Macroeconomic determinants of corporate CDS spreads: an empirical study

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ABSTRACT

Several theoretical studies suggest the importance of the macroeconomy for credit default swap (CDS) pricing. However, only few studies empirically investigate the effect of macroeconomic variables on CDS spreads. The previous analysis is further limited to only one or two macroeconomic variables. This provides a motivation for this PhD thesis to conduct an extended analysis on how macroeconomic variables, capturing various dimensions of the economy, affect CDS spreads. In addition, in contrast to the previous literature, the analysis here examines not only the effect of macroeconomic fundamentals but also macroeconomic uncertainty.

The thesis comprises three empirical chapters, all employing U.S. CDS data between March 2009 and December 2016. Chapter 3 employs the time-series framework to explore how macroeconomic variables affect spreads of investment-grade and high-yield CDX, which are traded CDS indices. Chapter 4 accounts for the firm heterogeneity by incorporating firm-specific variables and explores how macroeconomic level and macroeconomic volatility affect single-name CDS spreads within the panel data analysis framework. Chapter 5 adopts a different angle by studying how macroeconomic news announcements affect CDS spreads.

Chapter 3 finds that CDX spreads decrease with total nonfarm payroll growth but increase with industrial production growth volatility. A larger share of explained variation in CDX spreads is accounted for by macroeconomic level variables, while macroeconomic volatility is responsible for a smaller but, nevertheless, sizable share of explained variation. High-yield CDX spreads are more sensitive than investment-grade CDX spreads to macroeconomic variables. Chapter 4 further finds that single-name CDS spreads increase with leverage, industrial production growth volatility and 3-month Treasury Bill rate volatility but decrease with total nonfarm payroll growth. Firm-specific variables account for more than 90% of explained variation in single-name CDS spreads, with macroeconomic variables explaining a considerably smaller remaining share of variation. Similar to CDX spreads, single-name CDS spreads of high and low credit quality differ in their sensitivity to macroeconomic variables. Furthermore, Chapter 5 finds that unexpected announcements in total nonfarm payroll, advanced retail sales, and the ISM manufacturing index reduce CDX spreads. Unexpected announcements in total nonfarm payroll have the most profound effect. The analysis in all empirical chapters highlight the importance of nonfarm payroll, an employment indicator which has not been previously investigated in the CDS pricing literature, indicating its relevance for future theoretical and empirical CDS pricing models.

Keywords: Credit Default Swap Index; Credit Default Swap; Macroeconomic Conditions; Macroeconomic Volatility; Macroeconomic News Announcements

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1. INTRODUCTION

1.1 BACKGROUND

The credit default swap (CDS) is a type of credit derivative that is designed for transferring the credit risk of corporate bonds between two or more parties. In a CDS contract, the protection buyer makes periodic payments to the contract seller until the credit default swap's maturity. In return, the protection seller agrees to compensate the protection buyer when the bond issuer experiences default or other credit events. The bond on which the CDS contract is issued is called the reference obligation and the company that issues the bond is called the reference entity. The periodic payment is usually expressed as the percentage of the principal value of the reference obligation and is called the CDS spread. CDS contracts were first introduced by JP Morgan's Blythe Masters in 1994. Due to the nature of CDS, the CDS contract has become a popular hedging product that have been used by financial institutions to hedge the credit risk of bonds and loans. The global CDS market has experienced tremendous growth, with the notional amounts of total CDS contracts outstanding being 8.346 trillion U.S. dollars in May 2018.

1.2 MOTIVATION

Given the prominence of the CDS market, the CDS pricing mechanisms is of great interest to economic researchers and market regulators. The original structural model introduced by Merton (1974) shows that a firm defaults when the asset value fails to cover its promised payment at the bond's maturity. The Merton model provides a method of modelling the firm's default and addresses some key determinants of CDS spreads, such asset value, asset value growth, debt value, and risk-free interest rate, with a range of restrictive assumptions. The follow-up models release some of the strict assumptions of the Merton model and provide additional determinants. For example, Longstaff and Schwartz (1995) introduce a dynamic risk-free interest rate that follows a continuous Markov process. Collin-Dufresne and Goldstein (2001) allow for the firm to issue new debt during the bond maturity to keep its leverage within a bound. Zhou (2001) allows large and sudden jumps in the asset value by assuming the asset value follows a jump-diffusion process. Furthermore, another strand of structural models highlights the importance of cash flow in determining the corporate default. For example, Kim, Ramaswamy, and Sundaresan (1993) and Fan and Sundaresan (2000) modify the original default condition by assuming that the firm defaults when its cash flow fails to cover its interest payments.

Structural models link the firm's default directly to firms' characteristics. Therefore, extensive empirical research has studied the ability of these characteristics to explain CDS spreads. Although structural models have gained some success in explaining CDS spreads, they have been criticised for having relatively low explanatory power in empirical studies. A notable contribution in this respect is Huang and Huang (2012) that examines six major structural models and finds that all six models fail to fully explain observed spreads of Lehman Bond index.

Partly in response to this performance, more recent structural models have tried to build a link between macroeconomy and default risk. These models postulate that, in addition to the risk-free rate, the growth and volatility of several macroeconomic variables have significant effects on the firm's default risk. For example, Tang and Yan (2006) extend the structural model by incorporating economic output growth and economic output growth volatility. David (2008) examines and reports the importance of inflation in determining the risky bond price and the credit spread. The recent empirical literature incorporates several macroeconomic condition variables when pricing CDS spreads. For example, Tang and Yan (2010) report that real GDP growth and industrial production growth play a significant role in determining the CDS spread. Several recent papers also incorporate macroeconomic volatility variables within the modelling of CDS spreads. For example, Baum and Wan (2010) incorporate the volatility of industrial production growth and report that this has a significantly positive effect on single-name CDS spreads. Tang and Yan (2010) show that GDP growth volatility plays a significant role in determining the CDS spread in addition to the role played by real GDP growth itself.

Although several empirical papers have incorporated macroeconomic variables in the research, these papers tend to consider only a limited range of macroeconomic variables, typically the risk-free interest rate and economic output growth. However, the macroeconomy is a broad concept and single-measure-based economic indicators may be insufficient to provide a complete picture of macroeconomic developments.

Furthermore, despite some existing studies including a wider range of macroeconomic indicators, they focus largely on the effect of the level of the macroeconomy, with the effect of macroeconomic volatility rarely being explored. More recent structural models have sought to address this issue, introducing volatility in respect to economic activity and inflation and highlighting their importance for the determination of the CDS spread. Empirical papers also address the importance of the volatility of economic output growth in determining the CDS spread. All this suggests that macroeconomic volatility may be an important factor when pricing the CDS spread. As a result, it is necessary to conduct an extended analysis on how the level and the volatility of multiple dimensions of macroeconomy affect the CDS spread. Furthermore, if macroeconomic level variables and macroeconomic volatility variables have significant effects on the CDS spread, another interesting question arises: which group of variables plays the most important role in explaining the CDS spread. This is an interesting research topic.

In addition, some papers (e.g. Ericsson, Jacob and Oviedo, 2009; and Annaert *et al*. 2013) find that credit rating plays a role in whether and how macroeconomic variables affect CDS spreads. Given the fact that the creditworthiness of investment-grade and high-yield companies is affected to different degrees when the macroeconomy changes due to the differences in the ability to access external funding and the willingness to invest, it is likely that whether and how macroeconomic variables affect the CDS spread will depend upon credit quality of the reference obligation. The aforementioned studies provide a motivation for analysing whether CDS of relatively high and low credit-quality differ in their sensitivities to changes in macroeconomic variables. Therefore, it is necessary to provide a more detailed analysis in this thesis of how CDS of relatively high and low credit quality differ in their sensitivity to various macroeconomic variables and their volatility.

In Chapter 3, the focus of analysis is the CDX, a weighted average CDS index. Use of such an index means that the effect of firm-specific risk in the single-name CDS spread might be diversified away through the construction, with macroeconomic risk being left in the CDX spread. In addition, our ability to investigate the effects of credit-quality at this level is limited by our capability to identify investment-grade and high-yield CDS indices, recognising that the same company could conceivably move across these indices on the basis of an adverse (or beneficial) credit-rating exercise. On the other hand, a single-name CDS is written on an individual firm and its spread should reflect firm-specific risk and macroeconomic risk at the same time. The prospective difference between the CDS index and single-name CDS is the motivation for Chapter 4 where the thesis extends the analysis to consider how macroeconomic variables affect the single-name CDS spread, accounting for the effects of firm heterogeneity.

Furthermore, theoretical models by Kim, Ramaswamy, and Sundaresan (1993), Anderson and Sundaresan (1996), and Tang and Yan (2006) highlight the potential importance of cash flow in the firm's default event by assuming that firm default occurs when the cash flow cannot cover interest payments. Despite this potential significance in determining the firm's default, cash flow measures have rarely been studied empirically. The lack of empirical literature that studies the effect of cash flow on the CDS pricing provides a motivation for exploring whether and how cash flow measures affect the CDS spread.

Several empirical papers have studied how macroeconomic announcements affect financial markets. For example, Flannery and Protopapadakis (2002) report news surprises, defined as the difference between actual news and expected news, of consumer price inflation and producer price inflation, decreases stock market index returns. Ouadghiri, Mignon, and Boitout (2010) find that positive surprises to the consumer confidence, consumer prices, total nonfarm payroll, and new home sales reduce bond prices significantly 15-minute after the macroeconomic news is released. Huang and Kong (2007) find that while investment-grade Bank of America Merrill Lynch corporate bond spreads are insensitive to macroeconomic new announcements, macroeconomic news surprises to nonfarm payroll, the NAPM index, advanced retail sales, and consumer confidence have negative effects on high-yield spreads.

Even though macroeconomic news announcements have been found to significantly influence these markets, the reaction of the CDS market to macroeconomic announcements has been little explored. This gap in the literature is addressed in the current thesis through an empirical analysis that whether and how macroeconomic announcements affect the CDS spread.

1.3 THESIS STRUCTURE AND OUTLINE OF EMPIRICAL CHAPTERS

This thesis is structured as follows. Chapter 1 provides the introduction to the thesis. It gives a brief introduction into the nature of the CDS market, highlights the gap in the literature and provides motivation for the empirical analysis in the thesis, outlining key research questions considered in the research. Chapter 2 first provides a theoretical literature review focusing on how models of CDS pricing have been developed. The empirical literature review that follows discusses firm-specific variables and macroeconomic variables that have been shown to affect the CDS spread empirically, which informs explanatory variable section for this thesis. Chapter 3 begins the empirical analysis by exploring the effects of macroeconomic level and volatility on the CDS index spread followed, in Chapter 4, by an investigation of the effects of macroeconomic level and macroeconomic volatility on the single-name CDS spread. The empirical analysis in Chapter 5, in turn, focuses on the effects of macroeconomic news announcements on the CDS index spread while conclusions are provided Chapter 6, summarizing the key findings of this thesis and the related contributions to the literature. Broader implications of the research, as well as some of the weaknesses and suggestions for future research, are also discussed in Chapter 6.

The thesis makes the following key contributions to the literature and our understanding of the CDS market. Chapter 3 contributes to the literature by addressing the following key questions:

(1) What is the role of macroeconomy, as measured by multidimensional macroeconomic levels indicator, for the determination of the CDS spread?

(2) What are the joint effects of macroeconomic level and macroeconomic volatility on influencing the CDS spread? As part of this analysis, Chapter 3 examines the relative importance of the macroeconomic level variables and measures of macroeconomic volatility for the determination of the CDS spread.

(3) Does credit quality play a significant role in the response of CDS spreads to macroeconomic factors?

To address the research questions, the analysis in Chapter 3 is conducted separately for investment-grade CDX and high-yield CDX indices using monthly data spanning from March 2009 to December 2016, in a time-series regression framework. The industrial production growth, the total nonfarm payroll growth, the consumer price inflation, and 3-month Treasury Bill rate are adopted to capture the multiple dimensions of the macroeconomy, with volatility measures of these indicators employed to capture macroeconomic volatility.

The analysis in Chapter 3 shows that the growth of total nonfarm payroll has a significantly negative effect on the CDX spread while the volatility of industrial production growth has a significantly positive effect on the CDX spread. The volatility of 3-month Treasury Bill rate has a significantly positive effect on the high-yield CDX spread but has no significant effect on the investment-grade CDX spread. Macroeconomic variables can jointly explain roughly 42% of total variation in the investment-grade CDX spread and 65% of total variation in the high-yield CDX spread.

Furthermore, the relative importance analysis shows that macroeconomic condition variables and macroeconomic volatility variables make 75% and 25% of marginal contribution to the explained variation in the CDX spread respectively. This result confirms the importance of macroeconomic condition variables and macroeconomic volatility variables in determining the CDX spread.

The sensitivity analysis shows that the high-yield CDX is substantially more sensitive than the investment-grade CDX to both macroeconomic level and volatility variables. In particular, the sensitivity of high-yield CDX spread to the total nonfarm payroll growth, the volatility of industrial production growth, and the volatility of 3-month Treasury Bill rate is 1.5 to 2 times greater than the sensitivity of investment-grade CDX spread to these variables.

Chapter 4 extends the analysis by studying how macroeconomic condition variables and macroeconomic volatility variables affect the single-name CDS spread in a panel-data regression framework. Alongside the study of the effects of macroeconomic variables on single-name CDS spreads, Chapter 4 also incorporates firm-specific variables and explores the role of leverage, operating cash flow over total asset, and operating cash flow volatility in determining the single-name CDS spread. The whole sample contains 18105 monthly

CDS spread from 197 CDS contracts, including 154 CDS contracts with 13116 investment-grade CDS spread quotes and 75 CDS contracts with 4989 high-yield CDS spread quotes.

The analysis in Chapter 4 concludes that the total nonfarm payroll growth has a significantly negative effect on the CDS spread while the volatility of industrial production growth and the volatility of 3-month Treasury Bill rate have a significantly positive effect on single-name CDS spread. Leverage is the only significant variable among firm-specific variables and has a positive effect.

Furthermore, Chapter 4 shows that the effect of some independent variables differs for CDS spreads of investment-grade and high-yield credit quality. In particular, the industrial production growth and the total nonfarm payroll growth have a significantly negative effect on the high-yield CDS spread but has an insignificant effect on the investment-grade CDS spread. The volatility of total nonfarm payroll growth and the volatility of operating cash flow have a significant positive effect on the investment-grade CDS spread but have no significant effect on the high-yield CDS spread.

The relative importance analysis finds that macroeconomic condition variables, as a group, make a greater marginal contributions to the single-name CDS spread relative to macroeconomic volatility variables, contributing around 68% and 32% of explained variation in the CDS spread respectively, with similar results holding for both investment-grade and high-yield CDS sub-samples. Comparing marginal contributions of macroeconomic condition variables, macroeconomic volatility variables, and firm-specific variables reveals that firm-specific variables attribute more than 90% of variation in the CDS spread relative to the macroeconomic group of variables.

The sensitivity analysis further shows that the high-yield CDS spread is 1.5 to 3 times more sensitive to the volatility of industrial production growth and the volatility of 3-month Treasury Bill rate relative to the investment-grade CDS spread.

Chapter 5 studies the effects of macroeconomy on the CDX spread from an alternative perspective from that adopted in previous chapters. The analysis examines how unexpected macroeconomic announcements separately affect daily changes in the investment-grade and high-yield CDX spreads using the multi-variate time-series framework.

The research period spans from March 3, 2009 to December 31, 2016. The analysis explores the effect of surprises in thirteen U.S. macroeconomic indicators, including the gross domestic product, industrial production, total nonfarm payroll, unemployment rate, consumer price index, consumer sentiment, the Federal Fund target rate, advanced retail sales, durable goods new orders, capacity utilization, ISM Manufacturing index, ISM Non-Manufacturing index, and trade balance. Macroeconomic surprises are defined in terms of standardised surprises of macroeconomic news.

The results show that macroeconomic surprises in total nonfarm payroll, advanced retail sales, and ISM Manufacturing index have a significantly negative effect on the CDX spread change. Surprises in the unemployment rate, however, have a significantly positive effect on the high-yield CDS spread change but has no significant effect on the investment-grade CDS spread change.

2. LITERATURE REVIEW

2.1 INTRODUCTION

This chapter first in Section 2.2, provides an overview of early structural models and explain how the models have been extended by the follow-up research. Section 2.3 reviews more recent structural models that incorporate macroeconomic variables. Section 2.4 and Section 2.5 review empirical studies that focus on the role of firm-specific variables and macroeconomic variables in determining the credit spread or CDS spread. Section 2.6 provides a thorough explanation on which variables are chosen for the empirical analysis in Chapter 3 and Chapter 4.

