decrease announcements on Mondays than on other days of the week. On the basis of these results I can reject the null hypothesis in favour of the alternative hypothesis only for model 1. When I used the linear binary model specification I did not find any evidence that the stock market reacts differently to dividend increase (decrease) announcements if they occur on Mondays than on other days of the week. So in the case of the Monday effect I cannot reject the null hypothesis.

This study has a number of limitations, which are (1) I used only four control variables, but in the future researchers can try to use more and different types of control variables, (2) my sample has a small number of dividend decrease observations, which means small statistical power to detect an effect, (3) future research can be done using more calendar anomalies i.e. day-of-the-week effect, Mark Twain effect, January barometer, (4) the study reported in this chapter simply tried to examine whether (but not to explain why) some calendar anomalies affect how the stock market responds to dividend announcements. I simply tried to uncover evidence that it does react differently due to some calendar effects. Future research should look into this issue more in detail and try to explain why calendar anomalies influence the reaction of the stock market to dividend announcements.

8.9. CONCLUSION

Many analysts cite calendar anomalies as evidence contrary to market efficiency because arbitrage should rule out the possibility that psychological or institutional factors would systematically affect asset prices. The present investigation focused on whether calendar anomalies play any role in the response of stock prices to dividend announcements. This is a novel question. I did not try to explain why some calendar anomalies affect how the stock market responds to dividend announcements. Mainly, in this chapter I tried to provide evidence that it does react differently due to some calendar effects. I used data from the London Stock Exchange starting from 1990 to 2015. To conduct this investigation I relied on four calendar anomalies, which are the Halloween effect, TOM effect, January effect and Monday effect. All these calendar anomalies were selected on the basis of their popularity.

To determine whether calendar anomalies play any role in reaction of the stock market to dividend announcements I chose two different model specifications. In one model specification I considered both the size and the direction of the dividend changes and in the other model specification I ignored the size of the dividend changes. In both model specifications I found some interesting results. When I considered the size and the direction of the dividend changes, the results showed that the stock market reacts less negatively (actually, positively) to dividend-decrease announcements during the TOM period than during the rest of the month, and that the stock market reacts more negatively to dividend-decrease announcements in January and on Mondays than during other periods of the year or week. I also found evidence that the stock markets reacts less negatively to dividend-decrease announcements during the November-April period than during the May-October period. On the other hand, the stock market reacts less positively to dividend-increase announcements in January and on Mondays than during the rest of the year or week, but there is no evidence that the stock market reacts differently to dividend-increase announcements during the November-April and TOM period than during other periods of the year.

When I ignored the size of the dividend changes and focused on the direction alone I found similar results for the Halloween effect but for the TOM and Monday effects I did not find any evidence that the stock market reacts differently to dividend announcements. I also found evidence that the stock market reacts more negatively to dividend-decrease announcements when they occur in January than during the rest of the year.

In summary, my results are consistent with the dividend-signalling theory. These results provide at least marginal evidence that calendar or seasonal anomalies do play a role in the reaction of the stock market to dividend announcements. Future research should look into this issue more in detail and try to explain why calendar anomalies influence the reaction of the stock market to dividend announcements.

9 DISCUSSION

This thesis investigated the dividend-signalling theory from the perspective of orthodox finance and from the perspectives of two areas of unorthodox finance (behavioural finance and the calendar anomalies literature) using UK data. More specifically, the thesis revolved around four research questions. First, do dividend changes contain any information about future earnings? Second, do dividend increase (decrease) announcements have a positive (negative) effect on stock returns? Third, does investor sentiment play any role in the reaction of the stock market to dividend announcements? And fourth, do calendar anomalies play any role in the relationship between dividend announcements and stock returns? This thesis employed an empirical approach and makes original contributions to the behavioural finance literature, corporate finance literature and literature on calendar anomalies.

In the first empirical chapter (chapter 5) my main contribution was in the area of corporate finance literature. After analysing the data I found that there is only very weak evidence that dividend-increase (decrease) announcements are followed by increases (decreases) in firm earnings. However, at the same time in chapter 6 I documented that dividend-increase (decrease) announcements are accompanied by abnormal increases (decreases) in stock market returns. These conflicting findings represent a puzzle; at the end of chapter 6 I speculated on a possible reason behind these conflicting findings. Later in chapter 7 and 8 I made some original contributions to the behavioural finance literature and calendar anomalies literature. More specifically, I found some evidence that investor sentiment and calendar effects influence the response of stock prices to dividend announcements. In chapter 7 I considered investor sentiment because it offers some scope for testing behavioural finance theories.

To answer the four questions mentioned above, I used two different types of model specifications. The first one I called interaction model specification and the second one I called binary model specification. The interaction model specification takes into account both dividend change size and direction. The interaction model specifications have two different types of interaction terms, one for positive dividend changes and one for negative dividend changes. On the other hand, in the binary model specification one dummy captures the effect of positive dividend changes and the other dummy captures the effect of negative dividend changes. These binary models ignore the size of the dividend changes and focus on the direction alone, i.e. whether dividends increase or decrease regardless of the size of the changes. The reason for the use of two different model specifications is because the binary model specification may mitigate the impact of outliers on the results, and therefore it complements the interaction model specification.

In chapter 5 I tried to find out whether current dividend changes contain any information about future firm profitability. Chapter 5 is based on Nissim and Ziv (2001) and Grullon's et al. (2005) previous studies, where such studies have found conflicting results. Nissim and Ziv (2001) argued that, when using a regression analysis that controls for a particular (linear) form of mean reversion in earnings, dividend changes are positively correlated with future earnings changes. Later Grullon et al. (2005) showed that Nissim and Ziv's (2001) assumption of linear mean reversion in earnings is inappropriate. According to Grullon et al. (2005) the reason behind this is that the mean reversion process of earnings is highly nonlinear (Brooks and Buckmaster, 1976; Fama and French 2000). Since assuming linearity when the true functional form is nonlinear has the same consequences as leaving out relevant independent variables, it is possible that the positive correlation documented in Nissim and Ziv (2001) between dividend changes and future earnings changes is spurious. Without controlling for the nonlinearity of the earnings process Nissim and Ziv (2001) documented that there is a positive correlation between dividend changes and future earnings changes. But after controlling for the well-known nonlinearity of the earnings process Grullon et al. (2005) did not find any relationship between current dividend changes and future earnings changes.

In my interaction model specification I used both Nissim and Ziv's (2001) model (linear interaction model) and Grullon et al.'s (2005) model (nonlinear interaction model). I did not find any evidence that current dividend changes contain any information about future earnings changes when I used both of these models (interaction model specification). One of my results differs from both Nissim and Ziv (2001) and Grullon et al.'s (2005): when I used the linear model there was no evidence that dividend changes convey any new information about future profitability, whereas they found supporting evidence. On the other hand, another one of my results is in line with Grullon et al. (2005): when I used the nonlinear interaction model there was no evidence that dividend changes convey new information about future profitability. When I used the binary model specifications I found very weak evidence that dividend changes contain information about future profitability. In the case of the binary model specifications I used both linear and nonlinear binary models. I found very minor evidence that dividend decreases predict future earnings decreases (two years into the future) only in the nonlinear binary model. Instead, the linear binary model's results show no significant evidence that dividend changes convey new information about future earnings changes. In summary, in chapter 5 I used two different model specifications (interaction model and binary model). According to the interaction model specification there is no evidence that current dividend changes contain information about future earnings changes, whereas according to the binary model specification there is at least minor evidence that dividend changes contain information about future earnings changes. The reason behind this conflicting results may be: (1) the results are not robust and (2) the binary model specification mitigates the impact of outliers on the results (see section 5.4). In a nutshell, even after mitigating the impact of outliers (binary model), my analysis produced only very minor evidence in support of the dividend-signalling theory.

For robustness purposes I did an additional test; I examined the correlation between current dividend changes and future earnings levels. To do this additional test I used both interaction (linear and nonlinear model) model and binary model (linear and nonlinear model). Rather than using earnings changes I used ROE as my dependent variable. When I used the interaction model specification I found that there is no significant correlation between dividend changes and future ROE (up to two years into the future). These results are consistent with Nissim and Ziv (2001) and Grullon et al.'s (2005) findings. I found similar results when I used binary model specifications (linear and nonlinear). At the end, overall, my results do not provide compelling evidence that current dividend changes convey new information about future earnings changes, which in turn casts doubt on the validity of the dividend-signalling theory.

In chapter 6 I tried to address a very classical stock market related question, which is whether dividend increase (decrease) announcements have a positive (negative) effect on stock returns. According to Dasilas and Levenis (2011) the first reason behind dividend distribution is based on market imperfections, which happen due to information asymmetries. Managers have all kind of important information about the current and future financial position of the firm, and for this reason they use dividends to send signals about the firm's future earnings (Dasilas et al. 2008). Dividend announcements may convey some sort of information about firm value; more specifically previous researchers documented that dividend increases (decreases) convey positive (negative) information about firm value (Kato and Loewentein, 1995; Ho and Wu, 2001; Nguyen, 2014; Al-Yahyaee, 2014). The majority of studies have found that dividend announcements have a statistically significant effect on stock returns (Yilmaz And Gulay, 2006; Pan et al. 2014; Dasilas and Leventis, 2011; Kumar, 2017). My results also suggest that dividend increases (decreases) have a positive (negative) effect on stock returns, which is consistent with the dividend signaling theory and previous researchers' findings.

To conduct this analysis I used two different model specifications like in chapter 5, which are the interaction model specification and binary model specification. In this chapter I used the event study methodology to examine my research question. I used a 3-day event window to do the empirical analysis and to do robustness tests I used a 2-day event window. In both model specifications I found economically and statistically significant evidence that dividend increases (decreases) have a positive (negative) effect on stock returns. When I used the linear interaction model specifications I found that a 10% dividend increase is estimated to increase stock returns by approximately 0.63%. On the other hand, when dividend decrease by 10%, stock returns are estimated to decrease by about 0.64%. But when I used the linear binary model specifications, which ignore the size of the dividend change, I found that, on average, across firms that increase dividends stock returns are 1.27% higher than for firms that leave dividends unchanged. Similarly, on average, across firms that decrease dividends, stock returns are 1.208% lower than for firms that leave dividends unchanged. When I conducted some robustness tests I found similar economically and statistically significant results. These results are consistent with the dividend-signalling theory and previous literature.

I also have done an additional test to examine whether the Great Recession (2008-2009) changed the relationship between dividend changes and stock returns. My interaction model specification found no evidence that the Great Recession (2008-2009) affected the reaction of the stock market to dividend increase announcements, but the reaction of the stock market is more negative to dividend decrease announcements during the Great Recession period. These results are economically significant. One of the reasons for the high economic significance may be that there are only 17 dividend-decrease announcements in the Great Recession period, and consequently the estimates are not very reliable. The linear interaction model specification suggests that a 10% decrease in dividends decreases stock returns by about 2.99% if it occurs in the Great recession period, whereas it decreases stock returns by only about 0.42% during other periods of time. However, the binary model specification provides only very weak support in favour of the previous conclusion, which suggests that the results obtained from the linear interaction model may be due to outliers and are not robust (see section 6.4).

In chapter 5 I found very weak evidence that current dividend changes contain information about future earnings, yet in chapter 6 I found very strong evidence that dividend increase (decrease) announcements have a positive (negative) effect on stock market returns. These two sets of results appear to be in conflict with each other.

Explaining these contradictory findings is complex and goes beyond the scope of this thesis. Further research on this topic is needed. Here I simply speculate on two possible explanation. In chapter 5 I showed that dividend changes cannot predict earnings changes up to two years into the future, but it is possible that such earnings changes take place at a later date, for example after 3 years or after 5 years. It may be that my analysis focused only on the short term (2 years), and for that reason I found only very weak evidence in chapter 5. Secondly, it is possible that dividend changes drive changes in earnings expectations, which are embedded in consensus analyst forecast revisions, and which may or may not match actual earnings. Future studies may want to extend the time horizon over which the relationship between current dividend changes and future earnings changes is analysed.

Chapter 7 was based on investor sentiment. I used some weather factors as investor sentiment proxies. My three investor sentiment proxies were temperature, air pollution and rain, all measured in the city of London. Weather is one of the most widespread environmental variables in human life, it is a factor that influences the agricultural economy, and it breaks or makes recreational plans and serves as a perennial topic for superficial conversation (Cunningham, 1979). Many scholars argue that weather has controlling power over both emotion and social behaviour (Campbell and Beets, 1977). Clinical and psychological surveys have uncovered that weather has significant effects on human mood and behaviour. It is also well established in the psychological literature that mood and feelings have a huge effect on the human decision making process (Schwartz, 1990; Loewenstein et al. 2001), and in particular on economic decision making (Etzioni, 1988; Romer, 2000; Hanock, 2002).

Based on these insights, in chapter 7 I extended my research by examining the role of three investor sentiment proxies. The question that I tried to answer in chapter 7 is whether investor sentiment plays any role in the relationship between dividend announcements and stock returns. To investigate this topic I used two model specifications, similar to the ones employed in the previous chapters. The key innovation was that in chapter 7 the investor sentiment proxies were interacted with the two existing model specifications from chapter 6. Like in chapter 6, I used a 3-day event window in chapter 7.

Both the interaction and binary model results did not provide any evidence that positive investor sentiment (proxied by high temperature) affects the reaction of stock prices to dividend increase announcements. However, in both model specifications dividend decreases were found to have a smaller negative effect than usual on stock returns when the temperature is high, and as a result investor sentiment is likely positive. In both model specifications, the effect of investor sentiment on the impact of dividend decreases is economically significant as well, which could have interesting implications for the decision-making process of investors, managers, and policy makers. When I used the linear interaction model specification the results showed that a 10% decrease in dividends decreases stock returns by about 0.77% if it happens when temperature is at its average value (i.e. 21.3 degree Celsius). On the other hand, a 10% decrease in dividends decreases stock returns by about 1.74% if it happens when the temperature in London is equal to 0 degrees Celsius (where cold temperature proxies for negative investor sentiment). According to the binary model specification, when the temperature is at its average value (21.3 degree Celsius) dividend-decrease announcements, on average, are accompanied by a drop in stock market returns of about 1.68%, whereas, when the temperature is low (0 degree

Celsius), and as a result investor sentiment is likely negative, dividend-decrease announcements lead to a drop in stock market returns of about 5.18%. These results are consistent with the dividend-signalling theory and with previous studies arguing that high temperature makes people happier and low temperature makes people sadder (Denissen et al., 2008; Widrich, 2013; Klimstra et al., 2011; Chang et al., 2006).

With regard to the second sentiment proxy, people are more pessimistic when air pollution rises and they use probability estimates more biased towards negative outcomes (Li and Peng, 2016). Ambient air pollution leads to heightened level of depression, anxiety, tension, helplessness and anger (Evans et al., 1987). Lepori (2016) found that air pollution is negatively correlated with stock returns. Levy and Yagil (2011 and 2013) found a negative relation between daily stock returns and the air-quality index (AQI).

For the air pollution sentiment proxy, both the interaction and binary model specifications provided no evidence that high levels of air pollution (i.e. negative sentiment) affect the reaction of the stock market to dividend increase announcements. However, both model specifications suggest that the negative impact of dividend-decrease announcements on returns is bigger than usual when the air pollution level is high and, as a result, investor sentiment is negative. In both model specifications, the effect of investor sentiment on the impact of dividend decreases is economically significant as well, which could have interesting implications for the decision-making process of investors, managers, and policy makers. According to the linear interaction model specification, a 10% decrease in dividends is estimated to decrease stock returns by about 1.62% if it happens when investor sentiment is negative (proxied by high air pollution levels). On the other hand, a 10% decrease in dividends is estimated to decrease stock returns by only about 0.34% if it happens when investor sentiment is positive, i.e. air pollution levels are low. According to the binary model specification, when investor sentiment is negative (air pollution levels are high), across firms decreasing dividends, on average stock market returns are about 3.46% lower, whereas when investor sentiment is positive (air pollution level is low), on average, across firms decreasing dividends stock market returns are only about 0.55% lower. When using the interaction model specification I found statistically significant results across all four models, while when using the binary model specification I found statistically significant results in the first three models and insignificant results in model 4 . This may suggest that the results are not fully robust and/or that the results produced by the interaction model specification are partially affected by outliers (see section 7.4). However, taken as a whole, this set of results is consistent with the dividend-signalling theory and with the previous literature on the investor sentiment hypothesis.

When it comes to the third investor sentiment proxy, both model specifications provided no evidence that rain affects the reaction of stock prices to dividend increase (decrease) announcements. The previous two investment sentiment proxies showed that there is some evidence that temperature and air pollution affect the reaction of stock prices to dividend increase (decrease) announcements, but there is no evidence that rain affects the reaction of stock prices to dividend increase (decrease) announcements. One possible explanation behind these contradictory findings is that temperature and air pollution are better investor sentiment proxies than rain in the UK market. On average, in the UK, according to my data set 56% of days are rainy days. As such, it may be the case that UK investors are used to rainy days and, as a result, the occurrence of a rainy day has very little effect on UK investors' sentiment. If rain does not affect investor sentiment, then one should not expect a significant correlation between rain and the reaction of stock prices to dividend increase (decrease) announcements.

Chapter 8 was based on some well-known stock market anomalies also known as calendar anomalies. Calendar anomalies were first introduced by Wachtel (1942). In chapter 8 I examined four very well known calendar anomalies, which are the Halloween effect (Sell in May and go away), Turn-of-the-month effect, January effect and Monday effect. The main aim of chapter 8 was to answer the question of whether calendar anomalies play any role in the relationship between dividend announcements and stock returns. Chapter 8 was mainly exploratory in nature. I did not try to explain why some calendar anomalies affect how the stock market responds to dividend announcements; instead I simply tried to uncover evidence that the stock market does react differently due to some calendar effects. This question is related to chapter 6's results, where I found that dividend-increase (decrease) announcements have a positive (negative) effect on stock returns, which is consistent with the dividend-signalling theory. The key methodological innovation was that in chapter 8 the calendar anomalies were interacted with the two existing model specifications from chapter 6.

The two model specifications generated different results in case of the Halloween effect. The linear interaction model specification showed that the stock market reacts less strongly (i.e. less negatively) to dividend-decrease announcements during the November-April period than during the rest of the year, and these results were economically and statistically significant. A 10% decrease in dividends was estimated to decrease stock returns by about 0.08% if it happens in the November-April period, whereas the same decrease in dividends was estimated to decrease stock returns by about 1.84% if it happens in the May-October period. Conversely, there was no evidence that stock market reacts differently to dividend-increase announcements during the November-April period than during the May-October period.

The binary model specification, instead, showed that the stock market reacts more positively to dividend-increase announcements during the November-April period than during the rest of the year, and it reacts less negatively to dividend-decrease announcements during the November-April than during the rest of the year. The binary model specification's results are statistically and economically significant. During the months of November to April, across firms increasing dividends, stock market returns are about 1.53% higher on average (model 4), whereas during the months of May to October, on average, across firms increasing dividends stock market returns are only 0.53% higher than for firms leaving dividends unchanged. And during the months of November to April, on average, across firms reducing dividends stock market returns actually increase by about 0.3% , whereas during the other months of the year stock returns decrease by about 5.36%. For dividend-increase announcements during the November –April period I found contradictory results between the linear interaction model and linear binary model. In the linear interaction model I found no evidence that stock market reacts differently to dividend-increase announcements during the November-April period than during the May-October period. Instead, in the linear binary model I found that the stock market reacts more positively to dividend-increase announcements during November-April period than during the rest of the year. A possible explanation for these patterns is that the results of the linear interaction model are affected by a few outliers, whereas the binary model (which only focuses on the direction of dividend changes) is less susceptible to outliers (see section 8.4). Overall, these results are consistent with the dividend-signalling theory and the calendar anomalies literature. More in detail, my results are in line with Bouman and Jacobsen's (2002) findings.

Moving to the second calendar anomaly, according to previous studies returns are higher during the first few trading days of each month (Sharma and Narayan, 2014), which is consistent with the turn-of-the-month (TOM) effect. Arial (1987) first found that mean daily returns are positive at the beginning of the month and continuing through the first half of the month. But returns after this point are predominantly negative. According to Lakonishok and Smidt (1988) returns are higher in the last trading day of the month and first three trading day of the month. Previous studies have shown that there is still evidence of TOM effect in the stock market (see, for instance, Sharma and Narayan, 2014; Dzhabrov and Ziemba, 2010; Liu, 2013).