A general feature of this literature is that the structural models have been developed for pricing corporate bonds or bond credit spreads. However, the empirical literature tends to employ the model's predictions for analysing both bond credit spread and CDS premiums, assuming their equality. This assumption is based on the following no-arbitrage arguments as detailed in, for example, Duffle (1999), Hull and White (2000) and Blanco *et al.* (2005).

Suppose an investor buys a T-year par bond with yield to maturity of y issued by the reference entity and buys credit protection on that entity for T years in the CDS market at a cost of P_{CDS}. The investor has eliminated most of the default risk associated with the bond. If P_{CDS} is expressed annually as a percentage of the notional principal, then the investor's net annual return is y - P_{CDS}. By arbitrage, this net return should approximately equal the T- year risk-free rate, denoted by r. If y - P_{CDS} is less than r, then shorting the risky bond, writing protection in the CDS market, and buying the risk-free instrument would be a profitable arbitrage opportunity. Similarly, if y - P_{CDS} exceeds r, buying the risky bond, buying protection, and shorting the risk-free bond would be profitable. This suggests that the price of the CDS, P_{CDS}, should equal the credit spread, y - r.

2.2 TRADITIONAL STRUCTURAL MODELS

2.2.1 EARLY STRUCTURAL MODELS

In their pioneering work, Black and Scholes (1973) developed an option valuation model. Inspired by the work of Black and Scholes (1973), Merton (1974) adopted a similar method to develop a pricing model for corporate liabilities in general.

The Merton model considers a firm with a simple capital structure. The firm only has one type of debt, the zero-coupon bond, and equity. At the debt's maturity date T, debtholders received the promised payment from the firm and shareholders receive the difference between the asset value and the debt value. If the promised payment cannot be made at the debt's maturity, debtholders take over the firm immediately and shareholders receive nothing.

As for the company's equity, its value will be zero if the value of asset is less than the value of the promised debt payment, otherwise the equity value will be the difference between the asset value and the promised debt payment. Its payoff structure is equivalent to the payoff of a call option on the value of the firm. The following boundary condition must therefore hold:

$$E = Max\left(0, V - B\right) \quad \text{Equation (2.1)}$$

where V is the value of firm, E is the value of equity and B is the value of the promised debt payment.

The pricing formula for a European call option in the work of Black and Scholes (1973) can then be applied to the equity. In the call option pricing formula, the firm value corresponds to the stock price and the promised payment corresponds to the strike price. As a result, the equity can be priced using the Black-Scholes model:

$$E = V\Phi\left(x_1\right) - Be^{-rT}\Phi\left(x_2\right) \quad \text{Equation (2.2)}$$

where

$$\Phi(x)=\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{x}\exp\left(-\frac{1}{2}z^2\right)dz$$

$$x_1=\left[\log\left(\frac{V}{B}\right)+\left(r+\frac{1}{2}\sigma^2\right)T\right]/\sigma\sqrt{T}$$

$$x_2=x_1-\sigma\sqrt{T}$$

σ is the volatility of the firm value growth.

Furthermore, since the present value of debt, D, is expressed as:

$$D=V-E \qquad \text{Equation (2.3)}$$

From Equation (2.1) to (2.3), the value of the bond is expressed as:

$$D=V\Phi(-x_1)+Be^{-rT}\Phi(x_2) \qquad \text{Equation (2.4)}$$

The credit spread can be computed as:

$$CreditSpread=-\frac{1}{T}\log\left[\Phi(x_2)+\frac{V}{B}e^{rT}\Phi(-x_1)\right] \qquad \text{Equation (2.5)}$$

Moreover, Equations (2.1) to (2.5) identify firm-specific variables that are relevant to bond pricing. In addition to the firm's current asset value V and the promised payment B, the bond price also relies on the riskless interest rate, the bond's time to maturity, and the volatility of the corporation's asset return. Some key bond pricing determinants (e.g. the bond's time to maturity, and the risk-free rate) are available in the real world and some unobservable key determinants (e.g. the firm's asset value, and the volatility of the asset return) can be approximately proxied by the firm's observed variables. Therefore, the Merton model provides a method that can be applied to empirical studies.

2.2.2 FIRST PASSAGE MODELS AND EXTENSIONS

The research of Black and Scholes (1973) and Merton (1974) have encouraged researchers to subsequently extend the structural model for pricing a wider range of financial instruments.

To build the structural model, several essential assumptions are made. One essential assumption of the Merton model is that the company can only default on the debt's maturity date. An alternative approach that is defined as the first-passage model was introduced by Black and Cox (1973). In their case, the firm defaults for the first time when asset value falls below the default threshold, with the possibility of default occurring prior to bond's maturity date.

Longstaff and Schwartz (1995) extend their idea further. Longstaff and Schwartz (1995) first set a constant threshold value, K, as the default boundary below which the corporation cannot meet its current obligations and defaults. However, Longstaff and Schwartz (1995) extend the analysis to allow a time and risk-free rate dependent threshold later. In addition, Longstaff and Schwartz (1995) consider a different asset allocation policy if default occurs and assume that bondholders only receive a proportion of the total asset value when the corporation experiences bankruptcy. Another notable contribution of the Longstaff-Schwartz model is that it relaxes the assumption that the risk-free rate is constant. Instead, they assume that the short-term riskless interest rate follows a continuous Markov process. With these assumptions being relaxed, Longstaff and Schwartz establish a closed-form valuation formula to price the risky discount bonds and the floating-rate bond.

Although the Longstaff and Schwartz model enriches the types of liability considered and abandons some restrictions on the Merton model, some of its assumptions still remain unrealistic in the context of empirical application. Longstaff and Schwartz (1995) assume that additional bond issue is precluded. As a result, when the asset value reaches this default boundary, the debt-equity ratio increases correspondingly. However, several theoretical of papers, Goldstein, Ju, and Leland (2001), for example, introduce dynamic capital structure models that allows the firm to adjust its debt level in response to changes in firm value. Fischer, Heinkel and Zechner (1989) suggests that firms tend to restrict the leverage ratio within a narrow zone, with the leverage ratio exhibiting industry-specific characteristics. Furthermore, empirical evidence, such as Hovakimian, Opler, and Titman (2001), suggests that firms tend to move to a target debt-to-asset ratio, with the application of debt issuance and repurchase.

Inspired by the work of Fischer, Heinkel and Zechner (1989) and Goldstein, Ju, and Leland (2001) amongst others, Collin-Dufresne and Goldstein (2001) extend the first passage model by assuming that the firm maintains its leverage ratio within bounds, with the aim of maximizing firm value. In their work, they maintain the assumption that the firm's asset follows Brownian motion and that the firm defaults when the asset value falls below the default threshold for the first time. However, instead of using the asset value as a variable, they use log asset value. This ensures the following partial equation exists:

$$dv_t = \left(\mu - \delta - \frac{\sigma}{2} \right) dt + \sigma dz_t \qquad \text{Equation (2.6)}$$

where v_t is the logarithm of firm value at time t; μ is the expected return on the firm's asset; δ is the payout ratio.

In contrast with Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001) assume there is a dynamic default threshold. The log default threshold k_t, follows:

$$dk_t = \lambda \left(v_t - \upsilon - k_t \right) dt \qquad \text{Equation (2.7)}$$

where λ and υ are constants which are set by the corporation.

Equation (2.7) indicates that if k_t is less than $\left(v_t - \upsilon \right)$, the firm will increase k_t, and vice-visa. The advantage of this is that it captures the tendency of firms to issue debt when their leverage ratio is below the target ratio and the reluctance to replace maturing debt when the leverage ratio is above the target ratio.

Under the assumption of mean-reverting leverage, and additional assumptions regarding the recovery rate of 1- ω and initial leverage of l_0 , the price of the risky discount bond with the face value being 1 dollar can be written as:

$$P(l_0) = e^{-rT}\left(1 - \omega Q(l_0, T)\right) \qquad \text{Equation (2.8)}$$

Here $Q(l_0,T)$ is the risk-neutral probability that default occurs before time T given that the leverage is l_0 at time 0 and is expressed as:

$$Q(l_0, t_j) = \sum_{i=1}^{j} q_i \quad \text{j=2, 3, …, n} \qquad \text{Equation (2.9)}$$

where

$t_j = jT/n \equiv j\Delta t$ j=1,2,3, …, n

$$q_1 = \frac{N(a_1)}{N\left(b_{(0.5)}\right)};$$

$$q_i = \left(\frac{1}{N(b_{0.5})}\right)\left[N(a_i) - \sum_{j=1}^{i-1} q_j N\left(b_{i-j+0.5}\right)\right] \quad \text{i=2,3, …, n;}$$

$$a_i = \frac{M(i\Delta t)}{S(i\Delta t)};$$

$$b_i = \frac{L(i\Delta t)}{S(i\Delta t)};$$

$$M(t) = l_0 e^{-\lambda t} + \bar{l}\left(1 - e^{-\lambda t}\right);$$

$$L(t) = \bar{l}\left(1 - e^{-\lambda t}\right);$$

$$S^2(t) = \frac{\sigma^2}{2\lambda}\left(1 - e^{-2\lambda t}\right)$$

$\bar{l}$ is the long-run mean leverage;

N () is the standard normal cumulative distribution function.

The credit spread can be computed as:

$$CreditSpread = -\frac{1}{T}\log\left(1 - \omega Q(l_0, T)\right) \qquad \text{Equation (2.10)}$$

2.2.3. ASSET VOLATILITY AND JUMP PROCESS MODEL

Another contentious assumption in the Merton model is that the company's asset value follows a diffusion process. This process only allows asset value to change incrementally during a small time interval. Under the Merton diffusion process, a sudden drop in the firm value is impossible, hence firms never default by surprise. This assumption is inconsistent with empirical evidence, such as Wright and Zhou (2009), where there is sudden jumps in the excess bond return are reported. None of the previous theoretical models can explain a sudden unexpected change in bond price observed.

To price the bond in a manner that is more consistent with the observed behaviour of bond market pricing, Zhou (2001) prices the zero-coupon bond by introducing a structural model with the assumption that firm value follows a jump-diffusion process. In the Zhou model, the dynamics of firm value (V_t) are given by the following process:

$$\frac{dV_t}{V_t} = (\mu - \lambda v)\,dt + \theta dZ_1 + (\Pi - 1)\,dY \qquad \text{Equation (2.11)}$$

where μ is the expected return on the firm's assets; v, λ and θ are positive constants; Z_1 is a standard Brownian motion; dY is a Poisson process with intensity parameter λ; $\Pi > 0$ is the jump amplitude following a log-normal distribution.

The price of the risky discount bond with face value being 1 dollar can be then expressed as:

$$B(X,T) = e^{-rT} - \mathrm{e}^{-rT}\, E^{Q}\left[\omega(X_t)\, I_{\tau \le T}\right] \qquad \text{Equation (2.12)}$$

where X_t is the ratio of firm value and default threshold at time t

$\omega(X_t)$ is the loss given default if the risky discount bond defaults at time t_i and has a linear form of $\omega(X_t) = \omega_0 - \omega_1 X_t$;

Q is the risk-adjusted probability;

$$I_{\tau \le T} = \begin{cases} 1 & if\, \tau \le T, \\ 0 & otherwise \end{cases}$$

The spread can be computed as:

$$CreditSpread = -\frac{1}{T}\log\left(e^{-rT} - \mathrm{e}^{-rT}\, E^{Q}\left[\omega\left(X_t\right) I_{\tau\le T}\right]\right) \qquad \text{Equation (2.13)}$$

Equation (2.11) suggests that there are two random components in the asset value evolution: a continuous diffusion component that causes gradual changes in the asset value and a discontinuous jump component that causes sudden changes in the asset value on the arrival of new information. In addition, due to the fact that sudden changes in asset values are allowed, the asset value $\left(V_t\right)$ is not necessarily equal to the default threshold when the company defaults – the company falls below the threshold due to the jump, which is different from the work of Merton (1974), and Longstaff and Schwartz (1995).

2.2.4 CASH FLOW AND STRATEGIC DEBT VALUATION MODELS

The structural models mentioned previously highlight the importance of the firm's asset value in determining the firm's default, the bond price and the credit spread. However, John (1993), Ericsson (2000), and Uhrig-Homburg (2005) argue that these early structural models are not well suited for modelling financial distress and offer an alternative definition of financial distress as a situation where firm cash flow cannot cover its current obligations. According to the Moody's Investors Service (1998), delayed or missed payments accounted for 43% of the corporate default during period 1982 to 1997. Based on this definition of financial distress, another class of structural models has emerged that allows for strategic debt service, by linking firms' bankruptcy decision-making and bond pricing to firms' cash flow.

In particular, Kim, Ramaswamy, and Sundaresan (1993) introduce a new structural model to price callable and non-callable bonds. They define the net cash flow as the difference between the operating cash flow and a predetermined investment outlay and incorporate an assumption that the firm will go bankrupt if the firm's net cash flow cannot meet contractual coupon obligations during a bond's life.

Mella-Barral and Perraudin (1993) also make the bankruptcy decision to depend upon cash-flow related variables and introduce an extended structural model that has a closed-form solution to price perpetual bonds with constant coupons over time. Their model allows for strategic debt service by assuming that the company will opt for liquidation when the capital that is financed by perpetual bonds cannot cover the firms' operating losses.

In an early structural model by Merton (1974), first passage models that started with Longstaff and Schwartz (1995), and a jump process model by Zhou (2001), bankruptcy is determined by the asset value, the default threshold or the level of net cash flow as in more recent models. However, these models do not account for interaction between debtholders and equity-holders. Based on the model of Mella-Barral and Perraudin (1993), Anderson and Sundaresan (1996) study the valuation of debt contacts by introducing a bankruptcy game. Within this framework, a firm will continue if it can fulfil debt obligations and cover coupon payments. If the firm defaults on its debt contracts, bondholders can either take the firm to bankruptcy with the expense of high liquidation cost or not liquidate the firm as long as they are persuaded by a sufficient amount paid by the firm. In addition, compared with Mella-Barral and Perraudin (1993), Anderson and Sundaresan (1996) extend the variety of bonds to be priced by studying discount bonds and coupon bonds, both with finite maturities.

In a follow-up study, Fan and Sundaresan (2000) study bond valuation with strategic interactions between debtholders and equity-holders and give Nash solutions to the bargaining game between debtholders and equity-holders. Similar to Anderson and Sundaresan (1996), Fan and Sundaresan (2000) also allow for debt-holders initiatives. A debt-equity swap, for example, will be chosen by debt holders if liquidation costs are higher than a threshold value while a takeover of the firm will be chosen by debt holders if liquidation costs are not sufficiently large. In addition, Fan and Sundaresan (2000) also extend their model from pricing of a perpetual bond to pricing coupon bonds with finite maturities.

2.3 STRUCTURAL MODELS WITH MACROECONOMIC VARIABLES

Several structural models, such as those of Merton (1974), and Longstaff and Schwartz (1995), have been proposed to theoretically explain credit risk pricing. One practical issue that arises when these models are applied to pricing credit risk instruments in practice is that they tend to underestimate the bond credit spread or the CDS spread. Some early empirical papers, such as Jones, Mason, and Rosenfeld (1983), Jones, Mason, and Rosenfeld (1985), and Ogden (1987), test Merton model's ability to explain corporate credit spreads and found model-implied credit spreads are much lower than actual credit spreads. Lyden and Saraniti (2001), a more recent paper, evaluate the performance of the Merton (1974) and the Longstaff and Schwartz (1995) models for valuing U.S. corporate bonds that satisfy bond conditions given in the work of Merton (1974) and Longstaff and Schwartz (1995). Compared with the actual credit spread, the credit spread generated by the Merton (1974) model is 80 to 90 basis points lower. Moreover, although the Longstaff and Schwartz (1995) model relaxes several of the strict assumptions underpinning the Merton (1974) model, its performance in estimating the credit spread is little better. The work of Huang and Huang (2012) is another prominent study that empirically examines the ability of several structural models to value bond prices. Following Lyden and Saraniti (2001), Huang and Huang (2012) ensure consistency with the key assumptions underlying the structural models by imposing strict restrictions on sample selection. Models of Leland (1994), Longstaff and Schwartz (1995), Leland and Toft (1996), Anderson and Sunadresan (1996), Anderson, Sundaresan and Tychon (1996), Mella-Barral and Perraudin (1997) and Collin-Dufresne and Goldstein (2001) are examined under similar assumptions and their predictable abilities for the credit spread are compared. Huang and Huang (2012) find that only a small percentage of the observed investment-grade corporate credit spreads is captured by structural models. Feldhutter and Schaefer (2014) find Merton model and Black-Cox model can correctly estimate investment-grade Merrill Lynch bond index spreads but underestimate high-yield Merrill Lynch bond index spreads.