My linear interaction model specifications and binary model specifications showed contradictory results concerning the TOM effect. The linear interaction model specification strongly supports the view that the stock market reacts less negatively (actually, positively) to dividend-decrease announcements if they occur at the turn-of-the-month than if they occur during the rest of the month. The size of the results was so significant that decision makers should take into account these results. According to the interaction model specification, a 10% dividend decrease actually increases stock returns by about 0.20% if it occurs at the turn of the month, whereas it decreases stock returns by about 0.80% if it occurs during the rest of the month. However, there was no evidence that the TOM effect affects the reaction of the stock returns to dividend-increase announcements. These results support the dividend-signalling theory and previous literature (see, for instance, Sharma and Narayan, 2014; Dzhabrov and Ziemba, 2010; Liu, 2013). The linear binary model specifications, instead, provided no evidence that stock market reacts differently to dividend-increase (decrease) announcements if they occur at the turn of the month than if they occur during the rest of the month. The interaction model and binary model specifications showed conflicting results, and the reason behind these conflicting results may be (1) the results of the linear interaction model are not robust due to the presence of outliers and (2) the binary model specification mitigates the impact of outliers on the results (see section 8.4).

As for the third calendar anomaly, the January effect states that returns are higher in January than in other months of the year. Usually investors obtain abnormally larger returns on small cap stocks at the turn of the calendar year, in this process investors buy stock in a small or underperforming company at the end of the year and then sell the stock when the price rises in January. Lakonishok and Smidt (1988) found no evidence of January effect when they used the DJIA market index. Some other studies also suggest that the January effect is disappearing (see, for instance, Gu, 2003; He and He, 2011).

Surprisingly, my analysis indicates that the stock market reacts less positively to dividend-increase announcements if they occur in January than if they occur during the rest of the year, and the stock market reacts more negatively to dividend-decrease announcements if they occur in January than if they occur during the rest of the year. These results are economically significant, and decision makers should take them into account. According to the linear interaction model specification, a 10% dividend increase increases stock returns by about 0.74% if it occurs in the February-December period, whereas it increases stock returns by only about 0.02% if it occurs in January. Analogously, a 10% dividend decrease is estimated to reduce stock returns by about

4% if it happens in January , whereas it is estimated to reduce stock returns by only about 0.58% if it happens in other months of the year.

The linear binary model specification, instead, provided no evidence that the January effect affects the reaction of stock returns to dividend increase announcements, but it provided evidence that the stock market reacts more negatively to dividend-decrease announcements when they occur in January than during the rest of the year. In January, on average, across firms reducing dividends, stock market returns decrease by about 9.5%, whereas during other months, on average, stock returns decrease by only about 1.26%. In summary, these results suggest that the stock market reacts more negatively to dividend-decrease announcements when they occur in January than during the rest of the year. Both linear interaction model and linear binary model's results are consistent with the dividend-signalling theory and suggests that in January the market seems to react differently to dividend announcements than it does during the rest of the year. However, it is worth highlighting that, when it comes to dividend decreases, the results are weak, because they are based on only 4 dividend decrease observations occurring in January. As a result, this set of results needs to be interpreted with care.

The last calendar anomaly that I examined is the Monday effect, where I found mixed results. The Monday effect is one of the most pronounced day-of-the-week-effects. The Monday effect suggests that asset returns are negative on Mondays. Negative Monday returns are robust over time and different markets (see, for instance, Jaffe, Westerfield, 1985; Keim and Stambaugh, 1984). Cross (1973) was the first academic who documented that Monday returns are negative (only -0.18%). After that a number of studies has shown that Monday returns are negative (see, for instant, French, 1980; Gibbons and Hess,1981; Lakonishok and Smidt, 1988). Later

Damodaran (1989) documented that firms usually report bad news on Fridays and this late announcement of bad news might cause the negative Monday returns. Kumara (1997) found Monday effects has diminished, and Connolly (1989) documented that Monday returns were statistically significant before 1974, but were not statistically significant after 1974, but they remain negative.

My linear interaction model specification revealed that only in model 1 and model 2 the stock market is estimated to react less strongly (i.e. less positively) to dividend-increase announcements on Mondays than on other days of the week. On the other hand, in the case of dividend-decrease announcements only model 1 provided statistically and economically significant evidence, suggesting that the stock market reacts more strongly (i.e. more negatively) to dividend-decrease announcements on Mondays than on other days of the week. According to the linear interaction model specification, on Mondays a 10% dividend-increase announcement increases stock returns by only about 0.38% (model 2), whereas it increases stock returns by about 0.64% if it occurs on other days of the week. Analogously, on Mondays a 10% dividend-decrease announcement is estimated to decrease stock returns by about 1.42% (model 1), whereas it decreases stock returns by only about 0.56% if it occurs on other days of the week. The results are consistent with the dividend-signalling theory and the signs are consistent with the Monday effect.

The linear binary model specification, however, did not provide any evidence that the stock market reacts differently to dividend-increase (decrease) announcements if they occur on Mondays than on other days of the week. The reason behind these conflicting results may be that (1) the results generated by the linear interaction model are influenced by outliers and, therefore, they are not robust (see section 8.4). Overall, these results are consistent with the previous studies on the Monday effect (see, Kumara, 1997; Connolly, 1989).

The main aim of these four empirical chapters was to examine the dividend-signalling theory from different perspectives. Chapter 5's results provided no evidence in favour of the dividend-signalling theory from the perspective of orthodox finance. On the other hand, chapter 6 provided very strong evidence that dividend-increase (decrease) announcements have a positive (negative) effect on stock market returns, and these results are consistent with the dividend-signalling theory and orthodox finance. These two sets of results appear to be in conflict with each other. Explaining these contradictory findings is complex and goes beyond the scope of this thesis. Further research on this topic is needed. Here I simply speculate on one possible explanation: in chapter 5 I showed that current dividend changes cannot predict earnings changes up to two years into the future, but it is possible that such earnings changes take place at a later date, for example after 3 years or after 5 years. It may be that my analysis focused only on the short term (2 years), and for that reason I found only very weak evidence in support of the dividend-signalling theory in chapter 5. Both sets of results are important for academic researchers. These contradictory results confirm the existence of a gap in the literature and open the space for academics to do more extensive research. As such, these findings are important for future academic research.

Chapter 7 and 8 were based on insights from two areas of unorthodox finance, that is behavioural finance and the literature on calendar anomalies. Behavioural finance tries to explain financial phenomena by assuming non-rational behaviour amongst investors. Behavioural finance combines psychology and economics, and according to its proponents it offers a better model of human behaviour. Dividends have been taxed at a higher rate than capital gains. That is why investors who pay taxes should always prefer that the firm repurchases shares rather than pay a dividend. Shefrin and Statman (1984) proposed a number of behavioural explanations for why shareholders exhibit a preference for dividends on the basis of behavioural finance. Their first idea relies on self-control, the second rationale for dividends is based on mental accounting and the third explanation argues that, by paying dividends, firms help investors avoid regret.

The main reason to introduce behavioural finance in chapter 7 was to see whether using behavioural finance I could shed more light on the empirical validity of the dividend-signalling theory. The results in chapter 7 suggest that there is evidence that investor sentiment plays a role in the relationship between dividend announcements and stock returns, which is consistent with the view that behavioural factors need to be taken into account when one tries to test the empirical validity of the dividend-signalling theory. Overall, these results are important for investors and academics. These results will help academics to realise that if they want to shed more light on dividend-signalling theory, then they have to consider investor sentiment as well. On the other hand, chapter 7's results can be important for investor as well, as they suggest that investor sentiment seems to influence how investors respond to dividend announcements. So, future research could investigate whether it is possible to build a profitable trading strategy based on these insights.

We can observe similar results in chapter 8, which provided some evidence that calendar anomalies play a role in the relationship between dividend announcements and stock returns. Chapter 8's results are important for investors and academics. These results will help academics to realise that if they want to shed more light on dividend-signalling theory, then they have to consider calendar anomalies very carefully. The results in chapter 8 suggest that calendar anomalies seem to influence how investors respond to dividend announcements. So, future research could investigate whether it is possible to set up a profitable trading strategy by combining calendar anomalies with the insights from the dividend-signalling theory.

From a methodological perspective, the main strengths of this thesis are: (1) for robustness purposes I used two different model specifications, one that I called linear interaction model specification and another one that I called linear binary model specification, which is a partially novel model specification; (2) I used a larger data set than previous studies; (3) I amended my data set to minimise the influence of outliers, and the use of the linear binary model further mitigated the influence of outliers on my results; (4) I used a very well-known methodology called event study methodology in chapters 6, 7 and 8. For my main empirical results I used 3-day event windows (-1, +1) and for robustness tests I used 2-day event windows (0,+1). Some of the previous studies used 5-day and 10-day event windows, and some went even further and used 21-day or 41-day event windows. The reason why I chose shorter event windows was to make sure that the results would not be contaminated by other events and news. (5) my data set contained a small number of observations concerning dividend-decrease announcements, which made some of my results statistically weak. However, this small number of dividend-decrease announcements also shows how much managers try to avoid reducing dividends in order to maintain good investor relations, which can be seen as a strength of this study.

The main weaknesses are: (1) I used only four control variables in chapters 6, 7 and 8. I used most common four control variables. Subsequent research could be done using more control variables to verify whether the results are robust. Some interesting candidates would be variables such as institutional holdings, idiosyncratic volatility, illiquidity etc.; (2) I used three very well-known weather variables as investor sentiment proxies in chapter 7, but further research could be done using some other different weather variables, e.g. sunshine, wind, snow etc.; (3) in chapter 8 I used only four calendar anomalies, but further research could be done using more and different types of calendar anomalies, for example the day-of-the-week effect, Mark Twain effect, January barometer, etc; (4) As I mentioned before I used the event study methodology in chapters 6, 7 and 8, and for main empirical analysis I used 3-day event windows (-1,+1) and for robustness tests I used 2-day event windows (0,+1). It would be wise to do more research using longer event windows and see whether results are robust; (5) To simplify the data set I included only final dividend announcements in my main data sample, and all other interim cash dividend and stock dividend announcements during the event period were excluded. It would be interesting to see whether the results are robust if other interim dividend and stock dividend announcements are included in the sample; (6) In this thesis I excluded from the sample all dividend changes outside of the range +50% to -50% to minimise the impact of outliers. Subsequent research could be done without excluding outliers to examine whether the results are robust; (7) according to previous literature the general implications of the dividend-signalling theory are (i) a positive relationship between dividend changes and the price reaction to dividend changes; (ii) a positive relationship between dividend changes and future earnings changes and (iii) a positive relationship between dividend changes and analysts' firm earnings forecasts. In this thesis I examined two first two implications but I did not examine the third one. Subsequent research could expand the scope of the analysis and examine the third implication as well.

10 CONCLUSION

This chapter summarises the key findings of the thesis and concludes with an outline and discussion of areas for further research.

To conduct this research I used a sample of companies from the FTSE 350 index from 1990 to 2015. The main objective of this research was to investigate the dividend-signalling theory. I investigated the dividend-signalling theory from the perspective of orthodox finance (chapters 5 and 6) and from the perspectives of two areas of unorthodox finance (chapters 7 and 8). In all four empirical chapters I used two different model specifications. One model specification is the traditional dividend signalling model, which I called interaction model specification and the second one is a partially novel model specification, which I called binary model specification (section 5.4).

I used secondary data collected from different sources. In chapter 6,7 and 8 I used the well-known event study methodology to conduct the research. I used panel data sets in chapters 5, 6, 7 and 8. In chapter 5 I used both linear and nonlinear models (section 5.4), while in chapter 6,7 and 8 I used only linear model specifications (section 6.4, 7.4 and 8.4).

In chapter 5 I tried to answer a well-known question, which is whether dividend announcements contain new information about future firm profitability of firms. To conduct this investigation I used Nissim and Ziv (2001) and Grollun's (2005) linear and nonlinear model specifications. I also used a partially novel model that I called binary model specification, which is my main contribution in chapter 5; also, to the best of my knowledge, this is the first piece of research that employed UK data to investigate whether dividend announcements contain any new information about the future profitability of firms. When I used the interaction model specifications (linear and nonlinear) I did not find any evidence that current dividend announcements convey new information about future firm profitability. On the other hand, when I used the binary model specifications (linear and nonlinear) I found very minor evidence that dividend decreases predict future earnings decreases (two years into the future) in the nonlinear model. As a robustness test when I used ROE as my dependent variable I found no evidence in favour of the dividend signaling theory, as the data did not support the conclusion that current dividend announcements convey new information about future firm profitability.

In the following empirical chapter (chapter 6), using an event study methodology I found strong evidence that dividend-increase (decrease) announcements have a positive (negative) effect on stock market returns. The two sets of results from chapter 5 and 6 appear to be in conflict with each other. Explaining these contradictory findings is complex and goes beyond the scope of this thesis. Further research on this topic is needed. Here I simply speculated on one possible explanation: in chapter 5 I showed that current dividend changes cannot predict earnings changes up to two years into the future, but it is possible that such earnings changes take place at a later date, for example after 3 years or after 5 years. It may be that my analysis focused only on the short term (2 years), and for that reason I found only very weak evidence in chapter 5. An additional and interesting finding is that, in chapter 6, when I used interaction model specification, I did not find any evidence that the Great Recession (2008-2009) affected the reaction of the stock market to dividend increase announcements, but the reaction of the stock market was found to be more negative to dividend-decrease announcements during the Great Recession period. Conversely, the binary model specification did not provide any evidence that the Great Recession affected the reaction of the stock market to dividend-increase (decrease) announcements.

Chapter 7 and 8 were based on two areas of unorthodox finance, that is behavioural finance and the calendar anomalies literature. In chapter 7 and 8 I extended the model specifications of chapter 6 by introducing variables to represent investor sentiment in chapter 7 and calendar anomalies in chapter 8. Chapter 7 was mainly based on investor sentiment and I used three weather variables as investor sentiment proxies, which were temperature, air pollution and rain in the city of London. I investigated whether investor sentiment plays any role in the relationship between dividend announcements and stock returns. My empirical results did not provide any evidence that positive investor mood (proxied by high temperature) affects the reaction of stock prices to dividend increase announcements, but I found that stock prices react less negatively to dividend decreases when investor mood is positive (proxied by high temperature), according to the interaction model specification. In both model specifications there was no evidence that negative investor mood (proxied by rain) affects the reaction of stock prices to dividend-increase (decrease) announcements. Lastly, according to the binary model specifications, stock prices react more negatively to dividend decreases when the air pollution level is high (and allegedly investor sentiment is negative).

In chapter 8 I investigated a novel question, which is whether calendar anomalies play any role in the relationship between dividend announcements and stock market returns. This chapter was exploratory in nature. In this chapter I simply tried to uncover evidence that calendar anomalies do affect how the stock market reacts to dividend announcements. However, I did not try to explain why some calendar anomalies affect how the stock market respond to dividend announcements; that is left for future research. My empirical results suggest that calendar or seasonal anomalies do play a role in the reaction of the stock market to dividend announcements. The stock market reacts less negatively to dividend-decrease announcements during the November to April period than during the May to October period (Halloween effect), according to the interaction model specification, and according to the binary model the stock market reacts less negatively to dividend-decrease announcements during the November to April period than during the May to October period. The stock market reacts less negatively (actually positively) to dividend-decrease announcements if they occur at the turn-of-the-month, according to the interaction model specifications. According to the interaction model specification, the stock market reacts less positively to dividend-increase announcements and more negatively to dividend-decrease announcement if they occur in January. On the other hand when I used linear binary model specification I did not find any evidence that the stock market reaction to dividend increase (decrease) announcements is different on Mondays than on other days of the week. All these results are consistent with the dividend signalling theory and the literature on calendar anomalies (section 8.6.3 and section 8.6.4).

The analysis reported in this thesis suggests a number of areas where the research into dividend policy could be usefully extended. To shed more light on the dividend policy puzzle subsequent studies could test other dividend related theories rather than the dividend signalling theory. They also could modify and extend models used in this thesis. In chapter 6, 7 and 8 I used only four control variables, but it will be interesting to see whether the results hold if new research is done using more or different control variables.

More research could be done using different investor sentiment proxies such as wind, sunshine etc. to determine whether the results reported here are robust to different sentiment proxies. The sample that I employed in this thesis contained a small number of dividend-decrease announcements; future research could extend the sample period to increase the number of relevant observations. In chapter 8 I used only four calendar anomalies; it would be interesting to see whether other calendar anomalies play any role in the relationship between dividend announcements and stock market returns.

My research findings can be helpful for different group of people, such as academic researchers, investors etc. The results in chapter 5 suggest that investors should be careful about extracting information about future earnings changes from current dividend changes, as there seems to be no evidence that the latter accurately predict the former. Yet, the results in chapter 6 indicate that the stock market significantly reacts to dividend announcements, which (according to the results in chapter 5) represents a puzzle that academic researchers may want to investigate further; further research may want to investigate this matter in greater details. For example, it would be interesting to see whether prospect theory can shed any light on this issue.

The results in chapter 7, too, can be useful for investors as they suggest that investor sentiment seems to influence how investors respond to dividend announcements. Future research could investigate whether it is possible to build a profitable trading strategy based on these insights. These findings also give a chance to academic researchers to explore whether other psychological variables influence investors' response to dividend announcements. Similar logic applies to the results discussed in chapter 8; future research could investigate whether it is possible to set up a profitable trading strategy by combining calendar anomalies with the insights from the dividend-signalling theory. Behavioural finance is a relatively new research area for academic researchers; there is lots of scope for academics to explore this area of research. My results suggest that behavioural finance provides a useful perspective for examining how investors respond to dividend announcements. Future research should investigate whether it is possible to build a profitable trading strategy based on behavioural finance with the insights from the dividend-signalling theory.

Overall, the main aim of this thesis was to investigate the dividend-signalling theory from the perspective of orthodox finance and from the perspectives of two areas of unorthodox finance (behavioural finance and the calendar anomalies literature). This thesis gave answer of four important questions. The results from this thesis will help investors to make their decisions, and at the same time for academics it create research gaps for further research. This thesis contributes to three areas of finance literature, which are corporate finance, behavioural finance and the literature on calendar anomalies. I used panel data sets in chapters 5, 6, 7 and 8. The contributions made by this thesis are several, such as the use of UK data in chapter 5, the use of a larger data set in chapters 6, 7 and 8 compared to previous studies, the use of a partially novel model specification called binary model specification in chapters 5, 6, 7, and 8, and the proposal of two novel questions in chapters 7 and 8. Overall, this thesis both provided additional evidence in favour of the dividend-signalling theory and raised some novel questions about the theory itself.

REFERENCES

Abeyratna, G., Lonie, A., Power, D. and Sinclair, C., 1996. The influence of company finanacial performance on the interpretation of dividend and earnings signals: a study of accounting- and market based data. *British Accounting Review*, 28, pp. 229-247.

Adedeji, A., 1998. Does the pecking order hypothesis explain the dividend payout ratios of firms in the UK?. *Journal of Business, Finance and Accounting*, 25 (9-10), pp. 1127−1155.

Adjaoud, F. and Ben-Amar, W. (2010), Corporate governance and dividend policy: shareholders' protection or expropriation?. *Journal of Business Finance & Accounting*, 37(5-6), pp. 648-667.

Agrawal, A. and Jayaraman, N., 1994. The dividend policies of all-equity firms: A direct test of the free cash flow theory. *Managerial and Decision Economics*, 15(2), pp. 139−148.

Aggarwal, R. and Kyaw, N. A., 2010. Capital structure, dividend policy, and multinationality: Theory verses empirical evidence. *International Review of Financial Analysis*, 19, pp. 140-150.

Aharony, J. and Swary, I., 1980. Quarterly dividend and earnings announcements and stockholders' returns: An empirical analysis. *Journal of Finance*, 35, pp.1–12.

Aharony, J. Falk, H. and Swary, I., 1988. Information content of dividend increases: the case of regulated utilities. *Journal of Business, Finance and Accounting*, 15(3), pp. 401-414.

Aharony, J. and Dotan, A., 1994. Regualar dividend announcements and future unexpected earnings: An empirical analysis. *Financial Review*, 29, pp. 125-151.