The phenomenon where structural models cannot fully match actual credit spreads is called the credit puzzle and this phenomenon inspires more recent structural models to incorporate systematic factors, such as macroeconomic variables, that can affect the firm's default and credit spread. The following subsection provides a brief introduction to how researchers developed and extended the original Merton (1974) model by incorporating or adding macroeconomic determinants, to enhance the ability of structural models to match empirical evidence.

2.3.1 THE MERTON MODEL AND ITS EXTENSIONS

Even though early structural models do not explicitly focus on the effect of macroeconomic fundamentals, the importance of risk-free rate, a key indicator of the monetary policy, is highlighted by structural class of models. The risk-free rate affects the firm value dynamics by acting as a risk-neutral drift parameter of the risk neutral process for asset value of a firm. Theoretically, if the risk-free rate goes up, the firm's value will drift away from the default threshold at a faster rate, which decreases the risk-neutral probability of default therefore reduces the credit spread. For the purpose of expositional convenience, Merton (1974) makes assumptions including a constant risk-free rate amongst others. These assumptions effectively allow Merton (1974) to model a simplified form of firm behavior. However, the assumptions have been criticized for being too restrictive and not reflecting some important properties of the observed data generating process.

Relaxing these assumptions, various extensions of the Merton (1974) model have been developed. For example, Shimko, Tejima and Van Deventer (1993) retain the structure of

Merton's model but allow for a stochastic risk-free rate that follows a mean-reverting process with constant volatility. The volatility of the risk-free rate is found to increase the credit spread. Changes in risk-free rate volatility affect the bond returns via affecting changes in the slope of the term structure and the correlation of the risk-free rate changes and asset value changes. This model not only supports the Merton model by showing the negative relationship between the credit spread and risk-free rate, but also confirms the importance of risk-free rate volatility in determining the credit spread. More recent papers, such as Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001) and Zhou (2001), also focus on introducing a stochastic riskless rate, as opposed to the constant riskless rate assumption in Merton (1974).

The only macroeconomic variable incorporated in the Merton structural model and its extensions is the risk-free interest rate, which at best, will struggle to capture the complex dynamics of the entire macroeconomy. Several recent papers, such as Tang and Yan (2006), and Bhamra, Kuehn and Strebulaev (2010), suggest that early structural models may omit some common determinants and that an extended model which incorporates macroeconomic determinants may perform better, which gives rise to structural models that incorporate macroeconomic variables, such as economic output growth and inflation.

2.3.2 STRUCTURAL TYPE MODELS WITH MACROECONOMIC INFLUENCES

Tang and Yan (2006) extend the conventional structural model by broadening the range of macroeconomic conditions that matter for the credit spread determination alongside firm characteristics. The model of Tang and Yan (2006) assumes the economic output follows a diffusion process with a mean-reverting economic output growth and a constant volatility of economic output. The economic output O(t) is described by:

$$\frac{dO(t)}{O(t)} = \mu_O(t)\,dt + \sigma_O dZ_O(t) \qquad \text{Equation (2.14)}$$

where $O(t)$ is the total output of the economy;

$\mu_O(t)$ is the mean-reverting economic output growth;

σ_o is the volatility of aggregate output;

$Z_O(t)$ is a standard Brownian motion.

The economic output growth $\mu_O(t)$ follows a mean-reverting process and is described by:

$$d\mu_O(t) = \theta\left(\overline{\mu}_O - \mu_O(t)\right)dt + \sigma_\mu dZ_O(t) \qquad \text{Equation (2.15)}$$

where θ is the speed of mean reversion;

$\overline{\mu}_O$ is the long-run mean of economic output growth;

σ_μ is the volatility of economic output growth.

The risk-free rate is given by:

$$r(t) = \zeta + \gamma\mu_O(t) - \frac{1}{2}\gamma(1+\gamma)\sigma_O^2 \qquad \text{Equation (2.16)}$$

where ζ is the time discount factor;

γ is the risk aversion coefficient.

Furthermore, Tang and Yan (2006) assumes that a firm's cash flow is a proportion of the aggregate economic output and the firm defaults when its cash flow cannot cover its interest payment. The firm's cash flow, K(t), is assumed to follow a diffusion process and is given by:

$$\frac{dK(t)}{K(t)} = \left(\beta\mu_O(t) + \xi(t)\right)dt + \sigma_K\rho Z_O(t) + \sigma_K\sqrt{1-\rho^2}\,dZ_K(t) \qquad \text{Equation (2.17)}$$

where K is the firm's cash flow;

β is the cash flow beta;

$\xi(t)$ is the firm growth rate;

σ_K is the volatility of the firm's cash flow growth;

ρ is the correlation between firm's cash flow and economic output;

$Z_K(t)$ is a standard Brownian motion.

Tang and Yan (2010) assume a risky coupon bond with coupon payment rate being c and the maturity being T. The risky bond is pledged on the firm cash flow K(t). During each period, Δt, the firm will pay the bondholders a fixed coupon, cΔt, before the bond matures. The firm defaults when its cash flow is not enough to cover the coupon payment. Tang and Yan (2010) also assume bondholders receive 1-ω of face value F. Under these assumptions, the payoff stream of the risky bond is expressed as:

$$g(t) = c \cdot I(t \le T) \cdot I(t < \tau) + F \cdot \pi(t - T) \cdot I(t < \tau) + (1-\omega) \cdot F \cdot \pi(t-\tau) \cdot I(t \le T)$$

Equation (2.18)

where

$\tau = \inf\{t : K(t) < c\}$ is the first passage time which represents the time of default;

$\pi(t-\tau)$ is the Kronecker delta.

The value of the risky debt with a face value F, coupon payment rate c, and maturity T is given by:

$$P = E^Q\left[\int_0^T e^{-\int_0^t (\zeta + \gamma\mu_O(s) - \frac{1}{2}\gamma(1+\gamma)\sigma_O^2) ds} g(t)\, dt\right]$$ Equation (2.19)

where Q is the risk neutral measure.

The price of the risk-free discount bond which pays 1 with maturity at time T is given by:

$$P(t,T,r(t)) = e^{A(t,T) - B_\theta(t,T) r(t)}$$ Equation (2.20)

where

$$A(t,T) = -\left[\bar{r} - \frac{1}{2}\gamma^2\left(\frac{2\sigma_o\sigma_\mu}{\theta} + \frac{\sigma_\mu^2}{\theta^2}\right)\right](T-t) + \bar{r}B_\theta(t,T)$$
$$-\frac{1}{2}\gamma^2\left[\left(\frac{2\sigma_o\sigma_\mu}{\theta} + \frac{2\sigma_\mu^2}{\theta^2}\right)B_\theta(t,T) - \frac{\sigma_\mu^2}{\theta^2}B_{2\theta}(t,T)\right]$$

$$B_\theta(t,T) = \frac{1 - e^{-\theta(T-t)}}{\theta}$$

$\bar{r}$ is the long-term risk-free rate.

The price of a risk-free bond with an identical payment structure to the risky bond is described as:

$$FV = c\int_0^T P\left(0,t,r\left(t\right)\right)dt + F\cdot P\left(0,T,r\left(t\right)\right) \qquad \text{Equation (2.21)}$$

The yield to maturity of this risky bond Y is defined by

$$P = \frac{c}{Y} + \left(F - \frac{c}{Y}\right)e^{-YT} \qquad \text{Equation (2.22)}$$

where c is the coupon payment;

F is the face value of the risky bond.

Similarly, the yield to maturity of the risk-free bond with the same payment structure, R, is given by:

$$FV = \frac{c}{R} + \left(F - \frac{c}{R}\right)e^{-RT} \qquad \text{Equation (2.23)}$$

The credit spread of the risky bond is defined as the difference between Y and the risk-free rate, R.

As Equation (2.17) suggest, the economic output growth works as the drift in the evolution process of the firm's cash flow. An increase in the economic output growth will increase the drift and lead the firm's cash flow drift away from the firm's interest payment, and therefore reduce the default probability and the credit spread.

In addition, the Tang and Yan (2006) model indicates a positive relationship between the credit spread and the volatility of economic growth. Tang and Yan (2006) define the market risk premium ζ as the product of the relevant risk aversion coefficient γ and the volatility of economic output growth σ_O. The market risk premium increases when the volatility of growth increases, which in turn, decreases the bond price but increases the credit spread.

Chen (2010) highlights the importance of the expected growth and the volatility of aggregate output in determining the credit spread within the context of a structural structure. As with the preceding modes, Chen (2010) permits an analysis of how the output influences the corporate credit spread and the likelihood of a firm's default. The representative household has recursive risk preferences therefore has high marginal utilities during the recession. Small negative shocks to the economy lowers the level of aggregate economic output and large negative shocks to the economy make the economy to switch to a worse economic state with a lower expected growth but a higher volatility of the aggregate output. Both shocks lead to a higher marginal utility and a higher discount factor, which results in a lower bond price and a higher credit spread.

Bhamra, Kuehn and Strebulaev (2010) developed a theoretical model that exhibits both features of structural models that follow literatures (e.g. Merton, 1974; Leland, 1994; Strebulaev, 2007) among others and consumption-based asset pricing models like those of Bansal and Yaron (2004) and Calvet and Fisher (2008). The model assumes that agents have Epstein-Zin-Weil preferences and agents' state price density depends on the consumption growth rate which jumps when the economy switches from one state to another state. A decrease in consumption growth rate will increase the state price density which further decreases the price of the bond, leading to a higher credit spread in the bad economy state.

While aforementioned structural models focus on the effects of the aggregate output growth and its volatility, David (2008) examines the role of inflation. Unlike the work of Bhamra, Kuehn and Strebulaev (2010) and Chen (2010), David (2008) assumes an unobservable state-switching economy; investors form their expectations about the economy by observing inflation. Inflation and real earnings follow Weiner processes with jumping drifts. Investors cannot observe current drifts of inflation and real earnings but can observe their historical drifts. The price kernel also follows a Weiner process and its drift is a linear negative function of drifts of inflation and real earnings. In this framework, investors' expectations on the current drifts of inflation and real earnings can be made conditionally on the observed historical drifts of inflation and earnings. The drift of the current price kernel then can be constructed based the expected current drifts of inflation and real earnings. Both high expected current inflation and real earnings lead to a lower price kernel which, in turn, leads to a higher bond price and a lower credit spread. Investors receive up-to-date information on inflation and earning, and correspondingly update their expectations on the current inflation and real earnings over time. Time-varying expectations on inflation, real earnings, and price kernel, in turn, result in the time-varying and volatile corporate bond price and credit spread.

2.3.3 GENERAL EQUILIBRIUM MODELS

Apart from structural models, some general equilibrium models also explore the linkage between asset pricing and macroeconomic variables by incorporating preferences of agents and time-series properties of cash flows.

In particular, Kim *et al.* (2009) propose a consumption-based asset pricing model featuring investors with Epstein-Zin-Weil preferences. They model time-varying consumption growth rate volatility using a logistic volatility function that controls state switching across two regimes. One regime has low volatility while the other has high volatility. Transitions between these volatility states occur smoothly when one regime switches to another regime slowly. Investors do not know which regime they belong to but, with Epstein-Zin-Weil preferences, they have a preference for resolving this uncertainty early. As a result, they require a higher risk premium because they do not like the uncertainty about the future regime. Although the two models belong to different classes of models and underpinning assumptions, the work of Kim *et al.* (2009) shares some similarity in insights with the work of Chen (2010). Namely, both models concur that investors require a higher premium on a security when faced with higher macroeconomic volatilities, namely aggregate output volatility and consumption growth rate volatility.

2.4 EMPIRICAL STUDIES OF FIRM-SPECIFIC DETERMINANTS OF THE CREDIT/CDS SPREAD.

In addition to theoretical models linking firm's characteristics and macroeconomic variables to the firm's default risk, there are a large number of papers that study how firm characteristics and macroeconomic variables affect the credit/CDS spread empirically. The most commonly used methodology to study the effect of firm-specific variables and macroeconomic variables on the credit/CDS spread is time series or panel data regression. Within this framework, firm-specific and macroeconomic variables are introduced to capture different aspects of the firm. This section conducts a review of relevant empirical literature that focuses on firm-specific variables studied in this literature, providing explanation of their effect on the credit/CDS spread on a variable-by-variable basis. Section 2.4 in turn continues the empirical literature review in a similar manner but with a focus on how different macroeconomic variables affect the credit/CDS spread.

2.4.1 FIRM-SPECIFIC VARIABLES AND CREDIT SPREAD

Leverage

According to the structural model framework (e.g. Longstaff and Schwartz, 1995; and Collin-Dufresne and Goldstein, 2001), the default is triggered when the firm's asset value goes below the default threshold. The default threshold is positively related to the debt value because promised interest payment increases with the debt value. Leverage, the percentage of debt that is used to finance asset, is a commonly used measure to capture the relationship between firm's asset value and firm's debt value. Higher leverage indicates the higher debt level and high default threshold, which suggests the firm value is more likely to fall below the default threshold if other conditions hold equally.

Collin-Dufresne, Goldstein and Martin (2001) explore the determinants of credit spread changes, using monthly U.S. data from July 1988 to December 1997. The dynamic relationship between the firm's asset value and the firm's debt value is captured by the firm's leverage. Collin-Dufresne, Goldstein and Martin (2001) define leverage as the book value of debt over the sum of book value of debt and the market value of the equity. Results of univariate regression show that there is a significantly positive relationship between credit spread changes and leverage changes, with leverage changes explaining between 0.3% and 6.5% of total variation in credit spread changes.

Variations in constructing leverage occur. Ericsson, Jacobs, and Oviedo (2009), for example, define leverage as the sum of book value of debt and book value of preferred equity divided by the sum of the market value of equity, the book value of debt and the book value of preferred equity. Ericsson, Jacobs, and Oviedo (2009) use the daily U.S. credit spread from January 1, 1999 to December 31, 2002, and find that leverage is significantly positive, explaining around 14% of the total variation in the change of the CDS spread. Using the same leverage construction method as Ericsson, Jacobs, and Oviedo (2009), Kim *et al.* (2017) explore the determinants of U.S. dollar denominated CDS spreads using monthly data from September 2004 to March 2012 and find the leverage change is significantly positive in determining the CDS change.

Asset Value Growth Volatility

Another important factor that potentially influence the credit and the CDS spread is asset value volatility. Structural models assume that the firm's asset value follows a diffusion process or a diffusion-jump process and that the firm defaults once its asset value is below the default threshold. The more volatile the asset value is, therefore the more likely that the firm's asset value will go below the default threshold, with the result that the firm is more likely to default and with the result that the credit/CDS spread is higher.

In addition, the effect of the asset value volatility can also be illustrated using the option pricing theory. Section 2.2.1 explains that the value of equity is the equivalent to the payoff of a call option where the firm value corresponds to the stock price and the promised payment corresponds to the strike price. As a result, the value of debt, the difference between the asset value and equity value, can be regarded as the equivalent to the payoff of a long position in a risk-free discount bond, with the face value being the firm's asset value, and a short position on a put option, with the firm value being the stock price and the promised payment being the strike price. The higher asset value volatility increases the value of the put option that, in turn, decreases the bond value but increases its credit risk and, consequently, CDS spread.

However, the firm's asset value is unobservable in principle, and thus cannot be measured directly. As a result, the asset value volatility is approximated by the equity volatility in the empirical literature. Several different measures of the asset value volatility are incorporated in the empirical literature.

Collin-Dufresne, Goldstein, and Martin (2001), for example, use the VIX index, the option-implied volatility of S&P 100 index, to capture the generic equity volatility and find a positive relationship between the credit spread change and the VIX change. Furthermore, Collin-Dufresne, Goldstein, and Martin (2001) use the option-implied jump as the measure of firm's jump risk and find the change of option-implied jump has a positive effect on the credit spread change and is statistically significant in most cases.

2.4.2 FIRM-SPECIFIC VARIABLES AND CDS SPREAD

Recent papers prefer to use CDS spread over the bond credit spread as a proxy for the firm's credit risk for several reasons. The biggest attraction of CDS spreads is that no adjustment or additional calculations are required for CDS spreads because they are already expressed as spreads. Bond yields, in particular, require an assumption about the appropriate benchmark risk-free rate before they can be converted into credit spreads. Hull, Predescu, and White (2004) suggest that the usual practice of calculating the credit spread as the excess of the bond yield over a similar Treasury yield is highly questionable. This is because this practice leaves many other factors such as liquidity, taxation, and regulation in the credit spread, therefore the credit spread cannot be regarded as a pure proxy for the firm's credit risk.

Leverage

There is one strand of literature that explores the relationship between the CDS spread and leverage. Tang and Yan (2007, 2010) subsequently define the leverage using the same method as adopted by Collin-Dufresne, Goldstein and Martin (2001) but use the CDS spread as the dependent variable. Using the monthly U.S. dollar denominated CDS spread from June 1997 to March 2006, two studies find a significantly positive relationship between the CDS spread and the leverage. Using the same method for leverage construction, Lesplingart, Majois, and Petitjean (2012) construct leverage similarly to focus on the daily Euro-denominated CDS spread and the crisis period from January 2005 to December 2009. The paper finds that leverage is significantly positive in determining the CDS spread, which is consistent with U.S. market-based papers.

Using the same leverage construction method, some papers study how the leverage change affects the CDS spread change. Coro, Dufour, and Varotto (2013) use the daily Euro-denominated CDS spread changes from January 1, 2006 to July 31, 2009 and find the leverage change has a significantly positive effect on the CDS spread change. Using monthly changes in the U.S. dollar denominated CDS spread from February 2002 to November 2009, Galil *et al.* (2014) find the leverage change has a significantly positive effect on the CDS spread change, which is consistent with Coro, Dufour, and Varotto (2013).

Baum and Wan (2010) alternatively define leverage as the book value of debt over book value of total asset and find a significantly positive relationship between the U.S. dollar denominated CDS spread and leverage using monthly data from January 2001 to December 2006.

Despite the difference in how leverage is constructed, a positive relationship between the credit/CDS spread and leverage is commonly found within the empirical literature, thereby empirically supporting common inference from the structural class of models.

Asset Value

As the structural framework suggests, a firm with higher asset value is less likely to default. As a result, the firm's asset value is also a prospective determinant of the CDS spread. The commonly used measure of the asset value in the empirical literature is the logarithm of the firm's market capitalization. Tang and Yan (2007) use this measure but find no obvious linkage between the CDS spread and asset value. Baum and Wan (2010) investigate the effects of the logarithm of market capitalization on U.S. corporate CDS spreads in the investment-grade ratings and speculative grade ratings, with the monthly sample spanning the period January 2001 to December 2006. In contrast with Tang and Yan (2007), Baum and Wan (2010) find the logarithm of market capitalization has a significantly negative relationship with the CDS spread. Lesplingart, Mjois, Petitjean (2012) use the same asset value measure adopted by Tang and Yan (2007) and Baum and Wan (2010) and find asset value has a significantly negative effect on the CDS spread.

Asset Value Growth

Apart from the firm's asset value, the evolution of firm's asset value also plays a prospective role in determining the credit spread in structural models. According to the structural framework, the firm is less likely to default if firm value is moving away from the default threshold. Empirically, the firm asset value is unobservable, which makes measuring firm value changes difficult. Several of studies proxy firm value changes using stock returns because the change in firm value is proportional to the change in equity value.

Blanco, Brennan, and Marsh (2005) use daily U.S. and European CDS spreads from January 2, 2001 to June 20, 2002 and use the firm's stock return as a proxy for the firm's asset value growth. They find that that there is a significantly negative relationship between the CDS spread and the firm's stock return. Baum and Wan (2010) also adopt stock returns as a proxy for the firm's asset value growth in the analysis of CDS spread determination and find that the stock return is significantly negative determinant for the CDS spread. Annaert *et al.*

(2013) study the determinants of Euro-area bank CDS spreads using weekly data from January 2004 to October 2008. They show that stock returns have a significant negative effect on the CDS spread and explain 0.78% of the total variation in the CDS spread before the crisis and 10.33% of total variation in the CDS spread during the financial crisis period. Pires, Pereira, and Martins (2015) study both U.S. and European single-name CDS spread using monthly data from August 2002 to February 2007 and find the stock return to have a significantly negative effect on the CDS spread.

Asset Value Growth Volatility

Another important factor that potentially influence the credit and the CDS spread is asset value volatility. Structural models assume that the firm's asset value follows a diffusion process or a diffusion-jump process and that the firm defaults once its asset value is below the default threshold. The more volatile the asset value is, therefore the more likely that the firm's asset value will go below the default threshold, with the result that the firm is more likely to default and with the result that the CDS spread is higher.

However, the firm's asset value is unobservable in principle, and thus cannot be measured directly. As a result, the asset value volatility is approximated by the equity volatility in the empirical literature. Several different measures of the asset value volatility are incorporated in the empirical literature.

One common measure of the asset value volatility is the historical standard deviation of stock returns. Annaert *et al.* (2013) construct the weekly standard deviation based on the daily stock return to capture the equity volatility. The paper shows that the equity volatility has a significantly positive effect on the Euro-denominated CDS spread. Baum and Wan (2010) also use the standard deviation of stock returns but measure monthly to capture monthly equity volatility and find that it has a significantly positive effect on the U.S. dollar denominated CDS spread. Galil *et al*. (2014) construct the variance of stock return using the previous 250-day window and use it as the proxy for the equity volatility. Univariate regression results show that the equity volatility change is significantly positive in determining the CDS spread change and can explain approximately 9% of the total variation in the CDS spread change.

The standard deviation measure is a historical measure of equity volatility because it is constructed based on historical stock returns. Apart from using the historical measure, some papers use an option-implied volatility measure as a forward-looking equity volatility indicator. Blanco, Brennan, and Marsh (2005) use the change in the implied volatility from near-the-money put options to capture the firm-specific equity volatility and find a significantly positive relationship between the CDS spread and the option-implied volatility change. Similar to Blanco, Brennan, and Marsh (2005), Kim *et al.* (2017) use the change in 3-month implied volatility from at-the-money options and find it has a significantly positive effect on the CDS spread change.

Apart from determining the CDS spread, the asset value volatility measure is also used to determine the CDS index spread. Breitenfellner and Wagner (2012) use daily data from June 16, 2004 to August 6, 2010 and study the determinants of spread changes of the iTraxx. The standard deviation of the portfolio return that has the same composition as the iTraxx is calculated based on a 20-observation rolling window. However, the paper finds no significant linkage between the spread change of the iTraxx spread and portfolio return volatility change.

Cash Flow and its volatility

Several theoretical models, such as Anderson and Sundaresan (1996) and Tang and Yan (2006), define the financial distress as a situation where firm cash flow cannot cover its current obligations. The lower and more volatile the cash flow is, the more likely the firm will default. Even though the importance of cash flow in determining the firm's credit risk has been highlighted in theoretical models, few empirical papers directly incorporate variables that capture firm's cash flow to examine the linkage between the CDS spread and the firm's cash-flow.

Few papers use indirect measures of the firm's cash flow. Baum and Wan (2010), for example, use the return on equity and find it has a significantly negative effect on the CDS spread. Chiaramonte and Casu (2013) is another study of the determinants of bank CDS spreads using monthly data running from January 2005 to June 2011. Using return on equity and return on assets as indicators of banks' ability to generate profit, the paper finds both two measures have a significantly negative effect on the bank CDS spread.

Tang and Yan (2010) studies the direct link between the CDS spread and the firm's cash flow, using the cash-flow volatility. They find that the cash-flow volatility has significantly positive effects on the CDS spread.

Credit Rating

Apart from the aforementioned variables that measure only one aspect of a firm's characteristics, there is another variable, credit rating that captures the overall credit condition of the firm. Credit rating is a forward-looking measure of a firm's probability of default and is assigned by credit rating agencies. Unlike other firm-specific variables, the credit rating is a type of categorical variable. As a result, some transformation is needed before introducing it into the analysis. Tang and Yan (2007) change credit rating into numerical rating, allocating 35 to AAA and 10 to D. The numerical rating is highly significant and has negative influence on the single-name CDS spread. Similarly, Lesplingart, Majois, and Petitjean (2012) transform credit rating into a numerical scale, with 1 given to AAA and 17 given to C, and report a significantly positive relationship between the CDS spread and credit rating. Coro, Dufour, and Varotto (2013) study the determinants of CDS spread changes applying the similar method to that of Tang and Yan (2007) and Lesplingart, Majois, and Petitjean (2012), giving 1 to AAA rating and 22 to D rating. However, Coro, Dufour, and Varotto (2013) find no significant relationship between the CDS spread change and the credit rating change using monthly data but a significantly positive relationship using the weekly data during the financial crisis.

2.5 EMPIRICAL STUDIES OF MACROECONOMIC DETERMINANTS OF CDS/CREDIT SPREADS

The empirical evidence of impacts of macroeconomic indicators on the credit spread and the CDS spread has been studied in a number of studies. Several macroeconomic variables have been employed to capture different aspects of macroeconomic influence on the credit/CDS spread. These macroeconomic variables can be classified into several categories which capture different aspects of the macroeconomy, such as real economic activity, inflation, and the risk-free interest rate.

2.5.1 MACROECONOMIC CONDITION VARIABLES AND CREDIT SPREADS

Real Economic Output Activity

According to Tang and Yan (2006), the drift of firm's cash flow process is positively related to the economic output growth. Firm defaults on their bonds if the cash flow is insufficient to cover coupon payments. As a result, a higher economic output growth results in a larger drift with cash flow drifting away above the default threshold level, which results in lower default risk.

One strand of literature analyses the link between the macroeconomic fundamentals and the term structure of credit spread using the no-arbitrage affine term structure modeling approach. This approach involves with constructing the standardized vector of a single economic activity indicator using the first principle component of several economic output series[1]. Amato and Luisi (2006) study the relationship between macroeconomic factors and

[1] The first step of constructing standardized vectors is to standardize each economic series by subtracting the series mean and dividing the series by the sample standard deviation. The next step is to form a vector using standardized series.

the term structure of credit spreads for bonds in low investment (BBB-rated) and speculative (B-rated) credit rating categories, by formulating a no-arbitrage affine term structure model. Their analysis employs monthly data between May 1992 and April 2004. In the analysis, real economic activity is captured by a common factor extracted from several relevant variables.[2] Estimated coefficients of the term-structure model show that an increase in real activity lowers instantaneous B-rated credit spreads but has insignificant effect on BBB-rated spread. Using the same method, Wu and Zhang (2008) similarly focus on the effect of real economic growth factor[3] on the term structure of credit spreads for bonds of various credit ratings. The factor loading analysis shows that a unit shock on real economic activity factor decreases BBB-rated and BB-rated credit spread but does not change AA-rated and A-rated credit spreads significantly. In this respect, this paper is consistent with Amato and Luisi (2006), suggesting that the sensitivity of corporate credit spreads to economic activity varies across different credit ratings. Zhou (2014) explores the determinants of credit spread in the context of a Gaussian affine term structure model, incorporating the real economic output dimension. The analysis utilizes U.S. based monthly data from December 1989 to May 2013. The dataset includes A-rated bond and BBB-rated bond at 2, 5 and 10-year maturity. Using the same method as Amato and Luisi (2006) and Wu and Zhang (2008), Zhou (2014) constructs an economic activity indicator using the unemployment rate, employment growth and output growth based on the growth of industrial production. A positive change in output factor lowers for credit spreads across credit ratings and maturities, a result which is consistent with the work of Amato and Luisi (2006) and Wu and Zhang (2008).

Inflation

Inflation is another dimension of the macroeconomy that is considered influential for the

[2] The real activity factor is constructed using the first principle component, based on the index of Help Wanted Advertising in Newspapers, the unemployment rate, the growth rate of employment and the growth rate of industrial production.

[3] The real economic growth activity factor is constructed using the first principle component, based on the real GDP, industrial production index, total nonfarm payroll, the real personal consumption expenditure.

credit spread through its effect on investors' pricing kernel. David (2008) suggests that high expected current inflation lead to a lower price kernel which, in turn, leads to a higher bond price and a lower credit spread. The major strand of literature analyses the link between the inflation and the term structure of the credit spread using the no-arbitrage affine term structure modeling approach.

Amato and Luisi (2006) investigate how the inflation factor[4] affects the term structure of credit spreads for investment-grade (BBB-rated) and speculative grade (B-rated) bonds. Estimated coefficients of the term-structure model show that an increase in the inflation raises instantaneous credit spreads. In addition, a factor loading analysis indicates that an increase in inflation widens the B-rated credit spread with short maturities but narrows the B-rated credit spread with long maturities. On the other hand, an increase in inflation has a negligible effect on the BB-rated credit spread. Wu and Zhang (2008) also focus on the relationship between the term structure of credit spreads and the inflation factor[5] . They find that the response of the credit spread to an increase in the inflation factor is positive for AAA-rated, A-rated, BBB-rated, and B-rated credit spread. However, a unit shock on the inflation factor narrows the BB-rated credit spread with short maturities but widen the BB-rated credit with long maturities. Following Amato and Luisi (2006) and Wu and Zhang (2008), Zhou (2014) construct the inflation indicator[6] to reduce the dimensionality. The factor loading analysis suggests that a positive inflation shock results in a lower A-rated and BBB-rated credit spread. This result differs from findings by with Amato and Luisi (2006) and Wu and Zhang (2008). One potential reason for the disparity of findings is that 3 papers

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[4] The inflation factor is constructed using the first principle component, based on the proportionate rates of change for the Consumer Price Index, Producer Price Index of finished goods, and a broad-based Commodity Prices Index.

[5] The inflation factor is constructed using the first principle component, based on the Consumer Price Index (CPI), core CPI, the Producer Price Index (PPI), core (PPI), the implicit deflator for Personal Consumption Expenditure (PCE), core PCE deflator, and the implicit deflator for and gross domestic GDP.

[6] The inflation factor is constructed using the first principle component, based on the consumer price index, the core consumer price index, the personal consumption expenditure deflator, the core personal consumption expenditure deflator, and the producer price index.

use the credit spread with different credit ratings and the credit rating plays a role in how the credit spread react to the inflation shock.

The Level of Risk-free Yield Curve

The risk-free interest rate captures another dimension of the macroeconomy that is often associated with the monetary policy implementation. The importance of the risk-free rate in influencing corporate credit risk is supported by both theory and evidence. The Merton (1974) model and its extensions assume that the risk-free rate acts as a drift factor in the risk neutral process for the firm value. If the risk-free rate increases, firm value will move away from the default threshold, leading to a lower default probability. The yield on government bonds is usually employed as a measure of the risk-free rate in the empirical literature because default risk of the government is relatively low. The 10-year Treasury yield rate, an indicator of the U.S. economy's long-term outlook and a pricing benchmark against the return on many financial instruments, such as mortgage, has been widely used in the U.S. dollar denominated bond/CDS pricing literature.

Collin-Dufresne, Goldstein, Martin (2001) study the determinants of credit spread changes using monthly U.S. data from July 1988 to December 1997, utilizing the yield on the 10-year Benchmark Treasury Bond to capture the level of the risk-free rate. Credit spread changes are regressed on contemporaneous changes in the 10-year Benchmark Treasury rate, together with contemporaneous changes in business conditions (measured by movements in the S&P 500, yield spread slope and VIX market indices) and contemporaneous changes in several firm-specific indicators, such as leverage and stock return volatility. The analysis suggests that changes in the 10-year Benchmark Treasury Bond yield have a significantly negative effect on changes in the credit spread. The negative relationship between the changes in the credit spread and changes in risk-free rate is consistent with the structural models.

Blanco, Brennan and Marsh (2005) investigate the relationship between credit risk for 33 U.S. and European investment-grade companies and the risk-free rate. They use the daily 10-year Treasury Bond yield as a measure of the level for the risk-free yield curve and utilize daily 5-year CDS spread and daily 5-year bond credit spread, with sample period spanning from January 2, 2001 to June 20, 2002. Blanco, Brennan and Marsh (2005) use OLS regression by regressing the change in both the corporate CDS spread and the credit spread on the change in macroeconomic variables and firm-specific variables. The results show that the change of 10-year Treasury Bond yield has significantly negative effect on both the change of the CDS spread and the change of the bond credit spread. The negative relationship between the credit spread change and risk-free rate change is consistent with the empirical findings of Collin-Dufresne, Goldstein, Martin (2001). Another interesting finding is that, as with the general findings in the literature, a large share of the variation in the changes in the CDS/credit spread remain unexplained. Blanco, Brennan and Marsh (2005) attribute this general poor performance of the model to the effect of an unidentified common factor which is not captured by the risk-free rate or the term structure slope.