Aivazian, V., Booth, L. and Cleary, S., 2003. Dividend policy and the organization of capital markets. *Journal of Multinational Financial Management*, 13(2), pp. 101-121.

Aivazian, V., Booth, L. and Cleary, S., 2006. Dividend smoothing and debt rating. *Journal of Financial and Quantitative Analysis*, 41(2), pp. 439-453.

Allais, M., 1953. Le Comportement de l'Homme rationnel devant le risque, critique des postulats et axiomes de l'Ecole Americaine. *Econimetrica*, 21, pp. 441-451.

Allen, F. and Michaely, R., 1995. In R. A. Jarrow, V. Masksimovic, and W.T. Ziemba (Eds.), *Dividend policy Handbooks in operations research and managements science, 9*, pp. 793-837.

Allen, F. and Michaely, R., 2002. *Payout policy*. In: George Constantinides, Milton Harris, & Rene Stulz (Eds.), *North Holland Handbook of Economics*, New York: North Holland.

Al-Najjar, B., 2011. The inter-relationship between capital structure and dividend policy: empirical evidence from Jordanian data. *International Review of Applied Economics*, 25(2), pp. 209-224.

Alpert, M. and Raiffa, H., 1992. *A progress report on the training of probability assessors*. In D. Kahneman, P. Slovic, and A. Tversky, ed., *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge: Cambridge University Press.

Al-Yahyaee, K. H., Pham, T. M. and Walter T. S., 2011. Dividend smoothing when firms distribute most of their earnings as dividends. *Applied Financial Economics*, 21, pp. 1175-1183.

Al-Yahyaee, K. H., 2014. Shareholders wealth effects of stock dividends in a unique environment. *Journal of International Financial Markets, Institutions and Money*, 28, pp. 66-81.

Ambarish, R., John, K. and Williams, J., 1987. Efficient signalling with dividends and investments. *The Journal of finance*. 42(2), pp. 321-343.

Ang, A. and Bekaert, G., 2007. Stock return predictability: is it there?. *Review of Financial Studies*, 20, pp. 651–707.

Anderson, L. R., Gerach, J. R. and DiTraglia, F. J., 2007. Yes, Wall Street, There is a January effect! Evidence from laboratory auctions. *The Journal of Behavioral Finance*, 8(1), pp. 1-8.

Andrade, S. C., Chhaochharia, V. and Fuerst, M. E., 2013. "Sell in May and go away" just won't go away. *Financial Analysts Journal*, 69(4), pp. 94-105.

Ariel, R., 1987. A monthly effect in stock returns. *Journal of Financial Economics*, 18, pp. 161-174.

Arjun, D. and Dale, M., 1983. Market responses to dividend increases and changes in payout ratios. *Journal of Financial and Quantitative Analysis*, 18(2), pp. 163-173.

Arrow, K. J., 1982. Risk perception in psychology and economics. *Economic Inquiry*, 2(1), pp. 1-9.

Asquith, P. and Mullins, D. W. Jr., 1983. The impact of initiating dividend payments on shareholders' wealth. *Journal of Business*, 56(1), pp. 77-96.

Asquith, P. and Mullins, D. W. Jr., 1986. Signalling with dividends, stock repurchases, and equity issues. *Financial Management*, 15, pp. 27–44.

Atanasova , C. V. and Hudson, R. S., 2010. Technical trading rules and calendar anomalies: are they the same phenomena?. *Economics Letters*, 106(2), pp. 128-130.

Autore, D. M. and Jiang, D., 2017. The preholiday corporate announcement effect. *Working paper*. Available: https://poseidon01.ssrn.com/delivery.php?ID=4031181150890900900100170740850960180980350910340110741170800260261140291260740930280330270320441090270401050810910000700941191030820070120110881020060051141060770500190

13124088101087100017088099124093083102096027076068087021074080120014017065072091&EXT=pdf . Access date [26th September 2017].

Bajaj, M. and Vijh, M. A., 1990. Dividend clienteles and the information content of dividend chnages. *The Journal of Financial Economics*, 26, pp. 193-219.

Bakar, A. A., Siganos, N. and vagenas-Nanos, E., 2014. Does mood explain the Monday effect?. *Journal of Forcasting*, 33, pp. 409-418.

Baker,M., Ruback, R. S. and Wurgler, J., 2004, Behavioral corporate finance : a survey, National Bureau OF Economic Research. *Working Paper* 10863. Available: http://www.nber.org/papers/w10863. Access date [16th March 2014].

Baker, M. and Wurgler, J., 2002. Market timing and capital structure. *Journal of Finance*, 57, pp. 1-32.

Baker, M. and Wurgler, J., 2004(a). A catering theory of dividends. *Journal of Finance*, 59, pp. 1125–65.

Baker, M. and Wurgler, J., 2004(b). Appearing and disappearing dividends: the link to catering incentives. *Journal of Financial Economics*, 73, pp. 271–88.

Baker, M. and Wurgler, J., 2013. Behavioural corporate finance: an update survey, *Handbook of the. Economics of Finance*, pp. 351-417.

Ball, R., 1978. Anomalies in relationships between securities' yields and yield surrogates. *Journal of Financial Economics*, 6, pp. 103–26.

Barberis, N. and Huang, M., 2001. Mental accounting, loss aversion, and individual stock returns. *Journal of Finance*, 56, pp. 1247-1292.

Barberis, N. and Thaler, R.H., 2003, A survey of behavioral finance. *Handbook of the Economics of Finance*, pp. 1052-1121.

Bartram, S., Brown, P., How, J. and Verhoeven, P., 2012, Agency conflicts and corporate payout policies: a global study. *Working Paper*, Lancaster University. Available: https://poseidon01.ssrn.com/delivery.php?ID=316105111106004106006119104106027094097057069013079039085087071107105006122070087075054034098101102014042108114093071111107103037027053089084031118072080069124098037033035091064080020024005074017072030020107008104076064015010116027023088068123082007&EXT=pdf. Access date [19th December 2014].

Baskin, J., 1989. An empirical investigation of the pecking order hypothesis. *Financial Management*, 18(1), pp. 26−35.

Basu, S., 1977. Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient markets hypothesis. *Journal of Finance*, 32(3) , pp. 663–82.

Basu, S., 1983, The relationship between earnings yield, market value, and return for NYSE common stocks: further evidence. *Journal of Financial Economics*, 12, pp. 129–56.

Bauer, M., Glenn, T., Grof, P., Rasgon, N. L., Marsh, W., Sagduyu, K., Alda, M., Murray, G., Quiroz, D., Malliaris, Y., Sasse, J., Pilhatsch, M., and Whybrow, P. C., 2009. Relationship among latitude, climate, season and self-reported mood in bipolar disorder. *Journal of Affective Disorders*, 116(1-2), pp. 152-157.

Benartzi, S., Michaely, R. and Thaler, R. H., 2005. Do changes in dividends signal the future or the past?. *Journal of Finance*, 52(3). pp. 1007-1034.

Benos, B. and Weisbach, M., 2004. Private benefits and cross-listings in the United States. *Emerging Markets Review*, 5(2), pp. 217-240.

Bernheim, B. D. and Wantz, A., 1995. A tax-based test of the dividend signalling hypothesis. *The American Economic Review*, 85(3), pp. 532-551.

Bhaduri, S., 2002. Determinants of corporate borrowing: Some evidence from the Indian corporate structure. *Journal of Economics and Finance*, 26, pp. 200–215.

Bhattacharya, S., 1979. Imperfect information, dividend policy and the‘‘Bird in the Hand’’ fallac. *Bell Journal of Economics and Management Science*, 10, pp. 259–70.

Bhattacharya, S., 1979. Nondissipative signalling structures and dividend policy. *Quarterly Journal of Economics*, 95, pp. 1-24.

Bhattacharyya, N., 2007. Dividend policy: a review. *Managerial Finance*, 33(1), pp. 4-13.

Bhojraj, S., Lee, C. M., & Oler, D. K., 2003. What's my line? A comparison of industry classification schemes for capital market research. *Journal of Accounting Research*, *41*(5), 745-774.

Binder, J., 1998. The event study methodology since 1969, *Review of Quantitative Finance and Accounting*, 11(2), pp. 111-137.

Black, F., 1976. The dividend puzzle. *Journal of Portfolio Management*, 2(2), pp. 5-8.

Booth, L., Aivazian, V., Demirguc-Kunt, A. and Maksimovic, V., 2001. Capital structures in developing countries. *Journal of Finance*, 56(1), pp. 87–130.

Boudoukh, J, Richardson, M. and Whitelaw, R. F., 1994. Industry returns and the Fisher effects. *Journal of Finance*, 49, pp. 1595-1615.

Bouman, S. and Jacobsen, B., 2002. The Halloween indicator, “sell in May and go away”: another puzzle. *The American Economic Review*, 92 (5), pp. 1618-1635.

Bowman, R. G., 1983. Understanding and conducting event studies, Journal of Business Finance and Accounting, 10(4), pp. 561-584.

Bozos, K., Nikolopoulos, K. and Ramgandhi, G., 2011. Dividend signaling under economic adversity: evidence from the London Stock Exchange. *International Review of Financial Analysis*, 20, pp. 364-374

Branch, B., 1977. A tax loss trading rule. *Journal of Business*. 50(2), pp. 198-207.

Brian, M. L. and Shelly, Z., 2008. Halloween or January? Yet another puzzle. *International Review of Financial Analysis*, 17, pp. 1055-1069.

Brav, A. and Heaton, J., 2002. Competing theories of financial anomalies. *Review of Financial Studies*, 15, pp. 575-606.

Brealey, R. A. and Myers, S. C., 1981. *Principles of corporate finance*, McGraw-Hill: New York.

Brealey, R. A., Myers, S. C., and Marcus, A. J., 2007. *Fundamentals of corporate finance* (5th International Eds.). McGraw-Hill Irwin: New York.

Brickley, J., 1983. Shareholder wealth, information signalling, and the specially designated dividend: An empirical Study. *Journal of Financial Economics*, 12, pp. 187-209.

Brockman, P. and Unlu, E., 2009. Dividend policy, creditor rights, and the agency costs of debt. *Journal of Financial Economics*, 92(2), pp. 276-299.

Brockman, P. and Unlu, E., 2011, Earned/contributed capital, dividend policy, and disclosure quality: an international study. *Journal of Banking and Finance*, 35(7), pp. 1610-1625.

Brooks, L. D. and Buckmaster, D. A., 1976. Further evidence on the time series properties of accounting income. *Journal of Finance*, 31, pp. 1359–73.

Brown , L. D. and Luo, L., 2006. The January barometer: further evidence. *The Journal of Investing*, 15(1), pp. 25-31.

Brown, P., Ferguson, A. and Sherry, S., 2010. Investor behaviour in response to Australia’s capital gain tax. *Accounting and Finance*, 50(4), pp. 783-808.

Brown, J. S. and Warner, J. B., 1985. Using daily stock returns: the case of event studies, *Journal of Financial Economics*, 14, pp. 3-31.

Brusa, J. and Pu, L., 2000. The weekend effect, ‘reverse’ weekend effect, and firm size. *Journal of Business Finance and Accounting*, 27(5/6), pp. 555.

Bryman, A., 1988. "Quantity and Quality in Social Science Research ", *Contemporary Social Research: 18,* Series Editor: Martin Bulmer, Routledge: London and New York.

Bulan, L.T. and Subramanian, N., 2008. The firm life cycle theory of dividends, *The Blackwell Companion to Dividends and Dividend Policy*, H. Kent Baker (ed.), Blackwell,

Bullinger, M., 1990. Environmental stress: effects of air pollution on mood, neuropsychological function and physical state. In: *Psychology of Stress*. NATO ASI Series, edited by Puglisi-Allegra, S. and Oliverio, A., Vol. 54. Dordrecht: Kluwer Academic Publishers.

Byrne, J. and O’Connor, T., 2012. Creditor Rights and the Outcome Model of Dividends. *The Quarterly Review of Economics and Finance*, 52(2), pp. 227-242.

Cadsby, C. B. and Ratner, M., 1992. Turn-of month and pre-holiday effects on stock returns: some international evidence, *Journal of Banking and Finance*, 16, pp. 497-509.

Camerer, C. E., 1989. An experimental test of several generalized utility theories. *Journal of Risk and Uncertainty*, 2, pp. 61-104.

Campbell, D. E. and Beets, J. L., 1977. Meteorological variables and behaviour: an annotated bibliography. *JSAS Catalog of Selected Documents in Psychology*,

Campbell, J. Y. and Shiller, R. J., 1988(a). The dividend–price ratio and expectations of future dividends and discount factors. *Review of Financial Studies*, 1, pp. 195–227.

Campbell, J. Y. and Shiller, R. J., 1988(b). Stock prices, earnings, and expected dividends. *Journal of Finance*, 43, pp. 661–676.

Campbell, J. Y. and Shiller, R. J., 2001. Valuation ratios and the long-run stock market outlook: an update. *NBER Working Paper 8221*. Available http://www.nber.org/papers/w8221.pdf . Access data [20th March 2015].

Campbell, J. Y. and Yogo, M., 2006. Efficient tests of stock return predictability. *Journal of Financial Economics*, 81, pp. 27–60.

Campbell, J. Y., Lo, A. W. and MacKinlay, C., 1997. *The Econometrics of Financial Markets*, Princeton, NJ: Princeton University Press.

Cao, M. and Wei, J., 2002. Stock market returns: a temperature anomaly, *Working Paper*, Schulich School of Business, York University, Toronto, Canada. Available < http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.195.5659&rep=rep1&type=pdf> Access date [18th May 2016].

Cao, M. and Wei, J., 2005. Stock market returns: a note on temperature anomaly. *Journal of Banking and Finance*, 29, pp. 1559-1573.

Carrazedo, T., Curto, J. D. and Oliveira L., 2016. The Halloween effect in European sectors, *Research in International Business and Finance*, 37, pp. 489-500.

Carton, S., Jiuvent, R., Bungener, C. and Widlocher, D., 1992. Sensation seeking and depressive mood. *Personality and Individual Differences*, 13, pp. 843-849.

Carton, S., Morand, P., Bungener, C. and Jiuvent, R., 1995. Sensation seeking and emotional disturbances in depression: relationships and evolution. *Journal of Affective Disorders*, 34, pp. 219-225.

Chang, B. and Dutta, S., 2012. Dividends and corporate governance: Canadian evidence. *Journal of Applied Finance*, 18(4), pp. 5-30.

Chang, R.P. and Rhee, S.G., 1990. The impact of personal taxes on corporate dividend policy and capital structure decisions. *Financial Management,* 19(2), pp. 21–31.

Chan, C. and Wu, C., 1998. The dynamic of dividends, earnings and stock price: Evidence and implication for dividend smoothing and signalling. *Journal of Empirical Finance,* 6(1), pp. 29-58.

Chang, T., Chen, C., Chou, R. and Lin, Y., 2008. Weather and intraday patterns in stock returns and trading activity. *Journal of Banking and Finance*, 32(9), pp. 1754-1766.

Chae, J., Kim, S. and Lee, E., 2009. Howcorporate governance affects payout policy under agency problems and external financing constraints. *Journal of Banking and Finance*, 33, pp. 2093–2101.

Chang, E. C., Pinegar, J. M. and Ravichandran, R., 1993. International evidence on the robustness of the day-of-the-week effect. *The Journal of Financial and Quantitative Analysis*, 28(4), pp. 497-513.

Chang, T., Nieh, C., Yang, M. J. and Yang, T., 2006. Are stock market returns related to the weather effects? Empirical evidence from Taiwan. *Physica A*, 364, pp. 343-354.

Charest, G., 1978. Dividend information, stock retunes, and market efficiency, ll. *Journal of Financial Economics*, 6, pp. 297-330.

Chen, L., 2009. On the reversal of return and dividend growth predictability: a tale of two periods. *Journal of Financial Economics*, 92, pp. 128–151.

Chen, K., Chen, Z. and Wei, K., 2009, Legal protection of investors, corporate governance, and the cost of equity capital. *Journal of Corporate Finance*, 15(3), pp. 273-289.

Cho, Y., Linton, O. and Whang, Y., 2007. Are there Monday effects in stock returns: a stochastic dominance approach. *Journal of Empirical Finance*, 14, pp. 736-755.

Choi, Y. M., Ju, H. K. and Park, Y. K., 2011. Do dividend changes predict the future profitability of firms?. *Accounting and Finance,* 51, pp. 869-891.

Christie, W.G., 1990. Dividend yield and expected returns: the zero dividend puzzle. *Journal of Financial Economics*, 28, pp. 95–125.

Christie, W.G., 1994. Are dividend omissions truly the cruellest cut of all?. *Journal of Financial and Quantitative Analysis*, 29(3), pp. 459-480.

Ciccone, S. J., 2011. Investor optimism, false hopes and the January effect. *Journal of Behavioral Finance*, 12(3), pp. 158-168.

Claessens, S. and Laeven, L., 2006. *A Reader in International Corporate Finance*, 1, Washington, DC : World Bank.

Cochrane, J., 2001. *Asset Pricing*, Princeton, NJ: Princeton University Press.

Cochrane, J. H., 2008. The dog that did not bark. A defence of return predictability. *Review of Financial Studies*, 21, pp. 1533–1575.

Cohen, S., Evans, G. W., Stokols, D. and Krantz, D. S., 1986. *Behavior, health, and environment stress*. New York: Plenum.

Cohen, M. Jaffray, J. and Said, T., 1987. Experimental comparison of individual behavior under risk and under uncertainty for gains and for losses, *Organizational Behavior and Human Decision Processes,* 39, pp. 1-22.

Cohen, D. A., Dey, A., Lys, T. Z. and Sunder, S.V., 2007. Earnings announcement premia and the limits to arbitrage, *Journal of Accounting and Economics*, 43, pp. 153-180.

Condoyanni, L., O'Hanlon, J. and Ward, C. W. R., 1987. Day of the week effects on stock returns: international evidence. *Journal of Business Finance and Accounting*, 14(2), pp. 159-174.

Connolly, R. A., 1989. An examination of the robustness of the weekend effect. *The Journal of Financial and Quantitative Analysis*, 24(2), pp. 133-169.

Connolly, M., 2013. Some like in mild and not too wet: the influence of weather on subjective well-being. *Journal of Happiness Studies,* Vol. 14, pp. 457-473.

Coren, S., 1996. Daylight savings time and traffic accidents. *The New England Journal of Medicine,* 334, pp. 924-925.

Coulton, J. J. and Ruddock, C., 2010. Corporate payout policy in Australia and a test of the life-cycle theory. *Accounting and Finance*, 51, pp. 381-407.

Creswell, J. W.,1994. *Research design: qualitative and quantitative approaches*. Thousand Oaks. CA: Sage.

Creswell, J. W., 2003. *Research design: qualitative, quantitative, and mixed methods approaches* (2nd ed.). Thousand Oaks, CA: Sage.

Cross, F., 1973. The behavior of stock prices on Fridays and Mondays. *Financial Analysts Journal*, 29(6), pp. 67-69

Cunningham, M. R., 1979. Weather, mood and helping behaviour: quasi experiments with the sunshine samaritan. *Journal of Personality and Social Psychology*, 37(11), pp. 1947-1956.

Dalton, T., 1993. An empirical investigation of the relation between tax-loss selling and the January effect. *Journal of the American Taxation Association*, 15(2), pp. 26-39.

Damiel, K. D., Hirshleifer, D. and Subrahmanyam, A., 1998. Investor psychology and security market under- and over-reactions. *Journal of Finance*, 53, pp. 1839-1886.

Damodaran, A., 1989. The weedend effect in information releases: a study of earnings and dividend announcements. *Review of Financial Studies*, 2(4), pp. 607-623.

Dasilas, A., Lyroudi, K. and Ginoglou, D., 2008. Joint effects of interim dividends and earnings announcements in Greece. *Studies in Economics and Finance*, 25, pp. 212-232.

Dasilas, A. and Leventis, S., 2011. Stock market reaction to dividend announcements: evidence from the Greek Stock Market. *International Review of Economics and Finance*, 20(2), pp. 302-311.

DeAngelo, H., DeAngelo, L, and Stulz, R.M., 2006. Dividend policy and the earned/contributed capital mix: A test of the life-cycle theory. *Journal of Financial Economics*, 81, pp.227-254.

DeAngelo, H. and DeAngelo, L., Skinner, D., 1996. Reversal of fortune dividend signaling and the disappearance of sustained earnings growth. *Journal of Financial Economics*, 40, pp.341–371.