2.5.2 MACROECONOMIC CONDITION VARIABLES AND CDS SPREAD

Empirical studies are also conducted on the CDS spread to explore how macroeconomic variables affect the CDS spread. The most commonly used methodology applied by this strand of literature to study the effect of macroeconomy on the CDS spread is multi-variate time series or panel data regression.

Real Economic Output Activity

Among the various proxies for economic activity, the growth rate of real gross domestic product (GDP) and the growth rate of industrial production is most frequently used.

Tang and Yan (2010) is another study focusing on the effect of macroeconomic determinants on U.S. corporate CDS spreads using monthly data from June 1997 to March 2006. Tang and Yan (2010) use the growth rate of real GDP and industrial production index as measures of economic growth and an AR (1) model extracts a measure of the volatility in two time series. Tang and Yan (2010) find, firstly, that the real GDP growth and industrial production index growth have a significantly negative relationship with the single-name CDS spread. Furthermore, Tang and Yan (2010) also show that the real GDP growth and industrial production growth have similar effects on of market average CDS spread as they do on the single-name CDS spread.

The Level of Risk-free Yield Curve

Ericsson, Jacobs, Oviedo (2009) regress the change of the CDS spread on the change of the 10-year U.S. Treasury bond yield using a sample of daily data between January 1, 1999 and December 31, 2002. The univariate regression results suggest that the coefficient on the change of the 10-year Treasury bond yield is significantly negative. Explanatory power, however, was low, roughly 6% of total variation in the CDS spread change. Furthermore, in a multivariate regression which involves leverage, equity volatility and the risk-free rate, the coefficient of the change of 10-year risk-free rate remains negative and statistically significant.

Annaert *et al.* (2013) focus on Euro-area bank CDS spreads and uses the weekly data spanning the period from January 2004 to October 2008. The sample only includes investment-grade A-rated and AAA-rated CDS contracts. The risk-free rate is measured by the 2-year government bond yield and its change is found to have a negative effect on changes in the CDS spread over the entire sample period and can explain roughly 5% of the total variation in the CDS spread. However, sub-sample analysis finds that the risk-free rate is insignificant during the pre-crisis time, becoming significant during the crisis.

Negative effects from the risk-free rate on credit risk also found by Coro, Dufour and Varotto (2013) for monthly Euro-denominated corporate CDS spreads in the Eurozone during the period January 2006 to July 2009. Coro, Dufour and Varotto (2013) use monthly 10-year

Euro government bond yield as a measure of the risk-free rate. Using a panel data regression analysis, changes in 10-year Euro government bond yield have a negative effect on changes in the CDS spread and the effect is statistically significant.

Galil *et al.* (2014) obtain similar results for a different sample period and variable set. The U.S. 5-year constant maturity Treasury rate is used to capture daily value of the risk-free rate, as it is consistent with the 5-year maturity of the CDS contracts in the sample. The change of risk-free rate is significantly negative in the analysis and explains approximately 8.34% of the total variation in the CDS spread change, which is comparable to the early findings by Ericsson, Jacobs, Oviedo (2009) and Annaert *et al.* (2013).

Drawing these results together, this chapter finds that the negative effects of the risk-free rate on the CDS spread, suggested by theoretical models, is found in practice.

2.5.3 MACROECONOMIC VOLATILITY VARIABLES AND CDS SPREADS

A theoretical model introduced by Tang and Yan (2006) shows that higher volatility of economic output growth increases the market risk premium, which in turn, decreases the bond price but increases the credit spread. Although the effect of the volatility of economic output growth has been highlighted, it is empirically incorporated by limited CDS pricing literature.

Baum and Wan (2010) investigate the effects of the volatility of GDP growth and the volatility of industrial production growth on U.S. corporate CDS spreads in the investment-grade ratings and speculative grade ratings. The monthly sample spans the period January 2001 to December 2006 and the measure of macroeconomic volatility is based upon the GARCH model. The pooled ordinary least squares regression results suggest that conditional variances of GDP growth and industrial production growth are significantly positive even when levels of other macroeconomic variables, such as short-term rate and term spread, are included. This result indicates that volatility in real economic activity plays an important role in determining the CDS spread.

Tang and Yan (2010) is another study focusing on the effect of macroeconomic volatilities on U.S. corporate CDS spreads. The paper finds that the coefficients on real GDP growth volatility and industrial production growth volatility are positive and statistically significant even with the presence of real GDP growth and industrial production index growth in the regression.

2.5.4 MACROECONOMIC VARIABLES AND FINANCING DECISIONS

In addition to influencing firms' credit risk directly, macroeconomy also plays an indirect role by affecting firms' financing decisions. A relationship between the leverage and macroeconomy indicators can be found in several empirical studies. It follows that the state of the macroeconomy not only affects the credit/CDS spread directly as discussed in the earlier sections but also by impacting firm-specific characteristics, such as firm's leverage and financing decision.

For example, based on quarterly data from period 1984-1999, Korajczyk and Levy (2003) study how macroeconomic conditions affect the pattern of corporate leverage. Their paper finds that macroeconomic variables, including the 2-year aggregate domestic non-financial corporate profit growth rate, and the return on a value-weighted index of stocks traded on NYSE, AMEX and NASDAQ, are found to have a significantly negative effect on corporate leverage 3 quarters ahead. Hackbarth, Miao and Morellec (2006) also link financial decision-making to macroeconomic conditions and find that firms adjust their leverage according to the state of the economy, with firm leverage being high in recessions but being low in expansions.

As with the macroeconomic level variables, macroeconomic uncertainty can also affect companies' credit risk indirectly, by affecting loan service offered by banks. Baum, Caglayan and Ozkan (2009) argue, for example, that macroeconomic uncertainty matters when banks provide loan services to new or existing customers. This is because higher economic volatility raises the default probability of borrowers. A potentially larger default probability leads bank managers to adjust the proportion of risky loans among bank assets to ensure an appropriate risk level on the bank's asset portfolio for a given expected return. Moreover, this reallocation is systemic because all banks receive signals of higher volatility and then behave homogeneously. In their empirical work, bank loan behavior is measured by the loan-to-asset ratio. Following Baum and Wan (2010), GARCH-based conditional variance of industrial production growth and consumer price inflation are used to capture economic activity and inflation volatility respectively. Current and 3 quarters' lagged macroeconomic volatility measures are found to have a significantly negative effect on the dispersion of banks' loan-to-asset ratio. The result found by Baum, Caglayan and Ozkan (2009) suggests that the macroeconomic volatility not only has an immediate effect but also a lagged effect on the bank's loan service. Quagliariello (2009) finds that the volatility of various macroeconomic indicators, such as inflation and real economic growth, affect banks' lending decisions and lead to changes in banks' asset allocation strategy. In the paper, the consumer price inflation and the industrial production growth are used to capture inflation and real economic growth respectively, with the conditional variance of these variables calculated using GARCH model being used as a measure of macroeconomic uncertainty. Results show that a negative relationship between dispersion of loan-to-asset ratios and volatilities of inflation and real economic growth. This negative relationship, as explained by Quagliariello, arises because higher macroeconomic volatility conveys negative information, which is associated with increased loan default risk and lower expected returns on loans. As a result, banks tend to homogenously reduce the capital allocated to loans and increase the percentage of risk-free assets so as to maintain the riskiness of the bank's portfolio at a reasonable level.

The work of Korajczyk and Levy (2003), Hackbarth, Miao and Morellec (2006), Baum, Caglayan and Ozkan (2009), Quagliariello (2009) indicates that macroeconomic conditions and volatility can affect firm-specific variables, notably leverage, or the bank's loan-to-asset ratio. These variables can in turn affect firms' credit riskiness, broadening the through the channel which macroeconomic conditions influence the credit/CDS spread.

2.6 VARIABLES SELECTION

The theoretical and empirical literature review provides implications with regards to which macroeconomic and firm-specific variables should be chosen for the empirical analysis in Chapter 3 and Chapter 4.

2.6.1 VARIABLES FOR CHAPTER 3

Economic output growth is of importance in determining the CDS spread. As suggested by Tang and Yan (2006), higher economic output growth increases the drift of the firm's cash flow process, therefore the firm is more likely to be able to cover its interest payments and less likely to default. This implication is further demonstrated by Tang and Yan (2010) empirically.

Inflation is another economic indicator that is predicted in the literature to influence the CDS spread. The theoretical model of David (2008) indicates a positive relationship between the credit spread and current inflation. The model assumes that agents' expectation of higher current inflation can change agents' preferences, leading to a higher price kernel which lowers the bond price and increases the credit spread.

At the same time, from the corporate perspective, moderate inflation has a negative effect on a company's default probability. Inflation stimulates consumption in the near future because investors are concerned that higher prices in the future will reduce purchasing power, which leads consumers to bring forward consumption, thereby boosting companies' output and profitability. Increased output requires companies to provide employees with a higher wage to attract and retain workers, maintaining the turnover rate. The increased wage will stimulate investor spending, which increases aggregate consumption in the economy.

Companies tend to expand and are less likely to default in the growing economy, which thereby reduces default risk. From the perspective of firms whose debts are nominally denominated, inflation decreases the real value of the interest payment and principal sum, which together leads to a lower default rate.

The risk-free rate is another important macroeconomic determinant of the CDX spread. As the Merton (1974) model suggests, higher interest rate in this setting is regarded as a drift factor in the risk-neutral process for firm value in structural models. Higher interest rates lead asset values to drift away from the default threshold, thus decreasing the default probability.

There is a rich empirical literature that uses various measures of the risk-free rate such as the U.S. Federal Fund rate (e.g. Yang, 2008), the 3-month U.S. Treasury rate (e.g. Duffie, Saita and Wang, 2007), the 5-year U.S. Treasury rate (e.g. Galil *et al.,* 2014), 10-year U.S. Treasury rate (e.g. Collin-Dufresne, Goldstein, and Martin, 2001; Blanco, Brennan and Marsh, 2005; Ericsson, Jacobs, and Oviedo, 2009), the 2-year European government yield (e.g. Annaert *et al*., 2013) and the 10-year Euro government bond yield (e.g. Coro, Dufour and Varotto, 2013). Despite choice of various risk-free rate measures, sample period, and data frequency, Collin-Dufresne, Goldstein, and Martin (2001), Ericsson, Jacobs, and Oviedo (2009), Galil *et al*. (2014) and Coro, Dufour and Varotto (2013) find a significantly negative relationship between credit spreads (changes)/CDS spreads (changes) and the risk-free rate.

Although some empirical studies adopt stock market index returns such as the S&P 500 return and return volatility or the VIX volatility index to model the macroeconomy and its volatility, respectively, the analysis in this thesis differs from this strand of literature in that it does not employ such stock market measures. The main reason is that stock market measures cannot be regarded as sufficiently pure macroeconomy measures. In particular, market valuations are affected by other market-wide influences, not directly related to macroeconomy, such as changes in market liquidity and capital re-allocation decisions by investors due to changes in relative performance of different asset classes (e.g. Goyenko and Ukhov, 2009 and Longstaff *et al*. 2005). Furthermore, stock index return volatility and the VIX index both can change over time when there is no change in macroeconomic volatility, for example, with changes in leverage, investor risk aversion or sentiment (Jurado *et al.*, 2015). Furthermore, stock market variables do not permit to distinguish specific macroeconomic influences such as those associated with economic output, inflation, employment or interest rates. For these reasons, the analysis in this thesis employs direct measures of macroeconomic conditions and volatility as opposed to indirect market-based measures.

Given the significantly positive effect of credit ratings on the CDS spread that are reported by Tang and Yan (2007) and Lesplingart, Majois, and Petitjean (2012), it is important to reflect how CDS with different credit ratings react differently to macroeconomic variables. Markit, the provider of the family of CDX indices, does not provide CDX sub-indices that are issued on specific credit ratings. Instead, Markit provides two CDX indices that are issued on investment-grade and high-yield credit qualities. Due to this data limitation, Chapter 3 cannot incorporate specific credit ratings while studying the CDS index pricing. Instead, Chapter 3 will utilize two sub-indices, CDX.NA.IG and CDX.NA.HY, with their credit qualities being investment grade and high yield separately.

2.6.2 VARIABLES FOR CHAPTER 4

The early structural models (e.g. Merton, 1974; Longstaff and Schwartz, 1995; Collin-Dufresne and Goldstein, 2001; and Zhou, 2001) mentioned in the theoretical literature suggest that the default of the reference entity is linked to the evolution of its asset value. Even though theoretical models suggest that asset value, asset value growth and its volatility may be important for capturing the evolution process of a firm's asset value, a fundamental obstacle in using these measures empirically is that they cannot be observed. To resolve this fundamental issue, some studies, such as Blanco, Brennan, and Marsh (2005), Baum and Wan (2010), Annaert *et al.* (2013), and Galil *et al.*(2014) employ stock market capitalisation, stock market return and its volatility as indicators of asset value, asset value growth and volatility.

However, there are several issues with this approach that employs stock market measures because stock return is not a pure measure of the firm-specific asset value growth. A number of papers provide evidence that stock market return is strongly influenced by macroeconomic fundamentals. Chen, Roll and Ross (1986) reports significant effects on stock returns of industrial production growth, changes in inflation, and changes in the term structure of interest rates. More recent studies of Andersen *et al.,* (2007), Baele, Bekaert and Inghelbrecht (2010), and Savor and Wilson (2013) also report significant effects of macroeconomic growth and macroeconomic news announcement on the stock return. Furthermore, the stock return volatility has also been found to be significantly affected by macroeconomic fundamentals in the work of Schwert (1989), Hamilton and Lin (1996), Perez-Quiros and Timmermann (2000), Diebold and Yilmaz (2008), and Engle, Ghysels and Sohn (2013). As a result, the stock market return and its volatility that both are shown to be contaminated by market-wide influences and, therefore, they cannot be considered as sufficiently pure measures for capturing the evolution of firm's asset value.

To avoid the issues around using the stock market measures, Chapter 4 follows another strand of empirical literature such as Collin-Dufresne, Goldstein and Martin (2001), Tang and Yan (2007), and Coro *et al.* (2013), that rely on observable firm characteristics such as firm leverage and operating cash flow measures.

According to the structural model framework (e.g. Longstaff and Schwartz, 1995; and Collin-Dufresne and Goldstein, 2001), the default is triggered when the firm's asset value goes below the default threshold. The default threshold is positively to the debt value because promised interest payment increases with the debt value. Leverage, the percentage of debt that is used to finance asset, is a commonly used measure to capture the relationship between firm's asset value and firm's debt value. Higher leverage indicates the higher debt level and high default threshold which suggests the firm value is more likely to fall below the default threshold if other conditions hold equally. A large number of empirical papers (e.g. Tang and Yan, 2008; Ericsson, Jacobs, and Oviedo, 2009; Tang and Yan, 2010; Baum and Wan, 2010; Lesplingart, Majois, and Petitjean, 2012) use leverage in the analysis and find a positive relationship between the CDS spread and leverage.

The importance of firm's cash flow and its volatility is supported by the strategic debt valuation models (e.g. Kim, Ramaswamy, and Sundaresan, 1993; and Fan and Sundaresan, 2000), the firm with higher and less volatile cash flow is less likely to default because firms are more likely be able to pay interest payments or debt re-payments on time. Implications from strategic debt valuation models and the structural model of Tang and Yan (2006) both inspire this thesis to choose proxies that can capture the level and volatility of the firm's cash flow and examine their explanatory power in explaining the CDS spread. Building on the structural model of Tang and Yan (2006), the empirical study of Tang and Yan (2010) provides a measure that capture cash shows volatility and empirical evidence where the cash flow volatility has a significantly positive effect on the CDS spread.

Finally, credit ratings are empirically reported to have significant effect on the CDS spread by some empirical studies, such as Tang and Yan (2007) and Lesplingart, Majois, and Petitjean (2012). However, this thesis does not include credit rating as an independent variable due to data-related problems. The first problem is that, particularly for high-yield CDS, there tend to be only a small number of observations in each rating group, especially for the earlier years of the sample period. Furthermore, it is technically challenging to be able to track movements of CDS between various credit ratings over the time span of the dataset. As a result, Chapter 4 will follow Chapter 3 by dividing the whole sample into two sub-samples, with one sub-sample containing investment-grade CDS spread and one sub-sample containing high-yield CDS spread.

2.7 SUMMARY

This chapter first gives a critical review of theoretical structural models that imply firms' characteristics and macroeconomy are of importance in determining firms' credit risk. In addition, this chapter discusses empirical papers that analyse the impact of model-implied variables. Leverage, stock return, cash flow, economic output growth, inflation, and risk-free rate among other commonly used variables are reported to have significant effects on the credit/CDS spread. Although there are many studies on how such firm-specific variables as leverage and stock market return and volatility affect the credit/CDS spread, few empirical studies focus on the effect of cash flow variables on the credit/CDS spread. As a result, cash flow and its volatility should be included as firm-specific determinants of credit spread and tested for whether they are important in determining the single-name CDS spread.

Although several empirical papers have incorporated macroeconomic variables in the research, only limited dimensions of the macroeconomy were explored in each paper. For example, Pires, Pereira and Martins (2010) incorporate the risk-free rate and the stock-market-implied volatility and Tang and Yan (2010) employ the level and slope of the yield curve, and GDP growth in their research. As macroeconomy is a broad concept, a single or very few economic indicators may not be sufficient to provide a reasonable picture of the whole macroeconomy. An extended analysis of the role played by macroeconomic factors would be therefore timely, embracing several important channels of macroeconomic influence, including real economic activity, employment, inflation and interest rates.

Furthermore, despite some exiting studies, such as Ang and Piazzesi (2003), include more dimensions of the macroeconomy, they mainly focus on the effect of the level of the macroeconomy, leaving the effect of the macroeconomic volatility rarely be explored. Macroeconomic volatility variables, such as economic activity volatility and inflation volatility, are introduced into structural models and their importance of determining the credit spread has been highlighted in theoretical literature. As a result, it is necessary to conduct an extended analysis on how level and volatility of different dimensions of macroeconomy affect the CDS spread. Furthermore, if macroeconomic level variables and macroeconomic volatility variables have significant effects on the CDS spread, the relative importance of these variable categories is another interesting question to be studied.

In addition, empirical studies, such as Collin-Dufresne, Goldstein and Martin (2001), Wu and Zhang (2008), Ericsson, Jacob and Oviedo (2009), and Annaert *et al*. (2013), consider the effect of the credit rating on how credit spreads and CDS spreads react to firm-specific and macroeconomic determinants, clustering credit/CDS spreads based on credit ratings in their analysis. These papers find that the magnitude of the effect of a unit increase/decrease in certain macroeconomic variables differs notably across rating groups. Furthermore, Collin-Dufresne Goldstein and Martin (2001) and Ericsson, Jacobs and Oviedo (2009) report that some macroeconomic variables only have significant effects on credit spreads with either low or high credit quality. Aforementioned studies provide motivations for a more detailed analysis in this thesis of how CDS with high and low credit quality differ in their sensitivity to various macroeconomic variables and their volatility.

Furthermore, most existing studies that focus on the CDS spread pricing are based on the pre-crisis (for instance, Alexander and Kaeck, 2008; Baum and Wan, 2010; Pires, Pereira and Martins, 2010) and crisis (e.g. Annaert *et al*., 2013; Coro, Dufour and Varotto, 2013) time periods. A study of how macroeconomic variables affect the CDS spread during the post-crisis period should be drawn to fill this gap.

3. MACROECONOMIC DETERMINANTS OF THE CDX SPREADS

3.1 INTRODUCTION

The chapter adopts the multivariate linear regression methodology to explore the relationship between the CDX spread and macroeconomic factors, with the monthly data sample spanning from March 2009 to December 2016.

The analysis in this chapter focuses on the CDX index which contains a basket of most liquid single-name CDS contracts that are traded in North America. As the CDX index contains a basket of single-name CDS contracts, its spread is usually regarded as an indicator of creditworthiness of companies with particular credit ratings. The CDX index is owned, managed, compiled, and published by Markit which produces a range of credit default swap indices. The first CDS index to be studied is the CDX.NA.IG index (hereafter referred to as CDX IG) which comprises 125 most liquid single-name CDS contracts with investment-grade credit ratings. The second CDS index to be studied is CDX.NA.HY index (hereafter referred to as CDX HY) that is composed of 100 liquid single-name CDS contracts with high-yield credit ratings[7].

The dependent variable is the investment-grade CDX spread and high-yield CDX spread, measuring the investment-grade credit quality CDS spread and high-yield credit quality CDS spread, respectively. As for independent variables, this chapter incorporates commonly used key economic indicators, including industrial production growth, consumer price inflation and 3-month Treasury Bill rate, to capture the economic output, inflation, and monetary policy.

[7] The credit rating referred to determine constituents for both the investment-grade and high-yield CDX indices is the long-term credit rating assigned to such entity by S&P, Moody's or Fitch. Investment-grade ratings are credit ratings of equal or above "BBB-" or "Baa3". High-yield ratings are credit ratings of below "BBB-" or "Baa3".

Total nonfarm payroll is also incorporated by this chapter as an additional economic indicator that measures the employment situation in the United States. An increase in employment shows an increase in firms' hiring which is likely to serve as an early indicator of business expansion, associated with a lower default risk in future. In contrast, a decrease in employment shows shrinking business hiring, indicating a distress in firms and higher future default risk. In addition, given the significantly positive relationship between the economic output and the employment that are reported by Okun (1962), and Sogner and Stiassny (2002), adding the total nonfarm payroll growth alongside with the industrial production growth that only includes output of manufacturing, mining, and utilities sectors, can capture a broader horizon of economic output.

Volatilities of macroeconomic level variables are constructed using an autoregressive moving average and autoregressive conditional heteroskedasticity (ARMA-GARCH) model. Compared with the historical standard deviation method and survey-based method, the GARCH model can capture the dynamics of time series data and it can be used to predict future volatility based upon more recent data. One exception to the volatility measure relates to the 3-month Treasury Bill rate. In contrast to other macroeconomic variables, Treasury yields data are available at a daily frequency. Consequently, the monthly volatility of the 3-month Treasury Bill rate is obtained as the standard deviation of daily data within the month.

This chapter makes contributions to the literature by addressing the following key questions:

(1) What is the role of the macroeconomy as measured by multidimensional macroeconomic indicator levels in influencing the CDX spread? In addressing this question, the chapter explores empirically the joint effect of various dimensions of the macroeconomy, thereby making a novel contribution. The analysis explicitly reflects the multidimensional nature of the macroeconomy by exploring the joint effect of several important dimensions of macroeconomy, including real economic

activity, inflation, employment and interest rates. This contrasts with most previous studies predominantly focusing on the effect on the CDS spread of a single macroeconomic factor, typically, the risk-free rate or output growth rate.

(2) What is the effect of macroeconomic volatility in influencing the CDX spread? In addressing this question, the chapter explores empirically the joint effect of various dimensions of the economy along with the associated sources of volatility, thereby making the second novel contribution. The second contribution of this chapter is that the effect of not only the level of macroeconomic variables, as in previous studies, but also of volatility measures is examined. As part of the analysis, the chapter assesses the relative importance of the macroeconomic level and macroeconomic volatility measures in determining the CDX spread.

(3) Building on earlier empirical evidence suggesting that CDX of high and low credit quality may differ in their sensitivity to macroeconomic factors, the analysis is conducted separately for investment-grade CDX and high-yield CDX, CDS indices of high and low credit quality, respectively. The two indices, representing CDS written on bonds of investment-grade and speculative grade credit quality, enable assessing potential differences in sensitivity of CDS spreads of high and low credit quality to various macroeconomic factors, representing various dimensions of the macroeconomy and macroeconomic volatility. To this end, the investment-grade CDX and high-yield CDX indices provide a natural proxy for studying how the level of creditworthiness, namely, investment-grade and speculative grade credit quality influences the sensitivity of the CDX spread to macroeconomic factors.

This chapter finds the macroeconomic factors, both level and volatility measures are significant in determining the CDX spread. This chapter finds that the growth of nonfarm payroll has a significant negative effect on the CDX spread while the volatility of industrial production growth has a significantly positive effect on the CDX spread. This chapter also finds that the volatility of the 3-month Treasury Bill rate has no significant effect on the investment-grade CDX spread but have a significantly positive effect on the high-yield CDX spread. Furthermore, macroeconomic level variables and macroeconomic volatility variables can jointly explain roughly 40% of the total variation in the investment-grade CDX spread and 65% of the total variation in the high-yield CDX spread. In addition, the analysis shows that macroeconomic variables account for a larger share of the variation in the CDX high-yield spread than the CDX investment-grade. This may due to the performance of high-yield companies depends more on the macroeconomy, and hence, their risk of default being more sensitive to the macroeconomy.

Furthermore, the analysis of the relative importance of macroeconomic level and macroeconomic volatility in determining the CDX spread shows that macroeconomic level variables contribute around 75% of the explained variation in both the investment-grade CDX spread and the high-yield CDX spread, suggesting that macroeconomic level variables jointly make a greater marginal contribution in determining the CDX spread. At the same time, these results show that both macroeconomic level variables and macroeconomic volatility variables are of importance in explaining the total variation in the CDX spread. Therefore, accounting for macroeconomic uncertainty in addition to macroeconomic level variables, typically considered in the literature, can help to substantially increase the model explanatory power.

The results also show that the high-yield CDX spread is more sensitive to both macroeconomic levels and volatility variables than the investment-grade CDX spread. In particular, the high-yield CDX spread is relatively more sensitive to nonfarm payroll growth, industrial production growth volatility, and the 3-month Treasury Bill rate volatility. A potential explanation for the higher sensitivity of high-yield CDX spread to macroeconomic variables is that high-yield companies rely more on the macroeconomy-sensitive external funding therefore their performance is more sensitive to macroeconomy.

The remainder of this chapter is organized as follows. Section 3.2 outlines macroeconomic level and volatility variables selected for the empirical analysis and details how these variables are constructed. Section 3.3 describes the dataset and methodology that is applied in the empirical analysis. Section 3.4 provides empirical analysis results and Section 3.5 reports results for the robustness check analysis. Finally, Section 3.6 provides a brief summary of this chapter.

3.2 DATA VARIABLES

In this section, the dependent variable and independent variables will be introduced. A list of macroeconomic level variables will be provided and how macroeconomic volatility variables are constructed will be detailed. Expectations on relationships between the CDX spread and macroeconomic variables will be developed at the end of each independent variable's description.

3.2.1 DEPENDENT VARIABLES

The CDS indices employed in this chapter are the North American investment-grade CDX index (CDX.NA.IG index) and the North American High-yield CDX index (CDX.NA.HY index). Spreads of North American investment-grade CDX index and North American high-yield CDX index provide an overview of the creditworthiness of companies with investment-grade and high-yield credit ratings. Their spreads are referred as the investment-grade CDX spread and the high-yield CDX spread respectively, hereafter. In what follows, this chapter employs the investment-grade CDX spread and the high-yield CDX spread as dependent variables.

There are multiple choices of building monthly CDS data from daily data and these choices include the last day of the month, monthly median, and the geometric mean, and the arithmetic mean.

Using the CDX spreads in last day of the month does not require any data transformation, which effectively reduce the possibility of new irrelevant information being added to the dataset or useful information being removed from the dataset. However, using the last day of the monthly data is not representative because it cannot provide a whole picture of the CDX spreads within a month.

The monthly median CDX spread is the middle value in distribution when the CDX spreads during a month are arranged in ascending or descending order. Compared with the CDX spread in the last day of the month, median lies at the middle part of the series and therefore is not affected by the extreme values. However, it is affected by sampling fluctuations as it is concerned with only one item, the middle item. In addition, it is not a fully representative indicator for a distribution because it does not depend on all the CDX spreads in a month.

The geometric mean of CDX spreads in a month is the nth root of their product where n is the number of trading days in a month. Compared with the last day of the month CDX spread and monthly median CDX spread, geometric mean of CDX spreads is based on all CDX spreads in a month and is not affected by extreme outliers. However, this measure has rarely used in the CDS pricing literature.

The arithmetic mean of CDX spread is the sum of the CDX spread during a month divided by the number of trading days in the month. Compared with the last day of the month and monthly median measures, the arithmetic mean uses every value in a month and therefore is a good representative of the data. Furthermore, its easy and fast calculation process also makes the arithmetic mean a widely used measure when converting daily CDS data to monthly CDS data in the CDS pricing literature (e.g. Baum and Wan, 2010; Tang and Yan, 2010; and Coro *et al.*, 2014)

Given advantages of using arithmetic mean, this chapter adopts the average of daily close-of-market spread values over the corresponding month as monthly values.

3.2.2 INDEPENDENT VARIABLES

Industrial Production growth

Chapter 3 incorporates the growth of industrial production index (IP), as a measure of the economic output growth. The industrial production index is an economic indicator that measures real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities (excluding those in U.S. territories). It works as an indicator of the U.S. production output and highlights structural developments in the U.S. economy. The positive industrial production growth indicates the increase in the production and a positive economic growth while the negative industrial production growth indicates the decrease in the production and a decrease in economic growth.

The industrial production growth in month t-1 is the logarithm difference between industrial production index in month t-1 and month t-2. Because there is a 1-month delay on the industrial production index announcement, the industrial production growth in month t-1 is latest industrial production growth information that is available to the CDS market in month t. In the following analysis, the CDX spread in month t will be regressed on industrial production growth in month t-1.

The growth rate of industrial production is expected to have a negative effect on the CDX spread.

Nonfarm Payroll Growth

Chapter 3 will use the growth of total nonfarm payroll (NonF) to capture the employment dynamics in the United States. The total nonfarm payroll is a measure of the number of U.S. workers in the economy that excludes proprietors, private household employees, unpaid volunteers, farm employees, and the unincorporated self-employed. An increase in employment shows an increase in firms' hiring which is likely to serve as an early indicator of business expansion, associated with a lower default risk in future. In contrast, a decrease in employment shows shrinking business hiring, indicating a distress in firms and higher future default risk.

In addition, the total nonfarm payroll is added to this chapter as an additional economic output growth indicator. The relationship between the employment and the output has been documented by several papers. For example, Okun (1962) introduce the Okun's law that states that 1-percentage decrease in unemployment leads to 3-percentage increase in the GNP in U.S. This law has been tested and evidenced by Sogner and Stiassny (2002) among others. A higher employment is likely to result in newly employed workers having more money to spend on goods and services, thereby increasing economic output and supporting economic expansion that is associated with lower default risk.

The growth of total nonfarm payroll in month t is the logarithm difference between total nonfarm payroll in month t and month t-1. Because there is a 1-month delay on the total nonfarm payroll data release, t-1 total nonfarm payroll growth will be used in this chapter.

The growth rate of total nonfarm payroll is expected to have a negative effect on the CDX spread.

Consumer Price Index Growth

Chapter 3 uses the growth of consumer price index for all urban consumers (CPI) to capture the inflation level in the United States. The consumer price index for all urban consumers is a measure of the average monthly change in the price for goods and services paid by urban consumers between any two-time period.

In this chapter, the growth of the consumer price index for all urban consumers (CPI) in month, as defined as the logarithm difference between consumer price index for all urban consumers in month t and month t-1, will be used to capture the inflation in the U.S. economy. Because there is a 1-month delay on the consumer price index announcement, one-month lagged CPI will be used.

The relationship between the CDX spread and CPI is left undecided.

Risk-free Rate (RF)

Chapter 3 uses the most commonly used interest rate measure, the 3-month Treasury Bill rate (RF). The monthly values of 3-month Treasury rate are represented as the average of daily 3-month Treasury Bill rate values over the corresponding month. Since the CDS market is well developed, the market can reflect to latest information quickly. As a result, 3-month Treasury Bill rate at time t will be used in this chapter to capture how CDX spreads react to the risk-free rate.

A negative relationship between the CDX spread and RF is expected to be held.

In summary, this chapter uses the growth rate of industrial production (IP), the growth rate of total nonfarm payroll (NonF), the growth rate of consumer price index (CPI), and 3-month Treasury rate (RF) as independent variables, to capture different aspects of the macroeconomy. The volatility of these variables signals uncertainty associated with the respective sources of macroeconomic risks. The corporate credit risk tends to increase in a riskier macroeconomic environment and, as a consequence, this chapter expects volatility measures of macroeconomic variables to have a positive effect on the CDX spread.

Macroeconomic Volatility Variables

Volatilities of IP, NonF and CPI are constructed applying the class of general autoregressive conditional heteroskedasticity (GARCH) models. The GARCH class of model has some advantages over other volatility construction methods because it can capture the dynamic of time series data and predict the future volatility based on more recent data. In applying the volatility measure, the mean and trend of the macroeconomic series will be modelled by an autoregressive moving average (ARMA) models. The result is that volatility is measured in the following way:

$$y_t = \mu + \sum_{k=1}^{m} \phi_k y_{t-k} + \varepsilon_{i,t} + \sum_{j=1}^{n} \theta_j \varepsilon_{t-j} \quad \varepsilon_t \sim (0, h_t) \qquad \text{Equation (3.1)}$$

$$h_t = \omega + \sum_{i=1}^{q} \delta_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \eta_i h_{t-i} \qquad \text{Equation (3.2)}$$

where q is the length of ARCH terms;

p is the length of GARCH terms;

y_t is the growth of macroeconomic variables which is defined as the macroeconomic variables' logarithm difference.