DeAngelo, H. and DeAngelo, L., Skinner, D., 2000. Special dividends and the evaluation of dividend signaling. *Journal of Financial Economics*, 57, pp.309–354.

DeAngelo, H. and DeAngelo, L., Skinner, D., 2004. Are dividends disappearing? Dividend concentration and the consolidation of earnings. *Journal of Financial Economics*, 72, pp. 425–456.

DeAngelo, H. and DeAngelo, L., 2006. The irrelevance of the MM dividend irrelevance theorem. *Journal of Financial Economics,* 79, pp.293–315.

DeAngelo, H. and Masulis, R.W., 1980. Optimal capital structure under corporate and personal taxation. *Journal of Financial Economics,* 8, pp. 3–29.

De Bondt, W. F. M. and Thaler, R., 1985. Does the stock market overreact?. *Journal of Finance,* 40, (3), pp. 793-805.

Denis, D. J., 1990. Defensive changes in corporate payout policy: share repurchases and special dividends. *The Journal of Finance,* 45(5), pp. 1433-1456.

Denis, D.J., Denis, D.K., and Sarin, A., 1994. The information content of dividend changes: cash flow signaling, overinvestment, dividend clienteles. *Journal of Financial and Quantitative Analysis,* 29, pp.567-587.

Denis, D. K. and McConnell J.J., 2003. International corporate governance, *Journal of Financial and Quantitative Analysis,* 38(1), pp. 1-36.

Denis, D.J. and Osobov, I., 2008. Why do firms pay dividends? International evidence on the determinants of dividend policy. *Journal of Financial Economics,* 89, pp.62-82.

Denissen, J. J. A., Butalid, L., Penke, L., Van Aken, M. A. G., 2008. The effects of weather on daily mood: a multilevel approach. *Emotion,* 8, pp. 662-667.

Desai, H. and Jain, P. C., 1997. Long-run common stock returns following stock splits and reverse splits. *Journal of Business,* 70, pp. 1-20.

Dichtl, H. and Drobetz, W., 2014. Are stock markets really so inefficient? The case of the "Halloween indicator", *Finance Research Letters,* 11, pp. 112-121.

Dichtl, H. and Drobetz, W., 2015. Sell in May and go away: still go advice for investors?. *International Review of Financial Analysis,* 38, pp. 29-43.

Dielman , T. E. and Oppenheimer, H. R., 1984. An examination of investor behavior during periods of large dividend changes. *Journal of Financial and Quantitative*

Analysis, 19, pp. 197-216.

Ding, D. K., Charoenwong. C. and Seetoh, R., 2004. Prospect theory, analyst forecasts, and stock returns. *Journal of Multinational Financial Management*, 14, pp.425-442.

Divecha, A. and Morse, D., 1983. Market Responses to Dividend Increases and Changes in Payout Ratios. *Journal of Financial and Quantitative Analysis,* 18(2), pp. 163-173.

Dolley, J. C., 1933. Characteristics and Procedure of common stock split-ups, *Harvard Business Review*, 11, pp. 316-326.

Dougal, C., Engelberg, J., Parsons, C. A. and Van Wesep, E. D., 2011. Anchoring and the cost of capital. *Working paper,* University of North Carolina. Available < http://public.kenan-flagler.unc.edu/faculty/engelbej/ANCHORING.pdf> . Access date [4th June 2015].

Dowling, M. and Lucey, B. M., 2005. Weather, biorhythms, beliefs and stock returns: some preliminary Irish evidence. *International Review of Financial Analysis*, 14(3), pp. 337-355.

Dowling, M. and Lucey, B. M., 2008. Mood and UK equity pricing. *Applied Financial Economics Letters*, 4(4), pp. 233-240.

Duliniec, A., 1998. *Struktura i koszt kapitału w przedsi¸ebiorstwie.* Warsaw: Wydawnictwo Naukowe pwn.

Duliniec, A., 2007. *Finansowanie przedsi¸ebiorstwa,* Warsaw: Polskie Wydawnictwo Ekonomiczne.

Dyl, E. A. and Weigand, R. A., 1998. The information content of dividend initiations: additional evidence. *Financial Management*, 27(3), pp. 27-35.

Dzhabarov, C. and Ziemba, W. T., (2010). Do seasonal anomalies still work?. *Journal of Portfolio Management*, 36(3), pp. 93-104.

Easterbrook, F.H., 1984. Two Agency-Cost Explanation of Dividends. *American Economic Review*, 74, pp. 650-659.

Easterby-Smith, M. , Thorpe, R. and Lowe, A., 2001. *Management research: an introduction*, London: Sage publications.Easterday, K. E. and Sen, P. K., 2016. Is the January effect rational? Insights from the accounting valuation model. *The Quarterly Review of Economics and Finance*, 59, pp. 168-185.

Easton, S., 1991. Earnings and dividends: is there an interaction effect?. *Journal of Business Finance and Accounting*, 18(2), pp. 255-266.

Edwards, E. O. and Bell, P. W., 1961. *The Theory and Measurement of Business Income*, Berkeley and Los Angeles, CA: University of California Press.

Eije, H. V. and Megginson, W. L., 2008. Dividends and share repurchases in the European Union, *Journal of Financial Economics*, 89(2), pp. 347-374.

Elgers, P.T. and Lo, M. H., 1994. Reductions in analysts' annual earnings forecast errors using information in prior earnings and security returns. *Journal of Accounting Research*, 32, pp. 290–303.

Ellsberg, D., 1961. Risk, ambiguity and the savage axioms. *Quarterly Journal of Economics*, 75, pp. 643-669.

Elton, E. J. and Gruber, M. J., 1970. Marginal stockholder tax rates and the clientele Effect. *The Review of Economics and Statistics*, 52(1), pp. 68-74.

Emory, C. W., 1980. "Business Research Methods", Richard D. Invin. Inc., USA.

Engsted, T. and Pedersen, T. Q., 2010. The dividend–price ratio does predict dividend growth: international evidence. *Journal of Empirical Finance*, 17, pp. 585–605.

Erasmus P. and Scheepers, R., 2008. The relationship between entrepreneurial intensity and shareholder value creation. *Managing Global Transitions*, 6(3), pp. 229–56.

Etzioni, A., 1988. Normative-affective factors: towards a new decision-making model. *Journal of Economic Psychology*, 9(2), pp. 125- 150.

Evans, G. W. and Cohen, S., 1987. Environmental stress. *In Handbook of Environmental Psychology*, Eds Stokols, D. and Altman, I. 571-609. New York, NY: Krieger.

Fama, E., 1970. Efficient capital markets: a review of theory and empirical work. *Journal of Finance*, 25, pp. 383-417.

Fama, E., 1981. Stock returns, real activity, inflation, and money. *The American Economic Review,* 71(4), pp. 545-565

Fama, E., 1991. Efficient capital markets II. *Journal of Finance*, 46(5), pp. 1575-1617.

Fama, E. and Babiak, H., 1968. Dividend policy: An empirical analysis. *Journal of the American Statistical Association*, 63(324), pp. 1132-1161.

Fama, F. E., Fisher, L., Jensen, C. M. and Roll, R., 1969. The Adjustment of stock prices to new information. *International Economic Review*, 10(1), pp. 1-21.

Fama, E. and MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81, pp. 607-636.

Fama, E. and Miller, M., 1972. *The Theory of Finance*. Hinsdale, IL:Dryden Press.

Fama, E. F. and French, K. R., 1988. Dividend yields and expected stock returns. *Journal of Financial Economics*, 22, pp. 3–25.

Fama, E. F. and French, K. R., 1992. The cross-section of expected stock returns. *Journal of Finance*, 47(2) , pp. 427–65.

Fama, E. F. and French, K. R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, pp. 3–56.

Fama, E. F. and French, K. R., 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance*, 51, pp. 55–84.

Fama, E. F. and French, K. R., 1998. Value versus growth: the international evidence. *Journal of Finance*, 53(6) , pp. 1975–99.

Fama, E. F. and French, K. R., 2001. Disappearing dividends: changing firm characteristics or lower propensity to pay?. *Journal of Financial Economics*, 60, pp. 3–43.

Fairfield, P.M., 1994. P/E, P/B and the present value of future dividends. *Financial Analysts Journal*, pp. 23-31.

Fellner, W., 1961. Distortion of subjective probabilities as a reaction of uncertainty. *Quarterly Journal of Economics*, 75, pp. 670-690.

Ferris, S. P., Sen, N. and Unlu, E., 2009. An international analysis of dividend payment behaviour. *Journal of Business Finance & Accounting*, 36(3-4), pp. 496–522.

Ferris, S. P., Noronha, G. and Unlu, E., 2010. The more, the merrier: an international analysis of the frequency of dividend payment. *Journal of Business Finance & Accounting*, 37(1-2), PP. 148–170.

Ferris, S. P., Sen, N. and Yui,H. P., 2006. God save the queen and her dividends: Corporate payouts in the UK. *Journal of Business*, 79, pp. 1149-1173.

Fiegenbaum, A. and Thomas, H., 1986. Dynamic and risk measurement. Perspectives on Bowman's risk-return paradox for strategic management: an empirical study. *Strategic Management Journal*, 7, pp. 395–407.

Fiegenbaum, A. and Thomas, H., 1988. Attitudes toward risk and the risk-return paradox: prospect theory explanations. *Academy of Management Journal*, 31, pp. 85–106.

Fiegenbaum, A., 1990. Prospect theory and the risk-return association: an empirical examination of 85 industries. *Journal of Economic Behavior and Organization*, 14, pp. 187–203.

Fishburn, P. C., 1977. Mean-risk analysis with risk associated with below target returns. *American Economic Review*, 67, pp. 116–126.

Fishburn, P. C. and Kochenberger, G. A., 1979. Two-piece Von Newmann-Morgenstern utility functions. *Decision Sciences*, 10, pp. 503–518.

Floros, C., 2008. Stock market returns and the temperature effect: new evidence from Europe. *Applied Financial Economics Letters*, 4, pp. 461-467.

Forgas, J. P. and Bower, G. H., 1987. Mood effects on person-perception judgments. *Journal of Personality and Social Psychology*, 53, pp. 53-60.

Fox, J., 2015. *Applied regression analysis and generalized linear models*. Sage Publications.

Franc-Dabrowska, J., 2007. *Value based management* – zarza˛dzanie przez warto´s´c, In: *Metody i techniki mened˙zerskie,* ed. M. Pietrzak, 57–79,Warsaw: Wydawnictwo sggw.

Franc-Dabrowska, J., 2009. Does dividend policy follow the capital structure theory?. *Managing Global Transitions*, 7 (4), pp. 367-382.

Francis, B. B., Hasan, I., Jone, K. and Liang, S., 2011. Corporate governance and dividend Payout policy: a test using Antitakeover legislation. *Financial Management*, pp. 83-112.

Frecka, T. J. and Lee, C. F., 1983. Generalized financial ratio adjustment processes and their implication. *Journal of Accounting Research*, 21, pp. 308–316.

Freeman, Robert N., Ohlson,J. A. and Penman, S. H., 1982. Book rate-of-return and prediction of earnings changes: An empirical investigation. *Journal of Accounting Research*, 20, pp. 639–653.

French, K. R., 1980. Stock returns and the weekend effect. *Journal of Financial Economics*, 8, pp. 55-69.

Fuchs, V. R., 1976. From bismark to woodcock: the “irrational” pursuit of national health insurance. *Journal of Law and Economics*, 19, pp347-359.

Fuller, K., 2003. The impact of informed trading on dividend signalling: a theoretical and empirical examination. Journal of Corporate Finance, 3, pp. 385-407.

Galai, D., Kedar-Levy, H. and Schreiber, B. Z., 2008. Seasonality in outliers of daily stock returns: A tail that wags the dog? *International Review of Financial Analysis*, 17, pp. 784-792.

Galanter, E. and Pliner, P., 1974. Cross-modality matching of money against other continua, *In: Sensation and Measurement*, ed. by H. R. Moskowitz et al. Dordrecht, Holland, pp. 65-76.

Garret, I. and Priestley, R., 2000. Dividend behaviour and dividend signalling. *Journal of Financial and Quantitative Analysis*, 35(2), pp.173-189.

Geske, R. and Roll, R., 1983. The fiscal and monetary linkage between stock returns and inflation. *The Journal of Finance,* 38(1), pp. 1-33.

Ghosh, C. and Woolridge, J. R., 1991. Dividend omission and stock market retionality. *Journal of Business, Finance and Accounting*, 18(3), pp. 315-330.

Goetzmann, W. N. and Jorion, P., 1993. Testing the predictive power of dividend yield. *The Journal of Finance*, 48(2), pp. 663-679.

Goetzmann, W. N. and Zhu, N., 2005. Rain or shine: where is the weather effect?. *European Financial Management*, 11(5), pp. 559-578.

Gonedes, N.J., 1978. Corporate signaling, external accounting, and capital market equilibrium: evidence on dividends, income, and extraordinary items. *Journal of Accounting Research,* 16, pp26–79.

Gombola, M. J. and Liu, F.Y., 1993. Considering dividend stability in the relation between dividend yields and stock returns. *Journal of Financial Research,* 16, pp. 139-50.

Gordon, M. J., 1963. Optimal investment and financing policy. *The Journal of Finance*, 18(2), pp. 264-272.

Gorman, L. R., Weigand, R. A. and Zwirlein, T. J., 2004. The information content of dividend resumptions. Studies in Economics and Finance, 22(2), pp. 70-99.

Graham, J. R., 1996. Debt and the marginal tax rate. *Journal of Financial Economics*, 41, pp. 41–73.

Graham, F. and Isaac, A.G., 2002. The behavioural life-cycle theory of consumer behaviour: Survey evidence. *Journal of Economic Behavior &organization*, 48, pp. 391-401.

Graham, J. R. and Tucker, A. L., 2006. Tax shelters and corporate debt policy, *Journal of Financial Economics*, 81, pp. 563–594.

Griffin, P. A., 1976. Competitive information in the stock market: an empirical study of earnings, dividends and analysis' forecasts. *The Journal of Finance*, 31(2), pp. 631-650.

Grinblatt, M., Masulis, R.W. and Titman, S., 1984. The valuation effects of stock splits and stock dividends. *Journal of Financial Economics*, 13, pp. 97-112.

Grossman, S.J. and Hart, O.D., 1980. Takeover bids, the free-rider problem, and the theory of the corporation. *Bell Journal of Economics*, 11, pp. 42–54.

Grullon, G., and Michaely, R., 2002. Dividends, share repurchases, and the substitution hypothesis. *The Journal of Finance*, 57, pp. 1649-1684.

Grullon, G., Michaely, R. and Swaminathan, B., 2002. Are dividend changes a sign of firm maturity?. *The Journal of Business*, 75, pp. 387-424.

Grullon, G. , Michaely, R. , Benartzi, S. and Thaler, R. H., 2005. Dividend changes do not signal changes in future profitability. *Journal of Business*, 78(5), pp. 1659-1682.

Gu, A. Y., 2003. The declining January effect: evidences from the US equity markets. *The quarterly Review of Economics and Finance*, 43(2), pp. 395-404.

Gunasekarage, A. and Power, M. D., 2002. The post-announcement of performance of dividend-changing companies: dividend signalling hypothesis revisited. *Accounting and Finance*, 42(2), pp. 131-151.

Gunasekarage, A. and Power, M. D., 2006. Anomalous evidence in dividend announcement effect. *Managerial Finance*, 32(3), pp. 209-226

Gurgul, H., Majdosz, P. and Mestel, R., 2003. GARCH modelling of Austrian stock market reactions on dividend announcements. *Dynamiczne Modele Ekonometryczne*, VIII, pp. 79-93.

Gwilym, O. A., Morgan, G. and Thomas, S., 2000. Dividend stability, dividend yield and stock returns: UK evidence. *Journal of Business Finance and Accounting*, 27 (3-4), pp. 261-281.

Hanley, W. K., 1993. Underpricing of initial public offering and the partial adjustment phenomenon. *Journal of Financial Economics*, 34, pp. 231-250.

Hanock, Y., 2002. Neither an angel nor an ant': emotion as an aid to bounded rationality. *Journal of Economic Psychology*, 23(1), pp. 1-25.

Hao, Q., Liuzzo, L. and Lu, E., 2013. The psychological impacts on the equity markets' reactions to earnings. *Pennsylvania Economic Review*, 20(2), pp. 80-97.

Haugen, R. A. and Senbet, L. W., 1978. The insignificance of bankruptcy costs to the theory of optimal capital structure. *Journal of Finance,* 33, pp. 383-393.

Haugen, R. A. and Senbet, L. W., 1986. Corporate finance and taxes: a review. *Finance Manage,* 15, pp. 5–21.

Hauser, R., 2013. Did dividend policy changes during the financial crisis? *Managerial Finance*, 39(6), pp. 584-606.

He, L. T. and He, S. C., 2011. Has the November effect replaced the January effect in stock markets?. *Managerial and Decision Economics*, 32(7), pp. 481-486.

Healy, P. M. and Palepu, K. G., 1988. Earnings information conveyed by dividend initiations and omissions. *Journal of Financial Economics*, 21, pp. 149–175.

Henkeer, J. and Debapriya, J. P., 2012. Retail investors exonerated: the case of the January effect. *Accounting and Finance*, 52(4), pp. 1083-1099.

Hensel, C. R. and Ziemba, W. T., 2000. Anticipation of the January small firm effect in the US futures markets. In D. B. Keim, and W. T. Ziemba (Eds). *Security market imperfections in world wide equity markets* (pp. 179-202). New York: Cambridge University Press.

Hershey, J. C. and Schoemaker, P. J. H., 1980. Prospect theory's reflection hypothesis: a critical examination. *Organizational Behavior and Human Performance,* 25, pp. 395-418.

Herbert J. R., 1983. *Applied Social Research*. Princeton: Merrill Publishing.

Hirshleifer, D. and Shumway, T., 2003. Good day sunshine: stock returns and the weather. *The Journal of Finance*, LVIII(3), pp. 1009- 1032.

Hjalmarsson, E., 2010. Predicting global stock returns. *Journal of Financial and Quantitative Analysis*, 45, pp. 49–80.

Ho, K. S. and Wu, C., 2001. The earnings information content of dividend initiations and omissions. *Journal of Business Finance and Accounting*, 28(7-8), pp. 963-977.

Ho, H., 2003. Dividend policies in Australia and Japan. *International Advances in Economic Research,* 9(2), pp. 91–100.

Holder, M.E., Langrehr, F.W. and Hexter. J.L., 1998. Dividend policy determinants: an investigation of the influences of stakeholder theory. *Financial Management*, 27(3), pp. 73–82.

Howarth, E. and Hoffman, M. S., 1984. A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology*, 75, pp. 15-23.

Howe, K. M., He, J., and Kao, G. W., 1992. One-time cash flow announcements and free cash flow theory: share repurchase and special dividends. *Journal of Finance*, 47, pp. 1963-1974.

Howe, S. J. and Lin, J., 1992. Dividend policy and the bid-ask spread: an empirical analysis. *The Journal of Financial Research*, 15(1), pp. 1-10.

Howatt, B., Zuber, R. A., Gandar, J. M. and Lamb, R. P., 2009. Dididends, earnings volatility and information. *Applied Financial Economics*, 19, pp. 5551-562.

Hobbs, J. and Schneller, M. I., 2012. Dividend signaling and sustainability. *Applied Financial Economics*, 22, pp. 1395-1408.

Holden, K., Thompson, J. and Ruangrit, Y., 2005. The Asian crisis and calendar effects on stock returns in Thailand. *European Journal of Operational Research*, 163, pp. 242-252.

Hsu, J., Wang, X. and Wn, C., 1998. The role of earnings information in corporate dividend decisions. *Management Science*, 44(12), pp.173-191.

Hu, A. and Kumar, P., 2004. Managerial Entrenchment and Payout Policy. *The Journal of Financial and Quantitative Analysis*, 39(4), pp. 759-790

Huang, S.G. and Song, F.M., 2006. The determinants of capital structure: Evidence from China. *China Economic Review*, 17, pp. 14–36.

Hughes, J. P., 2008. R & D and dividend payments as determinants of corporate value in the UK: empirical evidence after controlling for endogeneity. *International Journal of Managerial Finance*, 4(1), pp. 76-91.