In addition, the Engle's ARCH test is run on the growth of industrial production, the growth of total nonfarm payroll, and the growth consumer price index to detect the heteroskedasticity in data series, before the GARCH model is built. Results for the ARCH test are reported in Table 3.1. The p-value are smaller than 0.1 for the growth of industrial production, total nonfarm payroll, and consumer price index, which rejects the null hypothesis that there is no ARCH in the series at 90% confidence level. The results of Engle's ARCH test further suggest that GARCH category of model is a more appropriate model for this thesis because it can model the volatility while taking into the heteroskedasticity patterns in the series.

The ARMA-GARCH model is conducted for, IP, NonF and CPI separately and results for the exercise are reported in the Table 3.2. In each panel, the ARMA-GARCH model is sufficient enough to capture the trend and volatility of macroeconomic series. The conditional variance constructed by the GARCH model is used to measure the volatility of each macroeconomic series. The volatility of the IP, NonF, CPI are referred to as IPVol, NonFVol and CPIVol thereafter.

According to Equation (3.1) and (3.2), the volatility at time t is available at time t as long as growth variables at and prior to time t-1 are available. As a result, IPVol, NonFVol and CPIVol at time t will be used in the analysis to determine the CDX spread at time t.

The volatility of the risk-free rate measure is constructed differently by using the monthly standard deviation of the daily 3-month Treasury Bill rate. Unlike the growth of industrial production, total nonfarm payroll, and consumer price index, risk-free rates are available daily. The daily risk-free rate data naturally provides rich data for constructing a contemporaneous volatility measure while using the GARCH model can throw daily information away.

Furthermore, the Treasury market is liquid and can react quickly to daily information. The rationale behind GARCH model of predicting the current month's volatility using lagged month's volatility is inappropriate for conducting the volatility of risk-free rate because the volatility of risk-free rate in lagged months may be too old and not have predictive power of predicting the current month's volatility. As a result, the conditional variance of the monthly risk-free rate cannot capture the simultaneous volatility of the risk-free rate.

An alternative approach of constructing monthly volatility of 3-month Treasury rate is introduced by Diebold (1988). The monthly volatility can be obtained by multiplying the 1-day conditional variance by the square root of trading days within a month. However, this approach is subject to several issues. The first issue arises when selecting the 1-day conditional variance that is used to aggregate the monthly volatility. Choosing the 1-day volatility on an arbitrary day will remove useful information that is provided by rest of the month, which thereby cannot provide a whole picture of the 3-month Treasury Bill rate volatility within a month. In addition, as shown by Drost and Nijman (1993), aggregating daily conditional variance method also magnifies fluctuations in the conditional variance of long horizon returns, resulting in volatilities that are higher/lower than the real volatility.

Compared with the first GARCH measure, the monthly standard deviation method relies on the data from the current month and does not account for old information that is from previous month. Furthermore, the monthly standard deviation method has advantages over the second GARCH measure because it can capture every data in the month and can provide a more representative picture of the monthly volatility of 3-month Treasury rate.

Consequently, monthly standard deviation using daily data within month t will be used to capture month-t volatility of the 3-month Treasury Bill rate (RFVol hereafter).

TABLE 3.1 ENGLE'S ARCH TEST

	F-Statistics	P-value
IP	5.16**	0.03
NonF	264.54***	0.00
CPI	3.78*	0.05

Notes: The table shows the Engle's ARCH test on IP, NonF, and CPI. IP is the growth of industrial production, NonF is the growth of total nonfarm payroll and CPI is the growth of consumer price index. The sample period is from March 2009 to December 2016. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

TABLE 3.2 GARCH MEASURES FOR MACROECONOMIC VOLATILITY

	IP	NonF	CPI
Constant	0.1793***	0.1188***	0.1528***
(Mean equation)	(3.3701)	(4.1018)	(5.0859)
AR (1)		0.7431***	0.3536***
		(18.5145)	(3.4766)
Constant	0.1919***	0.0039***	0.0082*
(Variance equation)	(5.7173)	(3.1574)	(1.8176)
ARCH (1)	0.2457*	0.6868**	0.1548**
	(1.7321)	(2.4425)	(2.1345)
GARCH (1)			0.6219***
			(5.3421)
Log likelihood	67.4244	97.3147	20.8541
No. Obs	94	94	94

Notes: The dependent variables for each panel are IP, NonF, and CPI. IP is the growth of industrial production, NonF is the growth of total nonfarm payroll and CPI is the growth of consumer price index. AR=Autoregressive; ARCH=Autoregressive Conditional Heteroskedasticity; Mean equation=GARCH conditional mean equation; Variance equation=GARCH conditional variance equation. All dependent variables are sampled on a monthly basis. The sample period is from March 2009 to December 2016. T-Statistics are given in parentheses. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

3.3 DATA DESCRIPTION AND METHODOLOGY

3.3.1 DATA DESCRIPTION

The dataset combines data from two sources: Bloomberg, and the Federal Reserve Economic Database (FRED). The former data source provides end-of-day mid-spread for investment-grade CDX and high-yield CDX time stamped with New York time.

The CDX indices used are the CDX.NA.IG index (CDX IG) and CDX.NA.HY index (CDX HY). Both CDX indices focus on the Northern America market and their spreads are measured in basis points. The investment-grade CDX contains 125 most liquid North American CDS contracts with investment-grade credit ratings. The high-yield CDX contains 100 liquid North American CDS contracts with high-yield credit ratings.

The FRED provides sources for macroeconomic series used in the study which includes real gross domestic product, the industrial production index, total nonfarm payroll, the consumer price index, and the 3-month Treasury Bill rate.

The data frequency of the research is monthly basis. The industrial production index, total nonfarm payroll, and the consumer price index are available on monthly basis. As for the 3-month Treasury Bill rate that is available daily, the monthly average of daily values within the month is calculated to represent the monthly value.

Perron (1989) points out that, structural change and unit roots are closely related, and researchers should bear in mind that conventional unit root tests are biased toward a false unit root null when the data are trend stationary with a structural break. The Chow breakpoint test is carried on investment-grade CDX spreads and high-yield CDX spreads spanning from October 2005 to December 2016. The results of Chow breakpoint test are reported in Table 3.3. The null hypothesis of the Chow breakpoint test is that there is no ex-ante expected break point in March 2009 in investment-grade and high-yield CDX spreads. P-values are smaller than 0.1, which suggests the rejection of null hypothesis at 90% confidence level.

As a result, there is a breakpoint in March 2009 in both investment-grade and high-yield CDX spreads series.

The Chow breakpoint test results show that both CDX indices spreads have a structural breakpoint in March 2009, with time trend and drift having different dynamics before and after the breakpoint. In order to eliminate errors caused by breakpoints, this chapter will focus on the period from March 2009 to December 2016 which is defined as the post-crisis period.

To establish meaningful and effective ARMA-GARCH model to construct macroeconomic volatility variables and to avoid spurious regressions when the empirical analysis is carried, the unit root test is conducted on all macroeconomic series for detecting non-stationarity. The augmented Dickey-Fuller (1979) test is widely used to test for stationarity. This chapter conducts the augmented Dickey-Fuller unit root test on dependent and independent variables. The null hypothesis of the test is that there is a unit root in time series data. Table 3.4 reports results of unit root test. P-value for CDX IG, CDX HY, IP, NonF, CPI, IPVol, NonFVol is 0.00, which means the null hypothesis should be rejected at 99% significance level. P-value for CPIVol, and RFVol is 0.02; and p-value for RF is 0.03, which means the null hypothesis should be rejected at 95% significance level. Table 3.4 confirms the stationarity in all variables, which suggests that all variable can be used without any transformation.

Table 3.5 reports the descriptive statistics summary of dependent and independent variables during the period from March 2009 to December 2016 which include 94 monthly observations. The investment-grade CDX spread has the mean of 93.33 basis points and standard deviation of 24.26 basis points. The high-yield CDX spread is relatively larger and more volatile than investment-grade CDX spread, with the mean of 520.60 basis points and the standard deviation of 195.43 basis points. As for IP, the economic output growth measure, it ranges from -1.59% to 1.54% with the standard deviation of 0.52%. The NonF ranges from

-0.62% to 0.40%, with the standard deviation of 0.16%. CPI ranges from -0.64% to 0.83%, with the standard deviation of 0.21%. RF ranges from 0.01% to 0.51%, with the standard deviation of 0.10%.

Furthermore, the skewness and kurtosis are also reported in Table 3.5, alongside with the Jarque–Bera normality test. The null hypothesis of the Jarque–Bera normality test is that there is no difference between the underlying distribution and a normal distribution. The p-value for IP is larger than 0.1. As a result, the null hypothesis where there is no difference between IP and a normal distribution cannot be rejected. The p value for the rest of series are smaller than 0.01. As a result, the null hypothesis is rejected at 99% confidence level and rest of macroeconomic series are not normally distributed.

Figure1 plots the investment-grade and high yield CDX spreads using data from March 2009 to December 2016. Figure 1 shows that investment-grade and high-yield CDX spreads share similar trend across time. However, the investment-grade CDX spread is comparatively lower and less volatile than high-yield CDX spread, which is consistent with the information given by Table 3.5.

Figure 2 and Figure 3 present the time series of macroeconomic condition and volatility variables. One noteworthy finding is that the growth of industrial production, the growth of total nonfarm payroll, and the growth of consumer price index exhibit heteroskedasticity during the sample period, which further indicates the GARCH model is an appropriate method of modelling the volatility in macroeconomic series.

Table 3.6 reports pair-wise correlation coefficients between CDX spreads and macroeconomic level and volatility variables during the period from March 2009 to December 2016. Correlation coefficients between CDX spreads and most of macroeconomic variables are consistent with expectations outlined in Section 3.2.2. CPI has a positive correlation with the CDX spread, which empirical confirms David (2008) theory where high inflation decreases bond price and widens credit spread. RF has a positive correlation with the CDX spread, which has conflicts with the expectation. One potential explanation for this conflict is that increased interest rate increases the company's interest payment therefore increases the possibility where the company fails to pay its interest payments. This positive effect exceeds the negative effect of interest rate on the company's default thus a positive sign exhibits in the Table 3.6. Correlations between independent variables are moderate, which mitigates the concern of multicollinearity problem in multivariate regressions.

TABLE 3.3 CHOW BREAKPOINT TEST FROM 2005M10 TO 2016M12

	F-statistics	p-value
CDX IG	3.59*	0.06
CDX HY	5.64***	0.00

Notes: The table shows the Chow breakpoint test on investment-grade and high-yield CDX spreads. CDX IG and CDX HY are spreads for the investment-grade CDX and high-yield CDX respectively. The sample is from October 2005 to December 2016. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

TABLE 3.4 UNIT ROOT TEST

Variables	t-Statistics	p-value
CDX IG	-6.70	0.00
CDX HY	-5.69	0.00
IP	-9.59	0.00
NonF	-8.07	0.00
CPI	-7.49	0.00
RF	-5.37	0.03
IPVol	-11.07	0.00
NonFVol	-8.56	0.00
CPIVol	-4.80	0.02
RFVol	-5.56	0.02

Notes: The table shows the augmented Dickey Fuller unit root test on dependent variables and independent variables. CDX IG and CDX HY are spreads for the investment-grade CDX and high-yield CDX respectively. IP is the growth of industrial production, NonF is the growth of total nonfarm payroll and CPI is the growth of consumer price index; RF is the 3-month Treasury Bill rate; IPVol, NonFVol, CPIVol and RFVol are the volatility of IP, NonF, CPI, RF respectively. The sample is from March 2009 to December 2016.

TABLE 3.5 SUMMARY STATISTICS OF DEPENDENT AND INDEPENDENT VARIABLES

	Mean	Med	Max	Min	Std. Dev.	N	Skew	Kurt	JB Prob
CDX IG	93.33	90.05	202.80	62.21	24.26	94	1.65	6.89	0.00
CDX HY	520.60	464.45	1486.10	307.63	195.43	94	2.29	9.35	0.00
IP	0.15	0.19	1.54	-1.59	0.52	94	-0.31	3.62	0.21
NonF	0.09	0.14	0.40	-0.62	0.16	94	-2.16	8.33	0.00
CPI	0.14	0.16	0.83	-0.64	0.21	94	-0.27	4.94	0.00
RF	0.11	0.08	0.51	0.01	0.10	94	1.56	5.50	0.00
IPVol	0.26	0.22	0.96	0.19	0.12	94	3.36	17.28	0.00
NonFVol	0.01	0.01	0.13	0.00	0.02	94	5.94	45.30	0.00
CPIVol	0.04	0.03	0.11	0.02	0.02	94	1.89	5.92	0.00
RFVol	0.02	0.01	0.05	0.01	0.01	94	1.73	5.73	0.00

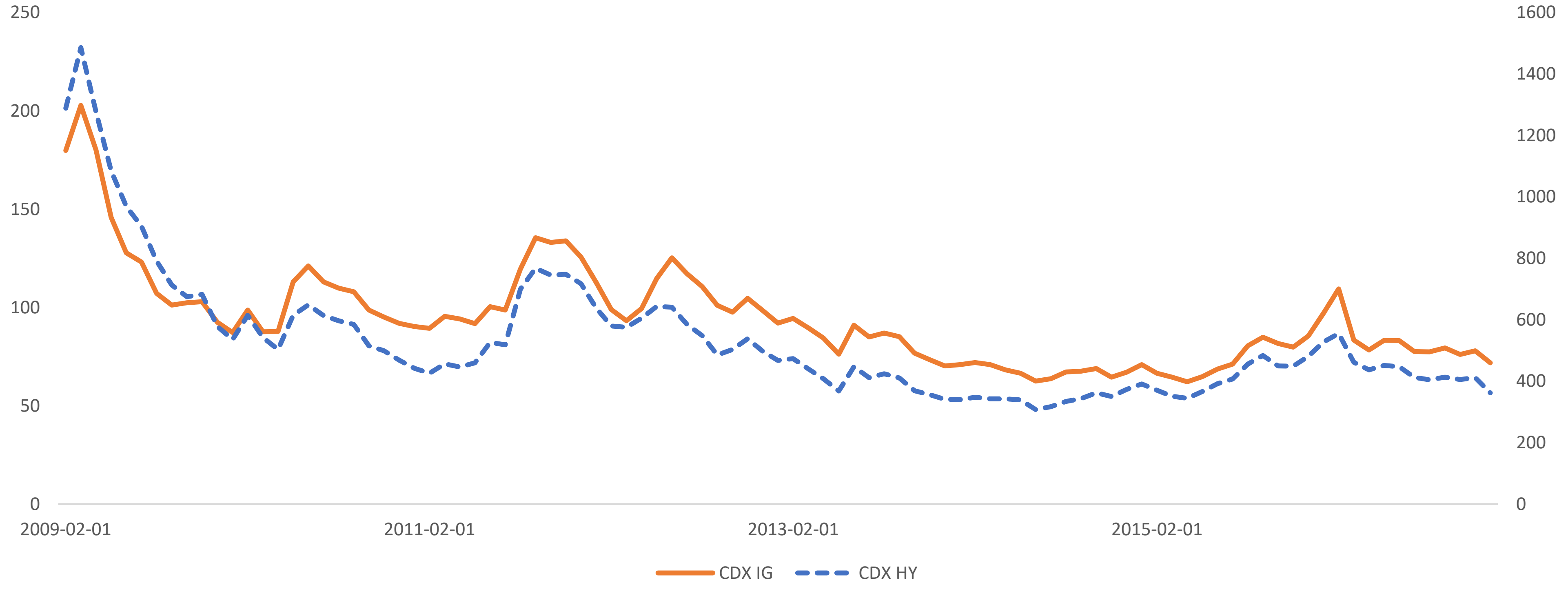
Notes: This table shows the descriptive statistics for the CDS spread, macroeconomic condition and macroeconomic volatility variables. CDX IG and CDX HY are spreads for the investment-grade CDX and high-yield CDX respectively. IP is the growth of industrial production; NonF is the growth of total nonfarm payroll; CPI is the growth of consumer price index; RF is the 3-month Treasury Bill rate; IPVol, NonFVol, CPIVol and RFVol are the volatility of IP, NonF, CPI, RF respectively. CDX IG and CDX HY spreads are measured in basis points; IP, NonF, CPI, RF and RFVol are measured in percentage; IPVol, NonFVol, and CPIVol are measured in squared percentage. Mean, Med, Max, Min, Std. Dev, N, Skew, and Kurt represent the mean, median, maximum, minimum, standard deviation, number of observations of variables, skewness, and kurtosis. JB Prob is the p value for the Jarque–Bera normality test. The sample is from March 2009 to December 2016.