Hung, M. and Wang. J., 2005. Asset prices under prospect theory and habit formation. *Review of Pacific Basin Financial Markets and Policie*, 8(1), pp.1-29.

Isen, A.M., 1993. Positive affect and decision making. *Handbook of Emotion*, 1, pp. 261-277.

Ishikawa, H., 2011. Empirical analysis on the dividend life-cycle theory: evidence from Japan. *The Japanese Accounting Review*, 1, pp. 40-60.

Jacobsen, B, and Zhang, C., 2010. Are monthly seasonal real? A three century perspective. *Working Paper*, Massey University. Available < http://www-stat.wharton.upenn.edu/~steele/Courses/434/434Context/Calendar%20Effects/SellInMayGoAway.pdf> . Access date [10th June 2014]

Jacobsen, B. and Visaltanachoti, N., 2009. The Halloween effect in US sectors, *Financial Review*, 44, pp. 437-459.

Jaffe, J. and Westerfield, R., 1985. The week-end effect in common stock returns: the international evidence. *The Journal of Finance*, XL(2), pp. 433-454.

Jagadeesh, N. and Titman, S., 1999. Profitability of momentum strategies: an evaluation of alternative explanations. *Working Paper*. National Bureau of Economic Research. Available< http://www.nber.org/papers/w7159.pdf>. Access date [10th January 2018].

Jain, V., 2012. An inside into behavioural finance models, efficient market hypothesis and its anomalies. *Journal of Arts, Science & Commerce*, 3 (3(1)), pp. 16-25.

Jegers, M., 1991. Prospect theory and the risk-return relation: some Belgian evidence, *Academy of Management Journal*, 34, pp. 215–225.

Jensen, M. and Meckling, W., 1976. Theory of the firm: managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3, pp. 305–360.

Jensen, M., 1986. Agency costs of free cash flow, corporate finance and takeovers. *The American Economic Review*, 76, pp. 323–329.

Jensen, G. R., Solberg, D. P. and Zorn, T. S., 1992. Simultaneous determination of insider ownership, debt, and dividend policies. *Journal of Financial and Quantitative Analysis*, 27(2), pp. 247−263.

Jiraporn, P., Kim, Y.S. Davidson, W.N. and Singh, M., 2006. Corporate governance, shareholder rights and firm diversification: An empirical analysis. *Journal of Banking and Finance*,.30, pp. 947–963.

Jiraporn, P. and Ning, Y., 2006, Dividend policy, shareholder rights, and corporate governance. *Journal of Applied Finance*, 16(2), pp. 24-36.

Jirporn, P., Kim, J. and Kim, Y., 2011. Dividend payouts and corporate governance quality: an empirical investigation. *The Financial Review*, 46, pp. 251-279.

Jo, H. and Kim, D. M., 2008. Recent development of behavioural finance. *International Journal of Business Research*, 8(2), pp. 89-101.

Jo, H. and Pan, C., 2009. Why are firms with entrenched managers more likely to pay dividends?. *Review of Accounting and Finance* 8, 87–116.

John, K. and Knyazeva, A., 2006. Payout policy, agency conflicts, and corporate governance. *Working Paper*, New York University. Available < https://poseidon01.ssrn.com/delivery.php?ID=475067021089026023012023027023124005125033039077095007109008097022025029089068089027011106020047055036105017069119025068064009094053092033071087005074096013097090073010118006092027003085065101005122089003006120006092119064029088097011106091122084&EXT=pdf> . Access date [12th June 2014].

John, K. and Williams, J., 1985. Dividend, dilution, and taxes: a signalling equilibrium. *Journal of Finance,* 40, pp. 1053-1070.

Johnson, H. J., 1994, Prospect theory in the commercial banking industry, *Journal of Financial and Strategic Decisions*, 7, pp. 73–89.

Julio, B. and Ikenberry, D. L., 2004. Reappearing dividends. *Journal of Applied Corporate Finance,* 16, pp. 89-100.

Kachelmeier, S. J. and Shehata, M., 1992. Examining risk preference under high monetary incentives: experimental evidence from the People's Republic of China. *The American Economic Review*. 82(5), pp. 1120-1141.

Kahneman, D. and Tversky, A., 1979. Prospect theory: an analysis of decision under risk. *Econometrica,* 47, pp.263-291.

Kalay, A. and Loewensrein, U., 1985. Predictable events and excess returns: The case of dividend announcements. *Journal of Financial Economics*, 14, pp.423–449.

Kale, J. R. and Neo, T. H., 1990. Dividend, uncertainty, and underwriting costs under asymmetric information. *Journal of Finance*, 39, pp. 265-277.

Kamara, A., 1997. New evidence on the Monday seasonal in stock returns. *The Journal of Business*, 70(1), pp. 63-84.

Kamstra, M. J., Kramer, L. A. and Levi, M. D., 2003. Winter blues: a sad stock market cycle. *American Economic Review*, 93(1), pp. 324-343.

Kane, A., Lee, Y. and Marcus, A., 1984. Earnings and dividend announcements: Is there a corroboration effect?. *Journal of Finance,* 39, pp. 1091–1099.

Kato, K. and Schallheim, J. S., 1985. Seasonal and size anomalies in the Japanese stock market. *The Journal of Financial and Quantitative Analysis*, 20(2), pp. 243-260.

Kato, K. and Loewentein, U., 1995. The ex-dividend-day bahevior of stock prices: the case of Japan. *The Review of Financial Studies*, 8(3), pp. 817-847.

Kaul, G., 1987. Stock returns and inflation, the role of the monetary sector. *Journal of Financial Economics,* 18, pp. 253-276.

Keef, S. P. and Roush, M. L., 2002. The weather and stock returns in New Zealand. *Quarterly Journal of Business and Economics*, 41, pp. 61-79.

Keef, S. P. and Roush, M. L., 2005. The influence of weather on New Zealand financial securities. *Accounting and Finance,* 45, pp. 415-437.

Keef, S. P. and Roush, M. L., 2007. Daily weather effects on the returns of Australian stock indices. *Applied Financial Economics,* 17, pp. 173-184.

Keim, D. B., 1983. Size- related anomalies and stock returns seasonality: further empirical evidence. *Journal of Financial Economics,* 12, pp. 13-32.

Keim, D. B. and Stambaugh, R. F., 1984. A further investigation of the weekend effect in stock returns. *Journal of Finance*, 39, pp. 819-835.

Keim, D. B., 1985. Dividend yields and stock returns: implications of abnormal January returns. *Journal of Financial Economics,* 14, pp. 473–89.

Keim, D. B., 1986, Dividend yields and the January *Effect. Journal of Portfolio Management,* 12, pp. 54-60.

Keller, M., Fredricson, B., Ybarra, O., Cote, S., Johnson, K., Mikels, J., Conway, A., and Wager, T., 2005. A warm heart and a clear head: the contingent effect of weather on mood and cognition. *Psychological Science*, 16, pp. 724-731.

Kelly. F., 1930. *Why you win or lose: psychology of speculation*. Boston: Houghton Mifflin.

Khang, K. and King, T. D., 2006. Does dividend policy relate to cross-sectional variation in information asymmetry? Evidence from returns to insider trades. *Financial Management*, 35(4), pp. 71-94.

Kliger, D. and Tsur, I., 2011. Prospect theory and risk-seeking behaviour by troubled firms. *The Journal of Behavioural Finance*, 12, pp. 29-40.

Klimstra, T. A., Frijns, T., Keijsers, L., Denissen, J. J. A., Raaijmakers, Q. A. W., Van Aken, M. A. G., Koot, H. M., Van Lier, P. A. C. and Meeus, W. H. J., 2011. Come rain or come shine: individual differences in how weather affects mood. *Emotion*, 11, pp. 1495-1501.

Klock, S. A. and Bacon, F. W., 2014. The January effect: a test of market efficiency. Journal of Business Behavioral Sciences, 26(3), pp. 32-42.

Knetsch, J. and. Sinden, J. A., 1984. Willingness to pay and compensation demanded: experimental evidence of an unexpected disparity in measures of value. *Quarterly Journal of Economics*, 99, pp. 507–521.

Knight, F. H., 1921. *Risk, Uncertainty, and Profit*. New York: Hart, Schaffner, and Mary.

Kohers, T, and Kohli, R. K., 1991. The anomalous stock market behaviour of large firms in January: the evidence from the S & P composite and component indexes. Quarterly Journal of Business and Economics, 30(3), pp. 14-32.

Kőszegi, B. and Rabin, M., 2006. A model of reference-dependent preferences. *Quarterly Journal of Economics*, 121, pp. 1133–1165.

Kőszegi, B. and Rabin, M., 2007. Reference-dependent risk attitudes. *American Economic Review*, 97, pp. 1047–1073.

Kooli, M. and L'Her, J.F., 2010. Dividend versus share repurchases evidence from Canada: 1985–2003. *The Financial Review,* 45, pp. 1–57.

Kormendi, R. and Zarowin, P., 1996. Dividend policy and permanence of earnings. *Review of Accounting Studies*, 1, pp 141-160.

Kosedag, A. and Qian, J., 2009. Do dividend clienteles explain price reactions to dividend changes?. *The International Journal of Business and Finance Research*, 3(1), pp. 47-57.

Kramer, W. and Runde, R., 1997. Stocks and the weather: an exercise in data mining or yet another capital market anomaly?. *Empirical Economics*, 22, pp. 637-641.

Krivin, D., Patton, R., Rose, E. and Tabak, D., 2003. Determination of the appropriate event window length in individual stock event studies. *NERA Economic Consulting*, *Working paper series*. Available < https://poseidon01.ssrn.com/delivery.php?ID=491127091069065002027090099079023026018022003031066092066125097089088081110017123052019111027093120100111066071025039088051028127023103007083071119117118127066015040031027099097091015121070111113085002123028094071110007119100087127028071068100&EXT=pdf> . Access data [15th June 2016].

Kumar, P. and Lee, B., 2001. Discrete dividend policy with permanent earnings. *Financial Management,* 30, pp. 55-76.

Kumar, S., 2017. New evidence on stock market reaction to dividend announcements in India. *Research in International Business and Finance*, 39, pp. 327-337.

Kunkel, R., Compto, W. S. and Beyer, S., 2003. The turn-of-the-month effect still lives, *International Review of Financial Analysis*, 12, pp. 207-221.

Lakonishok, J. and Smidt, S., 1988. Are seasonal anomalies real? A ninety-year perspective. *Review of Financial Studies,* 1, pp. 403- 425.

Lamont, O., 1998. Earnings and expected returns. *Journal of Finance*, 53(5), pp. 1563–87.

Lang, L. and Litzenberger, R., 1989. Dividend announcements: Cash-flow signaling vs. free cash flow hypothesis?. *Journal of Financial Economics,* 24, pp.181–191.

Lanne, M., 2002. Testing the predictability of stock returns. *Review of Economics and Statistics*, 84, pp. 407–415.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A. and Vishny., 1997. Legal determinants of external capital. *Journal of Finance,* 52, pp.1131-1150.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A. and Vishny., 2000. Agency problems and dividend policies around the world. *Journal of Finance*, 55, pp.1-33.

Laughhunn, D. J., Payne, J. W. and Crum, R., 1980. Managerial risk references for below-target returns. *Management Science,* 26, pp. 1238–1249.

Lean, H. H., 2011. The Halloween puzzle in selected Asian stock markets, *International Journal of Economics and Management*, 5(1), pp. 216-225.

Lee, C. F., Wu, C. and Djarraya, M., 1987. A further empirical investigation of the dividend adjustment process. *Econometrics*, 35, pp. 267-285.

Lee, K. F., 2010. An empirical study of dividend payout and future earnings in Singapore. *Review of Pacific Basin Financial Markets and Policies*, 13(2), pp. 267-286.

Lee, S., Isa, M. and Lim, W., 2012. Dividend changes and Future profitability: Evidence from Malaysia. *Asian Academy of Management Journal of Accounting and Finance*, 8(2), pp. 93-110.

Leger, D., 1994. The cost of sleep-related accidents: a report for the national commission on sleep disorders research. *Sleep*, 17(1), pp. 84-93.

Lehner, J. M., 2000. Shifts of reference points for framing of strategic decisions and changing risk-return associations. *Management Science*, 46, pp. 63–76.

Lepori, G. M., 2016. Air pollution and stock returns: evidence from a natural experiment. *Journal of Empirical Finance*, 35, pp. 25-42.

Lev, B., 1969. Industry averages as targets for financial ratios. *Journal of Accounting Research*, 7, pp. 290–299.

Levis, M., 1985. “ Are small firms big performers?”. Investment Analyst, 76, pp.21-27.

Levis, M., 1989. ‘Stock market anomalies – A re-assessment based on the UK evidence’. *Journal of Banking and Finance*, 13, pp. 675–96.

Levy, T. and Yagil, J., 2011. Air pollution and stock returns in the US. *Journal of Economic Psychology*, 32, pp. 374-383.

Levy, T. and Yagil, J., 2013. Air pollution and stock returns-extensions and international perspective. *International Journal of Engineering, Business and Enterprise Applications*, 4, pp. 1-14.

Li, K. and Zhao, X., 2008. Asymmetric information and dividend policy. Financial Management, 37(4), pp. 673-694.

Li, Q. and Peng, C. H., 2016. The stock market effect of air pollution: evidence from China. *Applied Economics*, 48(36), pp. 3442-3461.

Li, W. and Lie, E., 2006. Dividend changes and catering incentives. *Journal of Financial Economics*, 80, pp. 293-308.

Lichtenstein, S. and Slovic, P., 1971. Reversal of preference between bids and choices in gambling decisions. *Journal of Experimental Psychology*, 89. Pp. 46-55.

Lie, E., 2000. Excess funds and agency problems: an empirical study of incremental cash disbursements. *Review of Financial Studies,* 13(1), pp. 219-248.

Liu, L., 2013. The turn-of-the-month effect in the S & P 500 (2001-2011). *Journal of Business and Economics Research*, 11(6), pp. 269-275.

Liu, Y., Szewczyk, S. and Zantout, Z., 2008. Underreaction to dividend reductions and omission?. *Journal of Finance*, 63(2), pp. 987-1020.

Lintner, J., 1956. Distribution of incomes of corporations among dividends, retained earnings, and taxes. *American Economic Review,* 46, pp.97-113,

Lintner, J., 1962. Dividends, earnings, leverage, stock prices and the supply of capital to corporations. *The Review of Economics and Statistics*, 44(3), pp. 243-269.

Litzenberger, R. H. and Ramaswamy, K., 1979, The effect of personal taxes and dividends on capital asset prices: theory and empirical evidence. *Journal of Financial Economics*, 7, pp. 163–95.

Litzenberger, R.H. and Ramaswamy, K., 1982, The effects of dividends on common stock prices: tax effects or information effects. *Journal of Finance*, 37(2), pp. 429–43.

Ljunqvist, A. and Wilhelm, W., 2005. Does prospect theory explain IPO market behaviour?. *Journal of Finance*, 60(4), pp. 1759-1790.

Lo, A. W. and MacKinly, c., 1990. When are contrarian profits due to stock market overreaction. The Review of Financial Studies, 3(2), pp. 175-205.

Loewenstein, G., Weber, E., Hsee, C. and Welch, N., 2001. Risk as feelings. *Psychological Bulletin*, 127(2), pp. 267-286.

Lonie, A. A., Abeyratna, G., Power, D. M. and Sinclair, C. D., 1996. The stock market reaction to dividend announcements: A UK study of complex market signals. *Journal of Economic Studies*, 23(1), pp. 32-52

Loomes, G., Starmer, C. and Sugde, R., 1991. Observing violations of transitivity by experimental methods. *Econometrica*, 59, pp. 425–439.

Loughran, T. and Ritter, J., 1995. The new issues puzzle. *Journal of Finance*, 50, pp. 23-52.

Lu, J. and Chou, R. K., 2012. Does the weather have impacts on returns and trading activities in order-driven stock market? Evidence from China. *Journal of Empirical Finance*, 19, pp. 79-93.

Lu, C., Chin C. and Chang Y., 2012. Weather effects on earnings response coefficients: international evidence. *Asia-Pacific Journal of Accounting and Economics*, 20(3), pp. 315-333.

Lubatkin, M., 1987. Merger strategies and stockholder value, *Strategic Management*, 8(1), pp. 39-53.

Lubatkin, M. and Shrieves, R. E., 1986. Towards reconciliations of market performance measures to strategic management research, *The Academy of Management Review*, 11(3), pp. 497-512.

Lucey, B. M. and Zhao, S., 2008. Halloween or January? Yet another puzzle, International Review of Financial Analysis, 17, pp. 1055-1069.

Maberly, E. D., 1995. Eureka! Eureka! Discovery of the Monday effect belongs to the ancient scribes. *Financial Analysis Journal*, 51, Issue: 5, pp. 10-11.

Maberly, R. M. and Pierce, R. M., 2004. Stock market efficiency withstands another challenge: solving the “Sell in May/ Buy after Halloween” puzzle. *Econ Journal Watch*, 1(1), pp. 29-46.

Maberly, E. D. and Pierce, R. M., 2005. The Halloween effect and Japanese equity prices: myth or exploitable anomaly. *Asia-Pacific Financial Markets*, 10, pp. 319-334.

Maurice, A., 1953. Le comportement de Fhomme rationel devant le risque, critique des postulates et axiomes de l'ecole americaine. *Econometrica*, 21, pp.503-546.

Markowitz, H., 1959. The Utility if Wealth, portfolio selection, New York: Wiley.

Mazur, K., 2007. The determinants of capital structure choice: evidence from Polish companies. *International Advances in Economic Research*, 13(4), pp. 495–514.

McConnell, J. J. and Xu, W., 2008. Equity returns at the turn of the month. *Financial Analysts Journal*, 64(2), pp. 49- 64.

McManus, I., Gwilym, O. A. and Thomas, S., 2004. The roe of payout ratio in the relationship between stock returns and dividend yield. *Journal of Business Finance and Accounting*, 31(9-10), pp. 1355-1387.

McManus, I., Gwilym, O. A. and Thomas, S., 2006. Payment history, past returns and the performance of UK zero dividend stocks. *Managerial Finance,* 32(6), pp. 518–36.

McMillan, D. G. and Wohar, M. E., 2013. A panel analysis of the stock return-dividend yield relation: Predicting returns and dividend growth. *The Manchester School*, 81(3), pp. 386-400.

Mehdian, S. and Perry, M. J., 2001. The reversal of the Monday effect: New evidence from US equity markets. *Journal of Business Finance and Accounting*, 28(7/8), pp. 1043-1065.

Mehrani, S., Moradi, M. and Eskandar, H., 2011. Ownership structure and dividend policy: Evidence from Iran. *African Journal of Business Management*. 5(17), pp. 7516-7525.

Michaely, R., Thaler, R. H. and Womack, K.L., 1995. Price reactions to dividend initiations and omissions: overreaction or drift?. *Journal of Finance*, 50, pp. 573-608.

Michaely, R. and Roberts, M., 2006. Dividend smoothing, agency costs, and information asymmetry: lessons from the dividend policies of private firms. *Working paper*, Cornell University.

Miller, M., 1977. Debt and taxes: presidential address of annual meeting of American finance association. *Journal of Finance,* 32, pp. 261–297.

Miller, K. and Bromiley, P., 1990. “Strategic risk and corporate performance: an analysis of alternative risk measures”. *Academy of Management Journal,* 33, pp. 756–779.

Miller, M., and Modigliani, F., 1961. Dividend policy, growth, and the valuation of shares. *Journal of Business,* 34, pp. 411-433,

Miller, M. and Modigliani, F., 1966. Some estimates of the cost of capital to the electric utility industry. *American Economic Review,* 56 (3), pp. 333–391.

Miller, M. and Scholes, M., 1982. Dividends and taxes: some empirical evidence. *Journal of Political Economy*, 90(6), pp. 1118–41.

Miller, M. and K. Rock., 1985. Dividend policy under asymmetric information. *Journal of Finance*, 40, pp. 1031–52.

Mitton, T., 2004. Corporate governance and dividend policy in emerging markets. *Emerging Markets Review*, 5, pp. 409-426.

Modigliani, F. and Miller, M., 1958. The cost of capital corporation finance and the theory of investment. *American Economic review,* 48*(*3), pp. 261-97.

Modigliani, F. and Miller, M., 1961. Dividend policy, growth and the valuation of shares. *The Journal of Business,* 34(4), pp. 411–33.

Modigliani, F. and Miller, M., 1963. Corporate income taxes and the cost of capital: A correction. *American Economic Review,* 53(3), pp. 433–43.

Modigliani, F. and Cohn, R., 1979. Inflation, rational valuation and the market. *Financial Analysts Journal*, pp. 24-44.

Mondher, K., 2011. A re-examination of the MM capital structure irrelevance theorem: A partial payout approach. *International Journal of Business and Management*, 6(10), pp. 193-204.

Morgan, G. and S.H. Thomas., 1998. ‘Taxes, dividend yields and returns in the UK equity market’. *Journal of Banking and Finance*, 22(40), pp. 405–23.

Mullainathan, S. and Thaler, R. H., 2000. Behavioral economics. *Working Paper,* National Bureau of Economic Research: 7948.

Mueller, D. C., 1972. A life cycle theory of the firm. *Journal of Industrial Economics,* 20(3), pp. 199–219.

Muradoglu, G. and Harvey, N., 2012. Behavioural finance: the role of psychological factors in financial decisions. *Review of Behavioural Finance,* 4(2), pp.68-80.

Myers, S., 1984. The capital structure puzzle. *Journal of Finance,* 39(3), pp. 575–92.

Myers, S. and Majluf, N., 1984. Corporate investment and financing policies when firms have information that investors do not have. *Journal of Financial Economics,* 13, pp. 187–222.

Myers, S.C., 2000. Outside equity. *Journal of Finance,* 55, pp. 1005–1037.

Nguyen, k. H., 2014. Impact of a dividend initiation wave on shareholder wealth. *Applied Financial Economics*, 24(8), pp. 573-586.

Nicholas, N. and Thaler, R. H., 2003. A survey of behavioral finance. *Handbook of the Economics of Finance*, 1052-1121.

Nielsen, A.E.B., 2006. Corporate governance, leverage, and dividend policy. *Working paper*, Princeton University.

Nissim, D. and Ziv, A., 2001. Dividend changes and future profitability. *The Journal of Finance*, 56(6), pp.2111-2133 .

Nowakowicz-Debek, B. , Saba, L. and Bis-Wencel, H., 2004. The effects of air pollutants on the cortisol and progesterone secretion in polar fox (Alopex Lagopus). *Scientifur*, 28, pp. 218-221.

O'Connor, T., 2013. Dividend payout, corporate governance, and the enforcement of creditor rights in the emerging markets. *Journal of Corporate Governance*, 12(1), pp. 7-34.

Ofer, A. R. and Thakor, A. V., 1987. A theory of stock price responses to alternative corporate cash disbursement methods: stock repurchase and dividends. *The Journal of Finance*, 42(2), pp. 365-394.

Officer, M.S., 2007. Dividend policy, dividend initiations, and governance. *Working paper,* University of Southern California. Available < http://media.terry.uga.edu/documents/finance/officer.pdf> . Access date [16th June 2014].

O' Higgins, M. and Downes, J., 1990. *Beating the Dow, a high-return-low-risk method for investing n industrial stocks with a little as $5000*. Harper Collins: New York.

Owers, J. E. and Ince, U., 2012. The interaction of corporate dividend policy and capital structure decisions under differential tax regimes. *Journal of Economics and Finance*, 36, pp. 33-57.

Page, L., Hajat, S., and Kovats, R., 20007. Relationship between daily suicide counts and temperature in England and Wales. *The British Journal of Psychiatry*, 191, pp. 106-112.

Pan, R., Tang, X., Tan, Y. and Zhu, Q., 2014. The Chinese stock dividend puzzle. *Emerging Markets Finance and Trade*, 50(3), pp. 178-195.

Park, C., 2010. When does the dividend–price ratio predict stock returns?. *Journal of Empirical Finance*, 17, pp. 81–101.

Park, H. and Sohn, W., 2013. Behavioural finance: a survey of the literature and recent development. *Seoul Journal of Business*, 19 , number 1.

Paul, A. and Mullins, D. W. Jr., 1983. The impact of initiating dividend payments on shareholders' wealth. *Journal of Business,* 56, pp. 77–96.

Penman, S., 1983. The predictive content of earnings forecasts and dividends. *Journal of Finance*, 38, pp. 1181–1199.

Petersen, W., 1937. The patient and the weather. *American Journal of Medical science*, 193, pp. 115.

Petersen, M. A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, *22*(1), 435-480.

Petit, R. R., 1972. Dividend announcements, security performance, and capital market efficiency. *Journal of Finance*, 27, pp. 993–1007.

Phua, V., Chan, H., Faff, R. and Hudson, R., 2010. The influence of time, seasonality and market state on momentum: insights from the Australian stock market. *Applied Financial Economics*, 20(20), pp. 1547-1563.

Pilotte, E. A., 2003. Capital gains, dividend yields, and expected inflation. *Journal of Finance*, 58(1), pp. 447-466.

Pompian, M. M., 2012. *Behavioural Finance and Wealth Management*, New Jersey: John Wiley & sons, Inc.

Poterba, J. M. and Summers, L. H., 1984. New evidence that taxes affect the valuation of dividends. *The Journal of Finance,* 39(5), pp. 1397–415.

Quan, V. D. H., 2002. A rational justification of the pecking order hypothesis to the choice of sources of financing. *Management Research News*, 25(12), pp. 74–90.

Quiggin, J., 1982. A theory of anticipated utility. *Journal of Economic Behavior and Organization*, 3, pp. 323-343.

Rabin, M., 2002. Inference by believers in the law of small numbers. *Quarterly Journal of Economics*,117, pp. 775-816.

Ramalingegowda, S., Wang, C. and Yu, Y., 2013. The role of financial reporting quality in mitigating the constraining effect of dividend policy on investment decisions. *The Accounting Review*, 88(3), pp. 1007-1039.

Razek, Y. H. A., 2011. An overview of behavioral finance and revisiting the behavioural life cycle hypothesis. *Journal of Behavioural Finance,* Vlll(3), pp. 7-24.

Reinganum, M. R., 1983. The anomalous stock market behaviour of small firms in January: empirical test for tax-loss selling effects. *Journal of Financial Economics*, 12(1), pp. 89-104.

Remenyi, D., Williams, B., Money, A., and Swartz, E.,1998. Doing Research in Business and Management, London: Sage Publications.

Renneboog, L. and Szilagyi, P., 2006. How relevant is dividend policy under low shareholder protection?. *Working paper*, Tilburg University.

Ricciardi, V. and Simon, H. K., 2000. What is behavioral finance?. *The Business, Education and Technology Journal*, 2, pp. 26-34.

Ritter, J., 2002, Behavioural finance. *Science Direct-Pacific Basin Finance Journal*, pp. 2-12.

Ritter, J. and Warr, R., 2002. The decline of inflation and the bull market of 1982-1999. *Journal of Financial and Quantitative Analysis*, 37, pp. 29-61.

Rogalski, R. J., 1984. New finds regards day-of-the-week returns over trading and non-trading periods: a note. *The Journal of Finance*, 39, pp. 1603- 1614.

Roll, R. W., 1983. Vas ist das? The turn-of-the-year effect and the risk premia of small firms. *Journal of Financial Economics*, 3, pp. 18-28.

Roll, R. W., 1992. Weather. In: Malkiel, B., Newman, P., Milgrate, M., Eatwell, J. (Eds). *New Palgrave Dictionary of Money and Finance*. London: Macmillan.

Romer, P. M., 2000. Thinking and feeling. *American Economic Review*, 90(2), pp. 439-443.

Rosenthal, N., 1998. *Winter blues: seasonal affective disorder: what it is and how to overcome it*. The New York : Guilford Press.

Rosenblitt, J. C., Soler, H., Johnson, S. E. and Quadagno, D. M., 2001. Sensation seeking and hormones in men and women: exploring the link. *Hormones and Behavior,* 40, pp. 396-402.

Ross, S. A., Westerfield, R. W. and Jordan, B. D., 2006. *Fundamentals of corporate finance,* Sydney: Irwin McGraw-Hill.

Rozeff, M., 1982. ‘Growth, beta and agency costs as determinants of dividend payout ratios’. *Journal of Financial Research*, 5, pp. 249–59.

Rozeff, M. S. and Kinney, W. R., 1976. Capital market seasonality: the case of stock returns. *Journal of Financial Economics*, 3(4), pp. 379-402.

Saunders, E. M., 1993. Stock price and Wall Street weather. *American Economic Review,* 83(5), pp. 1337-1345.

Sagar, A., Bhattacharya, M., and Joon, V., 2007. A comparative study of air pollution-related morbidity among exposed population of Delhi. *Indian Journal of community Medicine*, 32(4), pp. 268-273.

Savage, L. J., 1954. *The Foundations of Statistics*, New York: Wiley.

Sawicki, J., 2009, Corporate governance and dividend policy in southeast Asia pre- and post-crisis. *European Journal of Finance*, 15(2), pp. 211-230.

Schiffman, S. S., Miller, E. A. S., Suggs, M. S. and Graham, B. G., 1995. The effect of environmental orders emanating from commercial swine operations on the mood of nearby residents. *Brain Research Bulletin*, 37, pp. 369-375.

Schmidt, U. and Hey, J. D., 2004. Are preference reversals errors? An experimental investigation. *Journal of Risk and Uncertainty*, 29, pp. 207–218.

Schmidt, U., Starmer, C. and Sugden R., 2008. Third- generation prospect theory. *Journal of Risk and Uncertainty*, 36, pp. 203-223.

Schmeidler, D., 1989. Subjective probability and expected utility without additivity. *Econometrica,* 57, pp. 571-587.

Scholz, J.K., 1992. A direct examination of the dividend clientele hypothesis. *Journal of Public Economics*, 49, pp. 261–85.

Schumpeter, J. A., 1934. *The Theory of Economic Development*. Cambridge, MA: Harvard University Press.

Schwarz, N., 1990. Feeling as information: informational and motivational functions of affective states. In E. T. Higgins (Ed.), *Handbook of Motivation and Cognition*, pp. 527-561, New York: Guildford Press.

Schwarz, N. and Clore, G., 1983. Mood, misattribution, and judgements of well-being: informative and directive functions of affective states. *Journal of Personal Social Psychology,* 45, pp. 513-523.

Shafir, E., Diamond, P. and Tversky, A., 1997. Money illusion. *Quarterly Journal of Economics*, 112, pp. 341-374.

Shao, L., Kwok, C. and Guedhami, O., 2009, Dividend policy: balancing interests between shareholders and creditors. *Working Paper,* Moore School of Business, University of South California.

Sharma, S. S. and Narayan, P. K., 2014. New evidence on turn-of-the-month effects. *Journal of International Financial Markets, Institutions and Money*, 29, pp. 92-108.

Shefrin, H., 2000. *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*, Boston, Massachusetts: Harvard Business School Press.

Shefrin, H., 2009. How Psychological Pitfalls Generated the Global Financial Crisis, In: L. Siegel (ed.): *Understanding the Global Financial Crisis.*

Shefrin, H. M. and Stateman, M., 1984. Explaining investor preference for cash dividends. *Journal of Financial Economis,* 13, 253-282.

Shefrin, H. M. and Thaler, R. H., 1988. The behaviour life-cycle hypothesis. *Economic Inquiry*, pp. 609-643.

Shiller, R. J. and Summers, L., 1990. The noise trader approach to finance. *Journal of Economics*, 4, pp. 19-33.

Shiller, R. J., 2001. Bubbles, Human Judgment, and Expert Opinion. *Cowles Foundation for Research in Economics. Discussion Paper No.* 1303.

Shon, J.J. and Zhou, P., 2009. Are earnings surprises interpreted more optimistically on very sunny days? Behavioral bias in interpreting accounting information. *Journal of Accounting, Auditing & Finance*, 24(2), pp. 211-232.

Shu, H. and Hung, M., 2009. Effect of wind on stock market returns: evidence from European markets. *Applied Financial Economics*, 19, pp. 893-904.

Sierpin´ska, M., 1999. *Polityka dywidend w spółkach kapitałowych,* Warsaw and Krakow:Wydawnictwo Naukowe pwn.

Sikes , S. A., 2014. The turn-of-the-year effect and tax-loss-selling by institutional investors. *Journal of Accounting and Finance*, 57(1), pp. 22-42.

Simonsohu, U., 2007. Clouds make nerds look good: field evidence of the impact of incidental factors on decision making. *Journal of Behavioral Decision Making*, 20(2), pp. 143-152.

Sinha, T., 1994. Prospect theory and the risk Return association: another look. *Journal of Economic Behavior and Organization*, 24, pp. 225–231.

Slovic, P., Griffin, D. and Tversky, A., 1990. Compatibility Effects in Judgment and Choice, In Robin Hogarth (ed), *Insights in Decision-Making*, Chicago: University of Chicago Press.

Smith, E. L., 1939. *Tides in the affairs of men*, New York : Macmillan.

Smith, V. L. and Walker, J. M., 1992. Monetary Rewards and Decision Cost in Experimental Economics, Unpublished manuscript, Economic Science Lab, University of Arizona.

Spetzler, C. S.,1968. The development of corporate risk policy for capital investment decisions. *IEEE Transactions on systems Science and Cybernetics*, SSC-4, pp. 279-300.

Spiess, D.K. and Affleck-Graves, J., 1995. Underperformance in long-run stock returns following seasoned equity offerings. *Journal of Financial Economics*, 38, pp. 243-68.

Statman, M. and Sepe, J. F., 1989. Project termination announcements and the market value of the firm. *Financial Management*, 18, pp. 74-81.

Steeley, J.M., 2001. A note on information seasonality and the disappearance of the weekend effect in the UK stock market. *Journal of Banking and Finance*, 25, pp. 1941-1956.

Stephen, P. F., Narayanan, J., and Sanjiv, S., 2009. Catering effects in corporate dividend policy: The international evidence. *Journal of Financial Economics.* 33(9), pp. 1730-1738.

Subrahmanyam, A., 2007. Behavioural finance: a review and synthesis. *European Financial Management*, 14(1), pp.12-29.

Sun, Q. and Tong, W. H. S., 2010. Risk and the January effect. *Journal of Banking and Finance*, 34(5), pp. 965-974.

Symeonids, L., Daskalakis, G. and Markellos, R. N., 2010. Does the weather affect stock market volatility?. *Finance Research Letters*, 7, pp. 214-223.

Teddlie, C. and Tashakkori, A., 2009. *Foundations of mixed methods research*. California: Sage.

Thaler, R. H., 1980. Toward a positive theory of consumer choice, *Journal of Economic Behavior and Organizations*, 1, pp. 39–60.

Thaler, R. H. and Shefrin H. M., 1981). An economic theory of self-control. *Journal of Political Economy*, 89(2) , pp. 392-406

Thaler, R. H. and Shefrin H. M., 1984. Explaining investor preference for cash dividend. *Journal of Financial Economics*, 13, pp. 253-282.

Thanatawee, Y., 2011. Life-cycle theory and free cash flow hypothesis: evidence from dividend policy in Thailand. *International Journal of Financial Research*, 2(2), pp. 52-60.

Theobald, M., 1979. Capital asset pricing: theory, empirics and implications for portfolio management. *Managerial Finance*, 5(1), pp. 57–64.

Thompson, S. B., 2011. Simple formulas for standard errors that cluster by both firm and time. *Journal of financial Economics*, *99*(1), 1-10.

Titman, S. and Wessels, R., 1988. The determinants of capital structure choice. *Journal of Finance*, 43(1), pp.1–19.

Tobin, J., 1958. Liquidity preferences as behavior towards risk. *Review of Economic Studies*, 26, pp. 65-86.

Tomei, F., Rosati, M. V., Ciarrocca, M., Baccolo, T. P., Gaballo, M., Caciari, T. and Tomao, E., 2003. Plasma cortisol levels and workers exposed to urban pollutants. *Industrial Health*, 41, pp. 320-326.

Tong, W., 2000. International evidence on weekend anomalies. *Journal of Financial Research*, 23, pp. 495-522.

Trombley, M. A., 1997. Stock prices and Wall Street weather: additional evidence. *Quarterly Journal of Business and Economics*, 36, pp. 11-21.

Tsai, H. J. and Wu, Y., 2015. Bond and stock market response to unexpected dividend changes. *Journal of Empirical Finance*, 30, pp. 1-15.

Tversky, A., 1969. Intransitivity of preference. *Psychological Review,* 76, pp. 31-48.

Tversky, A., 1972. Elimination by aspects: a theory of choice. *Psychological Review*, 79, pp. 281-299.

Tversky, A., Slovic, P. and Kahneman, D., 1990. The causes of preference reversal". *The American Economic Review*, 80(1), pp. 204-217.

Tversky, A. and Kahneman, D., 1986. Rational choice and the framing of decisions. *The Journal of Business*, 59(4), pp. S251-S278.

Tversky, A. and Kahneman, D., 1992. Advances in prospect Theory: cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5, pp-297-323.

Valkanov, R., 2003. Long-run regressions: theoretical results and applications. *Journal of Financial Economics*, 68, pp. 201–232.

Van Maanen, J., 1983. *Qualitative methodology*. Beverly Hills: Sage.

Vazakidis, A. and StergiosAthianos, 2010. Do dividend announcements affect the stock prices in the Greek stock market?. *International Journal of Economic Science and Applied Research*, 3(2), pp. 57-77.

Von Neumann, J. and Morgenstern, O., 1944. *Theory of Game and Economic Behavior*, Princeton: Princeton University Press.

Wachtel, S. B., 1942. Certain observation on seasonal movement in stock prices. *Journal of Business*, 15, pp. 184- 193.

Wakker, P. P. and Tversky, A., 1991. An Axiomatization of Cumulative Prospect Theory. Unpublished manuscript, University of Nijmegan, the Netherlands.

Wakker, P.P., 2010. *Prospect theory: For risk and ambiguity*. Cambridge: Cambridge University Press.

Wang, K., Yuming, L. and Erickson, J., 1997. A new look at the Monday effect. *The Journal of Finance*, LII(5), pp. 2171-2186.

Wansley, J. W., Sirmans, C. F., Shilling, J. D. and Lee, Y., 1991. Dividend change announcement effects and earnings volatility and timing. *The Journal of Financial Research*, 14(1), pp. 33-49.

Watson, D., 2000. *Mood and Temperature*. New York: Guildford Press.

Watts, R., 1973. The information content of dividends. *Journal of Business,* 46, pp. 191–211.

Wehrung, A. D., 1989. Risk taking over gains and losses: a study of oil executives. *Annals of Operations Research*, 19, pp. 115-139.

Weinstein, N., 1980. Unrealistic optimism about future life events. *Journal of Personality and Social Psychology,* 39, pp. 806-820.

Welch, I., 2004. Capital structure and stock returns. *Journal of Political Economy*, 112, pp. 106-131.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica, 48, pp. 817-838.

Widrich, L.,2013. The Science of How Temperature and Lighting Impact Our Productivity. *Buffer Social* [e-Journal], Published 14th February 2013, Available at: < https://blog.bufferapp.com/the-science-of-how-room-temperature-and-lighting-affects-our-productivity > [Accessed 5th September 2017].

Wiseman, R. and Bromiley, P., 1991. Risk-return associations: paradox or artifact? an empirical tested explanation. *Strategic Management Journal*, 12, pp. 231–241.

Witte, H. D., 2010. Outliers and the Halloween effect: comment on Maberly and Pierce. Econ Journal Watch, 7(1), pp. 91-98.

Wolf, M., 2000. Stock returns and dividend yields revisited: a new look at an old problem. *Journal of Business Economics and Statistics*, 18, pp. 18–30.

Woolridge, J. R., 1982. The information content of dividends. *Journal of Financial Research*, 5(3), pp. 237-247.

Yilmaz, A. K. and Gulay, G., 2006. Dividend policies and price-volume reactions to cash dividend on the stock market: evidence from the Istanbul Stock Exchange. *Emerging Markets Finance and Trade,* 42(4), pp. 19-49.

Yoon, S. and Kang, S., 2009. Weather effects on returns: evidence from the Korean stock market. *Physical A: Statistical Mechanics and its Applications*, 388(5), pp. 682-690.

Yoon, P. S. and Starks, L. T., 1995. Signalling, investment opportunities and dividend announcements. *Review of Financial Studies*, 8, pp. 995-1018.

Zarour, B. A., 2007. The Halloween effect anomaly: evidence from some Arab countries equity markets, *Studies in Business and Economics*, 13, pp. 68-76.

Zia, M. and Kochan, M., 2017. Bank dividend-cuts and the stock market reaction around the Great Recession, *The Journal of Finance Issues*, 16(1), pp. 18-30.

Ziemba, W. T., 2011. Investing in the turn-of-the-year effect. *Financial Markets and Portfolio Management*, 25(4), pp. 455-472.

Zuckerman, M., 1984. Sensation seeking: a comparative approach to a human trait. *Behavioral and Brain Science*, 7, pp. 413-471.

Zuckerman, M., Buchsbaum, M. S. and Murphy, D. L., 1994. Sensation seeking and its biological correlates. *Psychological Bulletin*, 88, pp. 187-214.

Zwergel, B. 2010. On the exploitability of the turn-of-the-month effect –an international perspective. *Applied Financial Economics*, 20, pp. 911-922.

APPENDIX -1

TABLE 47 REGRESSION ANALYSIS OF INVESTOR SENTIMENT ON DIVIDEND ANNOUNCEMENT DATES USING INTERACTION SPECIFICATIONS

Panel A. Temperature:

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * TEMP_{it} + \lambda_4 R\Delta DIV_{it} * DPD_{it} * TEMP_{it} + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMY + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.04195[a]	0.03954[a]	0.03765[a]	0.08214[a]
	t-statistics	6.12	2.91	2.76	3.59
	Standard Error	0.00686	0.01359	0.01363	0.02287
$R\Delta DIV * DPI\ (\lambda_1)$	Point Estimate	0.02925	0.03382	0.03474[c]	0.04677[c]
	t-statistics	1.51	1.60	1.65	1.82
	Standard Error	0.01932	0.02118	0.02109	0.02568
$R\Delta DIV * DPD\ (\lambda_2)$	Point Estimate	0.14121[a]	0.14585[b]	0.14823[b]	0.15325[b]
	t-statistics	4.04	2.10	2.15	2.28
	Standard Error	0.03494	0.06959	0.06897	0.06713
$R\Delta DIV * DPI * TEMP\ (\lambda_3)$	Point Estimate	0.00078	0.00081	0.00089	0.00057
	t-statistics	1.13	1.18	1.30	0.65
	Standard Error	0.00069	0.00069	0.00068	0.00088
$R\Delta DIV * DPD * TEMP\ (\lambda_4)$	Point Estimate	-0.00362[b]	-0.00393	-0.00409	-0.00414
	t-statistics	-2.40	-1.48	-1.55	-1.49
	Standard Error	0.00151	0.00266	0.00264	0.00279
$SIZE\ (\lambda_5)$	Point Estimate	-0.00528[a]	-0.00487[a]	-0.00508[a]	-0.01393[a]
	t-statistics	-6.60	-5.37	-5.52	-4.05
	Standard Error	0.00079	0.00091	0.00092	0.00344
$REVARSAL\ (\lambda_6)$	Point Estimate	0.66449[b]	-0.75255[c]	-0.75925[c]	-0.81489[c]
	t-statistics	-2.56	-1.82	-1.84	-1.80
	Standard Error	0.25978	0.41416	0.41183	0.45328
$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.12121	-0.16179	-0.16933	-0.15453
	t-statistics	-1.55	-1.36	-1.42	-1.25
	Standard Error	0.07815	0.11927	0.11927	0.12339
$DIVIDEND_{YIELD}\ (\lambda_8)$	Point Estimate	0.15200	0.15231	0.13021	0.16748
	t-statistics	1.57	1.17	1.01	0.60
	Standard Error	0.09669	0.13052	0.12910	0.28124
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.72%	4.88%	5.24%	15.05%
N		2,697	2,697	2,697	2,697

Panel B. Air Pollution:

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * AIR_{it} + \lambda_4 R\Delta DIV_{it} * DPD_{it} * AIR_{\ it} + \lambda_5\ SIZE_{it} + \lambda_6\ REVERSAL_{it} + \lambda_7\ MOMENTUM_{it} + \lambda_8\ DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMY + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03664[a]	0.03013[b]	0.02695[b]	0.05795[a]
	t-statistics	6.43	2.45	2.20	3.64
	Standard Error	0.00569	0.01230	0.01225	0.01590
$R\Delta DIV * DPI\ (\lambda_1)$	Point Estimate	0.04482[a]	0.05175[a]	0.05299[a]	0.06673[a]
	t-statistics	3.88	4.04	4.17	4.70
	Standard Error	0.01154	0.01279	0.01271	0.01419
$R\Delta DIV * DPD\ (\lambda_2)$	Point Estimate	0.02280	0.02278	0.02352	0.02724
	t-statistics	1.30	0.81	0.84	0.87
	Standard Error	0.01750	0.02822	0.02801	0.03137
$R\Delta DIV * DPI * AIR\ (\lambda_3)$	Point Estimate	0.00259	0.00281	0.00474	-0.00076
	t-statistics	0.19	0.21	0.36	-0.05
	Standard Error	0.01371	0.01332	0.01316	0.01462
$R\Delta DIV * DPD * AIR\ (\lambda_4)$	Point Estimate	0.13706[a]	0.13192[b]	0.12885[c]	0.12302[c]
	t-statistics	4.16	1.99	1.95	1.91
	Standard Error	0.03294	0.06622	0.06604	0.06436
$SIZE\ (\lambda_5)$	Point Estimate	-0.00492[a]	-0.00458[a]	-0.00485[a]	-0.01345[a]
	t-statistics	-7.28	-5.23	-5.55	-5.09
	Standard Error	0.00068	0.00088	0.00087	0.00264
$REVARSAL\ (\lambda_6)$	Point Estimate	-0.60566[a]	-0.71637[b]	-0.70572[c]	-0.77323[b]
	t-statistics	-2.62	-1.96	-1.95	-2.02
	Standard Error	0.23118	0.36485	0.36253	0.38315
$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.10383	-0.13141	-0.13779	-0.10123
	t-statistics	-1.48	-1.26	-1.32	-0.94
	Standard Error	0.07035	0.10424	0.10453	0.10740
$DIVIDEND_{YIELD}\ (\lambda_8)$	Point Estimate	0.26725[a]	0.23999[b]	0.20903[c]	0.25530
	t-statistics	3.16	2.11	1.83	1.15
	Standard Error	0.08450	0.11372	0.11409	0.22164
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.88%	5.11%	5.47%	13.82
N		3,407	3,407	3,407	3,407

Panel C. Rainfall:

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * RAIN_{it} + \lambda_4 R\Delta DIV_{it} * DPD_{it} * RAIN_{it} + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMY + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.04301[a]	0.04800[a]	0.04556[a]	0.09478[a]
	t-statistics	6.27	4.41	4.17	4.02
	Standard Error	0.00686	0.01088	0.01093	0.02358
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.05105[a]	0.05609[a]	0.05896[a]	0.06353[a]
	t-statistics	3.70	3.67	3.89	3.78
	Standard Error	0.01382	0.01530	0.01515	0.01681
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.09098[a]	0.08825[c]	0.08608[c]	0.08968[c]
	t-statistics	3.90	1.79	1.76	1.80
	Standard Error	0.02335	0.04941	0.04877	0.04977
$R\Delta DIV * DPI * RAIN$ (λ_3)	Point Estimate	-0.00975	-0.01023	-0.01079	-0.01026
	t-statistics	-0.67	-0.76	-0.80	-0.69
	Standard Error	0.01462	0.01346	0.01351	0.01498
$R\Delta DIV * DPD * RAIN$ (λ_4)	Point Estimate	-0.04703	-0.04439	-0.04156	-0.03834
	t-statistics	-1.44	-0.76	-0.72	-0.66
	Standard Error	0.03275	0.05874	0.05781	0.05809
$SIZE$ (λ_5)	Point Estimate	-0.00537[a]	-0.00489[a]	-0.00511[a]	-0.01406[a]
	t-statistics	-6.72	-5.35	-5.53	-4.04
	Standard Error	0.00079	0.00091	0.00093	0.00348
$REVARSAL$ (λ_6)	Point Estimate	-0.65236[b]	-0.74324[c]	-0.74887[c]	-0.81706[c]
	t-statistics	-2.51	-1.77	-1.80	-1.78
	Standard Error	0.26002	0.41918	0.41693	0.45802
$MOMENTUM$ (λ_7)	Point Estimate	-0.12735	-0.17152	-0.17827	-0.15492
	t-statistics	-1.63	-1.45	-1.51	-1.25
	Standard Error	0.07818	0.11831	0.11836	0.12373
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.13739	0.13679	0.11487	0.15831
	t-statistics	1.42	1.07	0.90	0.56
	Standard Error	0.09666	0.12827	0.12727	0.28064
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.56%	4.71%	5.04%	14.86%
N		2,697	2,697	2,697	2,697

Note: In here the depended variable is CAR (0,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. *TEMP* is average daily temperature. *AIR* is if London city air pollution goes beyond the Air Quality Index (AQI) number 3 then it takes value 1 otherwise 0. *RAIN* = If there is rain in Heathrow airport area then rain will take value 1 otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using the values of stoke returns one month before the dividend announcement month, it also repressing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where M_d, T_d, W_d , T_d and F_d are the dummy variables for Monday, Tuesday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

TABLE 48 REGRESSION ANALYSIS OF INVESTOR SENTIMENT ON DIVIDEND ANNOUNCEMENT DATES USING BINARY SPECIFICATIONS

Panel A. Temperature:

$$CAR_{it} \quad = \quad \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * TEMP_{it} + \lambda_4 DPD_{it} * TEMP_{it} + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMY + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03755[a]	0.03459[b]	0.03332[b]	0.07182[a]
	t-statistics	5.23	2.49	2.40	3.11
	Standard Error	0.00718	0.01387	0.01387	0.02312
DPI (λ_1)	Point Estimate	0.01251[a]	0.01286[a]	0.01341[a]	0.01563[a]
	t-statistics	2.92	2.91	3.05	2.78
	Standard Error	0.00429	0.00442	0.00440	0.00561
DPD (λ_2)	Point Estimate	-0.03586[a]	-0.03638[b]	-0.03664[b]	-0.04227[b]
	t-statistics	-3.35	-2.20	-2.22	-2.37
	Standard Error	0.01069	0.01653	0.01651	0.01784
$DPI * TEMP$ (λ_3)	Point Estimate	0.00009	0.00009	0.00012	0.00000
	t-statistics	0.78	0.88	1.05	0.06
	Standard Error	0.00011	0.00011	0.00011	0.00015
$DPD * TEMP$ (λ_4)	Point Estimate	0.00124[a]	0.00129[c]	0.00134[c]	0.00151[c]
	t-statistics	2.91	1.84	1.90	1.80
	Standard Error	0.00043	0.0007	0.00070	0.00084
$SIZE$ (λ_5)	Point Estimate	-0.00559[a]	-0.00538[a]	-0.00567[a]	-0.01360[a]
	t-statistics	-6.99	-5.65	-5.90	-4.00
	Standard Error	0.00080	0.00095	0.00096	0.00339
$REVARSAL$ (λ_6)	Point Estimate	-0.64943[b]	-0.71723[c]	0.71948[c]	-0.76523[c]
	t-statistics	-2.50	-1.77	-1.79	-1.70
	Standard Error	0.25985	0.40511	0.40233	0.44983
$MOMENTUM$ (λ_7)	Point Estimate	-0.11173	-0.14217	-0.14895	-0.11611
	t-statistics	-1.43	-1.21	-1.28	-0.95
	Standard Error	0.07792	0.11703	0.11659	0.12286
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.13405	0.12871	0.10542	0.19074
	t-statistics	1.40	1.01	0.83	0.70
	Standard Error	0.09596	0.12763	0.12639	0.2726
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES

Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.71%	4.76%	5.14%	14.88%
N		2,697	2,697	2,697	2,697

Panel B. Air Pollution:

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * AIR_{it} + \lambda_4 DPD_{it} * AIR_{it} + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMY + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03299[a]	0.02969[a]	0.02666[b]	0.05916[a]
	t-statistics	5.47	2.37	2.13	4.01
	Standard Error	0.00603	0.01251	0.01249	0.01477
$DPI\ (\lambda_1)$	Point Estimate	0.01359[a]	0.01372[a]	0.01444[a]	0.01506[a]
	t-statistics	4.22	4.45	4.69	3.92
	Standard Error	0.00322	0.00308	0.00308	0.00384
$DPD\ (\lambda_2)$	Point Estimate	0.00034	-0.00019	0.00032	-0.00131
	t-statistics	0.06	-0.03	0.05	-0.16
	Standard Error	0.00575	0.00666	0.00664	0.00814
$DPI * AIR\ (\lambda_3)$	Point Estimate	-0.00117	-0.00117	-0.00089	-0.00097
	t-statistics	-0.52	-0.54	-0.42	-0.37
	Standard Error	0.00226	0.00215	0.00212	0.00260
$DPD * AIR\ (\lambda_4)$	Point Estimate	-0.02569[a]	-0.02409	-0.02354	-0.02309
	t-statistics	-2.80	-1.40	-1.36	-1.24
	Standard Error	0.00917	0.01718	0.01725	0.01857
$SIZE\ (\lambda_5)$	Point Estimate	-0.00524[a]	-0.00505[a]	-0.00536[a]	-0.01327[a]
	t-statistics	-7.69	-5.61	-5.99	-5.03
	Standard Error	0.00068	0.00090	0.00089	0.00264
$REVARSAL\ (\lambda_6)$	Point Estimate	-0.62629[a]	-0.71406[c]	-0.70306[c]	-0.76313[c]
	t-statistics	-2.70	-1.94	-1.93	-1.95
	Standard Error	0.23187	0.36753	0.36487	0.39076
$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.08715	-0.09782	-0.10352	-0.04703
	t-statistics	-1.24	-0.94	-1.00	-0.43
	Standard Error	0.07013	0.10356	0.10338	0.10926
$DIVIDEND_{YIELD}\ (\lambda_8)$	Point Estimate	0.25022[a]	0.21305[c]	0.18249	0.25995
	t-statistics	2.97	1.90	1.63	1.20
	Standard Error	0.08424	0.11198	0.11209	0.21600
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.44%	4.52%	4.89%	13.08%
N		3,407	3,407	3,407	3,407

Panel C. Rainfall:

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * RAIN_{it} + \lambda_4 DPD_{it} * RAIN_{it} + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMY + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03847[a]	0.04337[a]	0.04138[a]	0.08215[a]
	t-statistics	5.36	3.75	3.56	3.62
	Standard Error	0.00718	0.01158	0.01164	0.02268
DPI (λ_1)	Point Estimate	0.01521[a]	0.01579[a]	0.01687[a]	0.01705[a]
	t-statistics	4.02	3.99	4.29	3.42
	Standard Error	0.00378	0.00396	0.00393	0.00499
DPD (λ_2)	Point Estimate	-0.01176	-0.01113	-0.00988	-0.01241
	t-statistics	-1.60	-1.10	-0.99	-1.05
	Standard Error	0.00737	0.01014	0.00997	0.01177
$DPI * RAIN$ (λ_3)	Point Estimate	-0.00157	-0.00176	-0.00197	-0.00237
	t-statistics	-0.65	-0.79	-0.88	-0.88
	Standard Error	0.00243	0.00222	0.00225	0.00271
$DPD * RAIN$ (λ_4)	Point Estimate	0.00442	0.00419	0.00333	0.00363
	t-statistics	0.48	0.29	0.23	0.23
	Standard Error	0.00921	0.01469	0.01440	0.01564
$SIZE$ (λ_5)	Point Estimate	-0.00566[a]	-0.00536[a]	-0.00565[a]	-0.01361[a]
	t-statistics	-7.06	-5.62	-5.87	-3.94
	Standard Error	0.00080	0.00096	0.00096	0.00346
$REVARSAL$ (λ_6)	Point Estimate	-0.66811[a]	-0.73849[c]	-0.74075[c]	-0.79471[c]
	t-statistics	-2.57	-1.78	-1.80	-1.73
	Standard Error	0.26018	0.41439	0.41197	0.46004
$MOMENTUM$ (λ_7)	Point Estimate	-0.11866	-0.15378	-0.15991	-0.11877
	t-statistics	-1.52	-1.33	-1.38	-0.97
	Standard Error	0.07803	0.11595	0.11552	0.12297
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.11472	0.10889	0.08509	0.17798
	t-statistics	1.20	0.85	0.67	0.65
	Standard Error	0.09585	0.12754	0.12653	0.27283
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	NO
R^2		3.41%	4.46%	4.80%	14.53%
N		2,697	2,697	2,697	2,697

Note: In here the depended variable is CAR (0,+1). The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. *TEMP* is average daily temperature. *AIR* is if London city air pollution goes beyond the Air Quality Index (AQI) number 3 then it takes value 1 otherwise 0. *RAIN* = If there is rain in Heathrow airport area then rain will take value 1 otherwise 0. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using the values of stoke returns one month before the dividend announcement month, it also repressing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of –the-week effect, where M_d, T_d, W_d, T_d *and* F_d are the dummy variables for Monday, Tuesday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted and superscripts a, b and c denote statistical significance at the1%, 5% and 10% level, respectively.

APPENDIX-2

TABLE 49 REGRESSION ANALYSIS OF CALENDAR ANOMALY ON DIVIDEND ANNOUNCEMENT DATES USING INTERACTION SPECIFICATIONS

Panel A. Halloween effect:

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * HALL_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * HALL_t + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMY + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03624[a]	0.03148[b]	0.02835[b]	0.05513[a]
	t-statistics	6.37	2.56	2.31	3.51
	Standard Error	0.00569	0.01230	0.01227	0.01569
$R\Delta DIV * DPI\ (\lambda_1)$	Point Estimate	0.03769[a]	0.04408[a]	0.04569[a]	0.06786[a]
	t-statistics	2.73	2.92	3.12	2.88
	Standard Error	0.01382	0.05828	0.01466	0.02352
$R\Delta DIV * DPD\ (\lambda_2)$	Point Estimate	0.16503[a]	0.16368[a]	0.16402[a]	0.16784[a]
	t-statistics	6.53	2.81	2.84	2.93
	Standard Error	0.02529	0.05828	0.05766	0.05733
$R\Delta DIV * DPI * HALL\ (\lambda_3)$	Point Estimate	0.01309	0.01405	0.01459	-0.00100
	t-statistics	0.96	1.00	1.06	-0.04
	Standard Error	0.01367	0.01404	0.01379	0.02620
$R\Delta DIV * DPD * HALL\ (\lambda_4)$	Point Estimate	-0.16087[a]	-0.16096[b]	-0.16154[a]	-0.16368[a]
	t-statistics	-5.24	-2.57	-2.61	-2.62
	Standard Error	0.03068	0.06268	0.06188	0.06238
$SIZE\ (\lambda_5)$	Point Estimate	-0.00495[a]	-0.00464[a]	-0.00493[a]	0.01388[a]
	t-statistics	-7.32	-5.27	-5.59	-5.26
	Standard Error	0.00068	0.00088	0.00088	0.00264
$REVERSAL\ (\lambda_6)$	Point Estimate	-0.60527[a]	-0.71165[c]	-0.70415[c]	-0.74367[c]
	t-statistics	-2.62	-1.95	-1.94	-1.93
	Standard Error	0.23074	0.36553	0.36294	0.38452
$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.08918	-0.11804	-0.12476	-0.08811
	t-statistics	-1.27	-1.12	-1.18	-0.81
	Standard Error	0.07026	0.10578	0.10598	0.10858
$DIVIDEND_{YIELD}\ (\lambda_8)$	Point Estimate	0.28830[a]	0.25968[b]	0.22783[b]	0.25897
	t-statistics	3.41	2.27	1.99	1.16
	Standard Error	0.08447	0.11443	0.11457	0.22342
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		4.19%	5.46%	5.85%	14.18%
N		3,407	3,407	3,407	3,407

Panel B. TOM effect:

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * TOM_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * TOM_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMY + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03739[a]	0.03109[b]	0.02753[b]	0.08166[a]
	t-statistics	6.54	2.52	2.24	5.12
	Standard Error	0.00571	0.01235	0.01231	0.01596
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.04677[a]	0.05373[a]	0.05554[a]	0.06746[a]
	t-statistics	4.31	4.44	4.61	4.85
	Standard Error	0.01084	0.01209	0.01204	0.01389
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.07203[a]	0.06971[b]	0.06966[b]	0.07093[b]
	t-statistics	4.45	2.31	2.33	2.25
	Standard Error	0.01617	0.03019	0.02995	0.03154
$R\Delta DIV * DPI * TOM$ (λ_3)	Point Estimate	-0.00705	-0.00578	-0.00438	-0.01295
	t-statistics	-0.36	-0.30	-0.23	-0.65
	Standard Error	0.01973	0.01908	0.01896	0.01977
$R\Delta DIV * DPD * TOM$ (λ_4)	Point Estimate	-0.10828[b]	-0.10012[b]	-0.10033[b]	-0.09283[c]
	t-statistics	-2.41	-2.47	-2.52	-2.26
	Standard Error	0.04485	0.04053	0.03988	0.04112
$SIZE$ (λ_5)	Point Estimate	-0.00502[a]	-0.00468[a]	-0.00495[a]	-0.01305[a]
	t-statistics	-7.39	-5.33	-5.66	-5.08
	Standard Error	0.00068	0.00088	0.00088	0.00257
$REVERSAL$ (λ_6)	Point Estimate	-0.59701[b]	-0.70133[c]	-0.69394[c]	-0.77089[b]
	t-statistics	-2.58	-1.91	-1.90	-2.00
	Standard Error	0.23130	0.36779	0.36530	0.38492
$MOMENTUM$ (λ_7)	Point Estimate	-0.10718	-0.13429	-0.14162	-0.09974
	t-statistics	-1.52	-1.27	-1.33	-0.92
	Standard Error	0.07053	0.10614	0.10638	0.10884
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.26155[a]	0.23439[b]	0.20218[c]	0.25889
	t-statistics	3.09	2.08	1.79	1.18
	Standard Error	0.08472	0.11281	0.11308	0.21961
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.56%	4.81%	5.19%	13.54%
N		3,407	3,407	3,407	3,407

Panel C. January effect:

$$CAR_{it} = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * Jan_t + \lambda_4 R\Delta DIV_{it} * DPD_{it} * Jan_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMY + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03684[a]	0.03269[a]	0.02985[b]	0.06299[a]
	t-statistics	6.46	2.66	2.43	3.99
	Standard Error	0.00569	0.01229	0.01229	0.01577
$R\Delta DIV * DPI$ (λ_1)	Point Estimate	0.04620[a]	0.05352[a]	0.05558[a]	0.06702[a]
	t-statistics	4.37	4.51	4.70	4.90
	Standard Error	0.01058	0.01187	0.01182	0.01368
$R\Delta DIV * DPD$ (λ_2)	Point Estimate	0.04915[a]	0.04758[c]	0.04737[c]	0.04899[c]
	t-statistics	3.19	1.83	1.84	1.76
	Standard Error	0.01539	0.02601	0.02579	0.02784
$R\Delta DIV * DPI * Jan$ (λ_3)	Point Estimate	-0.04499	-0.03561[c]	-0.03683[c]	-0.05202
	t-statistics	-0.88	-1.71	-1.65	-1.31
	Standard Error	0.05119	0.02079	0.02238	0.03964
$R\Delta DIV * DPD * Jan$ (λ_4)	Point Estimate	0.36158[a]	0.36272[c]	0.36317[b]	0.39404[b]
	t-statistics	4.04	1.91	1.97	2.08
	Standard Error	0.08946	0.18999	0.18404	0.18917
$SIZE$ (λ_5)	Point Estimate	-0.00490[a]	-0.00455[a]	-0.00480[a]	-0.01334[a]
	t-statistics	-7.24	-5.21	-5.51	-5.09
	Standard Error	0.00068	0.00087	0.00087	0.00262
$REVERSAL$ (λ_6)	Point Estimate	-0.64534[a]	-0.75183[b]	-0.74358[b]	-0.82263[b]
	t-statistics	-2.79	-2.12	-2.11	-2.22
	Standard Error	0.23114	0.35489	0.35288	0.37071
$MOMENTUM$ (λ_7)	Point Estimate	-0.10516	-0.12794	-0.13419	-0.10204
	t-statistics	-1.50	-1.21	-1.26	-0.94
	Standard Error	0.07034	0.10605	0.10623	0.10839
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.25222[a]	0.23629[b]	0.20526[c]	0.24761
	t-statistics	2.98	2.11	1.83	1.12
	Standard Error	0.08459	0.11217	0.11232	0.22059
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.88%	5.12%	5.49%	13.96%
N		3,407	3,407	3,407	3,407

Panel D. Monday effect:

$$CAR_{it} \quad = \lambda_0 + \lambda_1 R\Delta DIV_{it} * DPI_{it} + \lambda_2 R\Delta DIV_{it} * DPD_{it} + \lambda_3 R\Delta DIV_{it} * DPI_{it} * Mon + \lambda_4 R\Delta DIV_{it} * DPD_{it} * Mon_t + \lambda_5 \, SIZE_{it} + \lambda_6 \, REVERSAL_{it} + \lambda_7 \, MOMENTUM_{it} + \lambda_8 \, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW \, Effect + \vartheta_2 YEAR \, DUMMY + \vartheta_3 FIXED \, EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03869[a]	0.03153[b]	0.02728[b]	0.06630[a]
	t-statistics	6.73	2.53	2.20	3.74
	Standard Error	0.00575	0.01248	0.01238	0.01773
$R\Delta DIV \ * DPI \ (\lambda_1)$	Point Estimate	0.04997[a]	0.05625[a]	0.05677[a]	0.06808[a]
	t-statistics	4.62	4.68	4.65	4.78
	Standard Error	0.01082	0.01203	0.01220	0.01423
$R\Delta DIV \ * DPD \ (\lambda_2)$	Point Estimate	0.04730[a]	0.04598[c]	0.0465[c]	0.05184[c]
	t-statistics	2.95	1.76	1.79	1.91
	Standard Error	0.01603	0.02611	0.02597	0.02721
$R\Delta DIV \ * DPI * Mon \ (\lambda_3)$	Point Estimate	-0.03496[c]	-0.02971[c]	-0.01983	-0.01438
	t-statistics	-1.88	-1.92	-0.78	-0.49
	Standard Error	0.01862	0.01549	0.02536	0.02939
$R\Delta DIV \ * DPD * Mon \ (\lambda_4)$	Point Estimate	0.10944[b]	0.11035	0.10300	0.07753
	t-statistics	2.36	0.95	0.85	0.61
	Standard Error	0.04637	0.11651	0.12054	0.12741
$SIZE \ (\lambda_5)$	Point Estimate	-0.00515[a]	-0.00481[a]	-0.00497[a]	-0.01343[a]
	t-statistics	-7.56	-5.46	-5.66	-5.12
	Standard Error	0.00068	0.00088	0.00088	0.00262
$REVERSAL \ (\lambda_6)$	Point Estimate	-0.60150[a]	-0.70149[c]	-0.69741[c]	-0.76478[b]
	t-statistics	-2.60	-1.91	-1.92	-1.98
	Standard Error	0.23100	0.36705	0.36399	0.38643
$MOMENTUM \ (\lambda_7)$	Point Estimate	-0.10192	-0.12852	-0.13593	-0.09979
	t-statistics	-1.45	-1.20	-1.27	-0.91
	Standard Error	0.07043	0.10682	0.10704	0.10958
$DIVIDEND_{YIELD} \ (\lambda_8)$	Point Estimate	0.25135[a]	0.22693[b]	0.20588[c]	0.25315
	t-statistics	2.96	2.02	1.83	1.15
	Standard Error	0.08484	0.11256	0.11271	0.22055
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.65%	4.89%	5.17%	13.53%
N		3,407	3,407	3,407	3,407

TABLE 50 REGRESSION ANALYSIS OF CALENDAR ANOMALY ON DIVIDEND ANNOUNCEMENT DATES USING BINARY SPECIFICATIONS

Panel A. Halloween effect:

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * HALL_t + \lambda_4 DPD_{it} * HALL_t + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMY + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03202[a]	0.03252[a]	0.03014[b]	0.05481[a]
	t-statistics	5.32	2.63	2.43	3.55
	Standard Error	0.00602	0.01236	0.01241	0.01544
DPI (λ_1)	Point Estimate	0.01059[a]	0.01041[a]	0.01099[a]	0.01194[b]
	t-statistics	3.11	2.97	3.14	2.10
	Standard Error	0.00341	0.00351	0.00349	0.00570
DPD (λ_2)	Point Estimate	-0.03861[a]	-0.03906[a]	-0.03859[a]	-0.04424[a]
	t-statistics	-4.72	-2.84	-2.83	-3.12
	Standard Error	0.00818	0.01376	0.01363	0.01418
$DPI * HALL$ (λ_3)	Point Estimate	0.00432[c]	0.00478[b]	0.00525[b]	0.00456
	t-statistics	1.94	2.34	2.51	0.75
	Standard Error	0.00223	0.00205	0.00209	0.00609
$DPD * HALL$ (λ_4)	Point Estimate	0.04487[a]	0.04538[a]	0.04571[a]	0.05171[a]
	t-statistics	4.90	3.01	3.06	3.21
	Standard Error	0.00916	0.01507	0.01493	0.01611
$SIZE$ (λ_5)	Point Estimate	-0.00523[a]	-0.00507[a]	-0.00542[a]	-0.01375[a]
	t-statistics	-7.71	5.61	-6.02	-5.23
	Standard Error	0.00068	0.00090	0.00089	0.00263
$REVERSAL$ (λ_6)	Point Estimate	-0.60161[a]	-0.69605[c]	-0.69009[c]	-7.0866[c]
	t-statistics	-2.60	-1.94	-1.94	-1.85
	Standard Error	0.23109	0.35899	0.35598	0.38324
$MOMENTUM$ (λ_7)	Point Estimate	-0.06916	-0.08416	-0.08979	-0.03537
	t-statistics	-0.99	-0.81	-0.87	-0.32
	Standard Error	0.06993	0.10402	0.10375	0.10962
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.28514[a]	0.24821[b]	0.21769[c]	0.25947
	t-statistics	3.38	2.19	1.93	1.20
	Standard Error	0.08432	0.11318	0.11306	0.21681
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.99%	5.12%	5.53%	13.61%
N		3,407	3,407	3,407	3,407

Panel B. TOM effect:

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * TOM_t + \lambda_4 DPD_{it} * TOM_t + \lambda_5\, SIZE_{it} + \lambda_6\, REVERSAL_{it} + \lambda_7\, MOMENTUM_{it} + \lambda_8\, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\, Effect + \vartheta_2 YEAR\, DUMMY + \vartheta_3 FIXED\, EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03324[a]	0.02989[b]	0.02679[b]	0.07411[a]
	t-statistics	5.50	2.40	2.15	5.02
	Standard Error	0.00605	0.01245	0.01244	0.01477
DPI (λ_1)	Point Estimate	0.01289[a]	0.01307[a]	0.01386[a]	0.01446[a]
	t-statistics	4.09	4.04	4.29	3.70
	Standard Error	0.00315	0.00324	0.00323	0.00391
DPD (λ_2)	Point Estimate	-0.00824	-0.00812	-0.00737	-0.00861
	t-statistics	-1.55	-1.22	-1.12	-1.08
	Standard Error	0.00532	0.00664	0.00657	0.00798
$DPI * TOM$ (λ_3)	Point Estimate	0.00191	0.00198	0.00238	0.00128
	t-statistics	0.59	0.73	0.85	0.38
	Standard Error	0.00325	0.00271	0.00282	0.00340
$DPD * TOM$ (λ_4)	Point Estimate	0.00834	0.00698	0.00651	0.00363
	t-statistics	0.65	0.44	0.41	0.21
	Standard Error	0.01290	0.01589	0.01587	0.01738
$SIZE$ (λ_5)	Point Estimate	-0.00525[a]	-0.00505[a]	-0.00537[a]	-0.01288[a]
	t-statistics	-7.69	-5.61	-6.01	-5.06
	Standard Error	0.00068	0.00090	0.00089	0.00255
$REVERSAL$ (λ_6)	Point Estimate	-0.60795[a]	-0.69369[c]	-0.68534[c]	-0.75030[c]
	t-statistics	-2.63	-1.90	-1.89	-1.94
	Standard Error	0.23154	0.36442	0.36167	0.38759
$MOMENTUM$ (λ_7)	Point Estimate	-0.08528	-0.09646	-0.10263	-0.04325
	t-statistics	-1.21	-0.92	-0.98	-0.39
	Standard Error	0.07015	0.10446	0.10425	0.10963
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.24531[a]	0.20909[c]	0.17766	0.26425
	t-statistics	2.91	1.88	1.59	1.23
	Standard Error	0.08441	0.11137	0.11156	0.21453
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.23%	4.34%	4.72%	12.89%
N		3,407	3,407	3,407	3,407

Panel C. January effect:

$$CAR_{it} = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * Jan_t + \lambda_4 DPD_{it} * Jan_t + \lambda_5 SIZE_{it} + \lambda_6 REVERSAL_{it} + \lambda_7 MOMENTUM_{it} + \lambda_8 DIVIDEND_{YIELD_{it}} + \vartheta_1 DW\ Effect + \vartheta_2 YEAR\ DUMMY + \vartheta_3 FIXED\ EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03315[a]	0.03175[b]	0.02922[b]	0.06185[a]
	t-statistics	5.50	2.55	2.34	4.07
	Standard Error	0.00603	0.01246	0.01250	0.01518
DPI (λ_1)	Point Estimate	0.01307[a]	0.01332[a]	0.01412[a]	0.01460[a]
	t-statistics	4.18	4.21	4.47	3.79
	Standard Error	0.00312	0.00317	0.00316	0.00386
DPD (λ_2)	Point Estimate	-0.00542	-0.00535	-0.00467	-0.00627
	t-statistics	-1.06	-0.89	-0.78	-0.83
	Standard Error	0.00511	0.00603	0.00598	0.00755
$DPI * Jan$ (λ_3)	Point Estimate	-0.00331	-0.00186	-0.00224	-0.00199
	t-statistics	-0.35	-0.32	-0.35	-0.20
	Standard Error	0.00951	0.00580	0.00637	0.00994
$DPD * Jan$ (λ_4)	Point Estimate	-0.08882[a]	-0.08803[b]	-0.08786[b]	-0.09620[b]
	t-statistics	-3.10	-2.09	-2.20	-2.34
	Standard Error	0.02866	0.04219	0.03996	0.04107
$SIZE$ (λ_5)	Point Estimate	-0.00519[a]	-0.00498[a]	-0.00527[a]	-0.01329[a]
	t-statistics	-7.63	-5.54	-5.89	-5.04
	Standard Error	0.00068	0.00089	0.00089	0.00264
$REVERSAL$ (λ_6)	Point Estimate	-0.62836[a]	-0.71622[b]	-0.70714[b]	-0.76877[b]
	t-statistics	-2.72	-2.01	-2.00	-2.03
	Standard Error	0.23144	0.35553	0.35339	0.37809
$MOMENTUM$ (λ_7)	Point Estimate	-0.08684	-0.09347	-0.09866	-0.04760
	t-statistics	-1.24	-0.90	-0.95	-0.44
	Standard Error	0.07009	0.10397	0.10372	0.10916
$DIVIDEND_{YIELD}$ (λ_8)	Point Estimate	0.23609[a]	0.20965[c]	0.17951	0.24835
	t-statistics	2.80	1.89	1.62	1.16
	Standard Error	0.08431	0.11069	0.11083	0.21492
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.48%	4.57%	4.93%	13.19%
N		3,407	3,407	3,407	3,407

Panel D. Monday effect:

$$CAR_{it} \quad = \lambda_0 + \lambda_1 DPI_{it} + \lambda_2 DPD_{it} + \lambda_3 DPI_{it} * Mon_t + \lambda_4 DPD_{it} * Mon_t + \lambda_5 \, SIZE_{it} + \lambda_6 \, REVERSAL_{it} + \lambda_7 \, MOMENTUM_{it} + \lambda_8 \, DIVIDEND_{YIELD_{it}} + \vartheta_1 DW \, Effect + \vartheta_2 YEAR \, DUMMY + \vartheta_3 FIXED \, EFFECTS + \mu_{it}$$

Variables		**Model-1**	**Model-2**	**Model-3**	**Model-4**
Constant (λ_0)	Point Estimate	0.03465[a]	0.03037[b]	0.02681[b]	0.06274[a]
	t-statistics	5.70	2.43	2.16	4.19
	Standard Error	0.00608	0.01249	0.01239	0.01498
$DPI\ (\lambda_1)$	Point Estimate	0.01398[a]	0.01408[a]	0.01380[a]	0.01419[a]
	t-statistics	4.43	4.40	4.24	3.55
	Standard Error	0.00315	0.00320	0.00326	0.00399
$DPD\ (\lambda_2)$	Point Estimate	-0.00538	-0.00533	-0.00563	-0.00818
	t-statistics	-1.01	-0.79	-0.84	-1.01
	Standard Error	0.00533	0.00671	0.00669	0.00810
$DPI * Monday\ (\lambda_3)$	Point Estimate	-0.00623[b]	-0.00539[b]	0.00359	0.00549
	t-statistics	-2.04	-2.07	0.29	0.41
	Standard Error	0.00306	0.00261	0.01246	0.01347
$DPD * Monday\ (\lambda_4)$	Point Estimate	-0.01473	-0.01533	-0.00619	0.00138
	t-statistics	-1.19	-0.70	-0.26	0.05
	Standard Error	0.01241	0.02183	0.02380	0.02521
$SIZE\ (\lambda_5)$	Point Estimate	-0.00541[a]	-0.00519[a]	-0.00534[a]	-0.01317[a]
	t-statistics	-7.88	-5.76	-5.94	-5.03
	Standard Error	0.00069	0.00090	0.00089	0.00262
$REVERSAL\ \ (\lambda_6)$	Point Estimate	-0.59908[b]	-0.68369[c]	-0.68221[c]	-0.74385[c]
	t-statistics	-2.59	-1.87	-1.89	-1.92
	Standard Error	0.23134	0.36484	0.36152	0.38809
$MOMENTUM\ (\lambda_7)$	Point Estimate	-0.08317	-0.09440	-0.09946	-0.04381
	t-statistics	-1.19	-0.90	-0.95	-0.40
	Standard Error	0.07012	0.10459	0.10419	0.10995
$DIVIDEND_{YIELD}\ (\lambda_8)$	Point Estimate	0.23285[a]	0.20023[c]	0.18034	0.25499
	t-statistics	2.75	1.80	1.62	1.18
	Standard Error	0.08453	0.11142	0.11139	0.21526
Day-of-the-week effect (ϑ_1)		NO	NO	YES	YES
Year Dummy (ϑ_2)		NO	YES	YES	YES
FF (17) Industry Dummy (ϑ_3)		NO	YES	YES	NO
Firm Dummy (ϑ_3)		NO	NO	NO	YES
Clustered by Company ID and Date		NO	YES	YES	YES
R^2		3.36%	4.45%	4.72%	12.91%
N		3,407	3,407	3,407	3,407

Note: In here the dependent variable is CAR (-1,+1). $R\Delta DIV_0$ is annual dividend changes percentage. The dummy variables are DPI and DPD. If the dividend changes percentage increase then DPI=1, otherwise 0, and if the dividend changes percentage decrease then DPD =1, otherwise 0. *HALL* equal to 1 if *t* belongs to month November to April, and 0 otherwise. 1 if t belongs to the TOM interval of [-1,+3], and 0 otherwise. *Jan* takes value 1 if t belongs to month of January, and 0 otherwise. *Mon* takes value 1 if t belongs to Monday, and 0 otherwise. Size is representing the firm size, which is measured using the logarithmic market capitalization one day prior to the dividend announcement, and the Size values are in billions. Reversal is measured using cumulative stock returns over previous month, it also representing in percentage. Momentum is cumulated monthly stock returns from month t-12 to t-2. Dividend Yield calculated using the ratio of the annual dividend over the price one day prior to the dividend announcement. Day-of–the-week effect, where M_d, W_d , T_d and F_d are the dummy variables for Monday, Wednesday, Thursday and Friday. They each take value 1 on the respective day of the week and 0 otherwise. I also use year dummy and Fama and French 17 industry dummy. Significant coefficients are highlighted in a, b, and c denoted as significantly different from zero at the 1%, 5% and 10% level respectively.