TABLE 3.6 PAIR-WISE CORRELATION OF DEPENDENT AND INDEPENDENT VARIABLES

	CDX IG	CDX HY	IP	NonF	CPI	RF	IPVol	NonFVol	CPIVol	RFVol
CDX IG	1.00									
CDX HY	0.94	1.00								
IP	-0.13	-0.20	1.00							
NonF	-0.63	-0.77	0.28	1.00						
CPI	0.10	0.10	-0.01	-0.08	1.00					
RF	0.11	0.13	-0.19	-0.18	0.11	1.00				
IPVol	0.51	0.61	-0.31	-0.49	-0.05	0.19	1.00			
NonFVol	0.28	0.27	-0.04	-0.30	-0.03	0.08	0.23	1.00		
CPIVol	0.23	0.35	-0.18	-0.45	-0.09	-0.03	0.27	0.03	1.00	
RFVol	0.14	0.17	-0.15	-0.10	0.05	0.56	0.21	0.04	-0.03	1.00

Notes: This table reports the pair-wise correlation between CDX spreads and macroeconomic variables. CDX IG and CDX HY are spreads for the investment-grade CDX and high-yield CDX respectively. IP is the growth of industrial production, NonF is the growth of total nonfarm payroll and CPI is the growth of consumer price index; RF is the 3-month Treasury Bill rate; IPVol, NonFVol, CPIVol and RFVol are the volatility of IP, NonF, CPI, RF respectively. IP, NonF and CPI are values at time t-1 while CDX IG, CDX HY, RF, IPVol, NonFVol, CPIVol and RFVol are values at time t. The sample period is from March 2009 to December 2016.

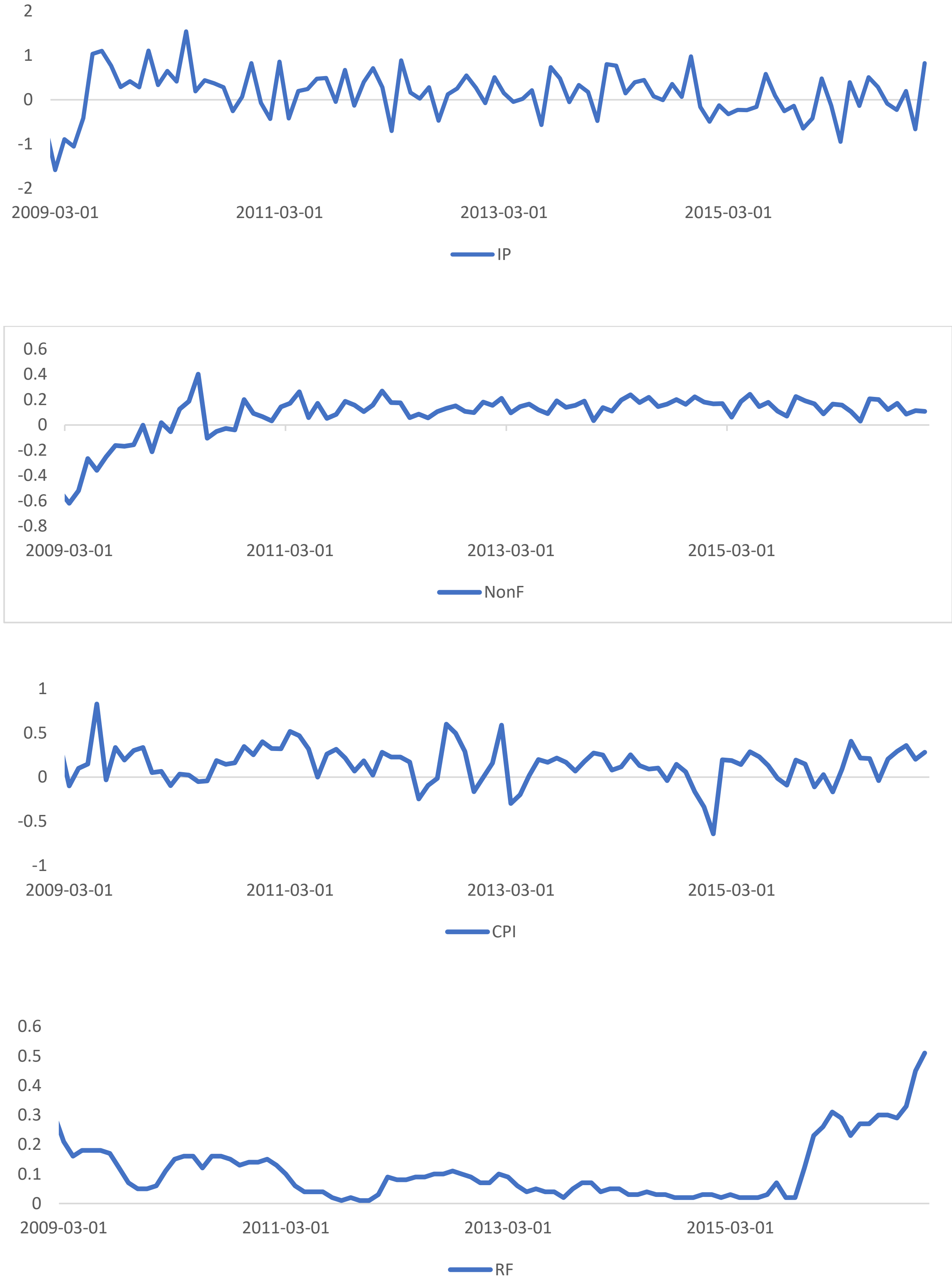
FIGURE 1 FIGURES OF INVESTMENT-GRADE AND HIGH-YIELD CDX SPREADS



Data Source: Bloomberg Professional

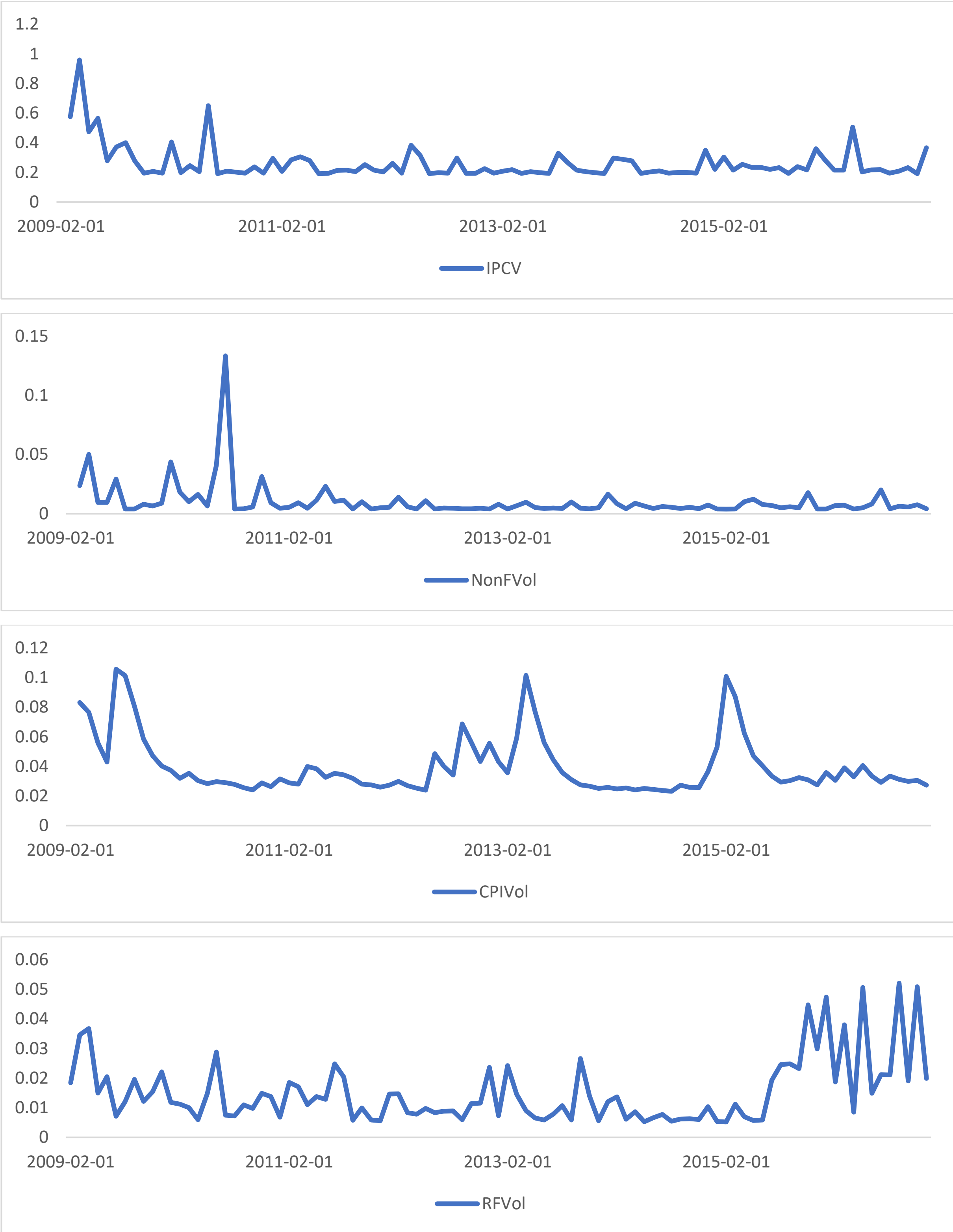
Notes: This figure represents the monthly investment-grade CDX spread and high-yield CDX spread from March 2009 to December 2016. The left vertical axis is measured in basis points and shows the values for the investment-grade CDX spread. The right vertical axis is measured in basis points and shows the values for the high-yield CDX spread.

FIGURE 2 MACROECONOMIC CONDITION VARIABLES.



Note: The Figure plots the growth of industrial production (IP), the growth of total nonfarm payroll (NonF), the growth of consumer price index (CPI), and 3-month Treasury Bill rate (RF). IP, NonF, CPI, and RF are measured in percentage. The sample is from March 2009 to December 2016.

FIGURE 3 MACROECONOMIC VOLATILITY VARIABLES



Note: The figure plots IPVol, NonFVol, CPIVol, RFVol. IPVol, NonFVol, CPIVol and RFVol are the volatility of industrial production growth, total nonfarm payroll growth, consumer price index growth, 3-month Treasury rate respectively. IPVol, NonFVol, and CPIVol are measured in percentage. RFVol are measured in squared percentage. The sample is from March 2009 to December 2016.

3.3.2 METHODOLOGY

A summary of expected effects of macroeconomic variables and their volatility variables on CDX spreads is reported in Table 3.7.

To test all expected relationships between the CDX spread and macroeconomic level variables, macroeconomic volatility variables, this chapter begins by studying the effect of macroeconomic level variables on the CDX spread in a multi-variate regression framework that has been widely adopted by the CDS pricing literature (e.g. Baum and Wan, 2010; and Tang and Yan, 2010)

The Regression (3.1) will be constructed and estimated to explain how macroeconomic level variables influence CDX spreads with different ratings:

$$CDX_{i,t} = \alpha_i + \beta_{i,1} IP_{t-1} + \beta_{i,2} NonF_{t-1} + \beta_{i,3} CPI_{t-1} + \beta_{i,4} RF_t + \varepsilon_{i,t} \qquad \text{Regression (3.1)}$$

where t=1,2, …, T denotes time in months. CDX i denotes investment-grade CDX spread and high-yield CDX spread. $\varepsilon_{i,t}$ is the error term. IP is the growth of industrial production. NonF is the growth of total nonfarm payroll. CPI is the growth of consumer price index. RF is the 3-month Treasury Bill rate.

The Regression (3.1) of the CDX spread with different credit ratings is estimated separately using least squares method.

Next, the Regression (3.2) is estimated to explore joint effects of macroeconomic level and volatility variables on the CDX spread:

$$\begin{aligned} CDX_{i,t} = {} & \alpha_i + \beta_{i,1} IP_{t-1} + \beta_{i,2} NonF_{t-1} + \beta_{i,3} CPI_{t-1} + \beta_{i,4} RF_t + \beta_{i,5} IPVol_t + \beta_{i,6} NonFVol_t \\ & + \beta_{i,7} CPIVol_t + \beta_{i,8} RFVol_t + \varepsilon_{i,t} \end{aligned}$$

Regression (3.2)

where t=1,2, …, T denotes time in months. CDX i denotes investment-grade CDX spread and high-yield CDX spread. $\varepsilon_{i,t}$ is the error term. IP is the growth of industrial production. NonF is the growth of total nonfarm payroll. CPI is the growth of consumer price index. RF is the 3-month Treasury Bill rate. IPVol, NonFVol, CPIVol and RFVol are the volatility of IP, NonF, CPI, RF respectively.

Furthermore, this chapter assess the relative importance of macroeconomic level variables and macroeconomic volatility variables by comparing their marginal contributions to the explained variation in the CDS spread in Regression (3.2). To construct the marginal contribution made by each group of variables, this chapter applies an instructive method proposed by Düllmann and Sosinska (2007) and Annaert *et al*. (2013). The marginal contribution of nth group of variables mc_n to the total explained R square in the Regression (3.2) is expressed as:

$$\frac{R^2 - R_n^2}{\sum_{n=1}^{2}\left(R^2 - R_n^2\right)}$$

where R^2 is the explained R square in Regression (3.2) and R_n^2 is the explained R square of the regression with nth group of variables being removed.

Finally, the sensitivity analysis is constructed to compare the different sensitivity of investment-grade and high-yield CDX spread to macroeconomic variables. This chapter follows the sensitivity analysis methodology adopted by Chuhan, Claessens, and Mamingi (1998) and Audzeyeva and Schenk-Hoppe (2010). This chapter constructs elasticity by dividing the slope coefficient of independent variables using the mean of dependent variable and then multiplying the mean of independent variables. The dependent variables with a higher elasticity for an independent variable are more sensitive to that independent variable.

TABLE 3.7 PREDICTED SIGNS FOR MACROECONOMIC CONDITION AND VOLATILITY VARIABLES

Independent Variable	Expected Sign
IP	-
NonF	-
CPI	-/+
RF	-
IPVol	+
NonFVol	+
CPIVol	+
RFVol	+

Notes: The table shows a summary of the expected signs for the relationship between CDX spreads and macroeconomic level, macroeconomic volatility variables. IP is the growth of industrial production; NonF is the growth of total nonfarm payroll; CPI is the growth of consumer price index; RF is the 3-month Treasury Bill rate; IPVol, NonFVol, CPIVol and RFVol are the volatility of IP, NonF, CPI, RF respectively. IP, NonF and CPI are values at time t-1 while RF, IPVol, NonFVol, CPIVol and RFVol are values at time t.

3.4 EMPIRICAL ANALYSIS

This empirical analysis starts with Section 3.4.1 that explores the effect of macroeconomic level variables on the investment-grade CDX spread and the high-yield CDX spread. Next, Section 3.4.2 explores the joint effect of macroeconomic level variables and macroeconomic volatility variables on the CDX spread. Based on results from Section 3.4.1 and Section 3.4.2, Section 3.4.3 explore the relative importance of macroeconomic level variables and macroeconomic volatility variables by comparing their marginal contributions to the explained variation in the CDX spread. Finally, Section 3.4.4 conducts sensitivity analysis to examine sensitivities of the investment-grade CDX spread and the high-yield CDX spread to macroeconomic variables.

3.4.1 MACROECONOMIC LEVEL VARIABLES AND THE CDX SPREAD

3.4.1.1 Regression (3.1) Results

The analysis starts with running Regression (3.1). Regression (3.1) is estimated separately for the investment-grade CDX spread and the high-yield CDX spread as the dependent variables and results are reported in the Column (a) and (c) of Table 3.8 respectively.

The growth of total nonfarm payroll has a significantly positive effect on the investment-grade CDX spread and high-yield CDX spread at 99% confidence level. The sign of coefficient is consistent with the expectation in the Data Variables Section. One-percentage increase in the growth of total nonfarm payroll lowers the investment-grade CDX spread by 92.00 basis points and lowers the high-yield CDX spread by 898.13 basis points. The growth of industrial production, consumer price inflation, and 3-month Treasury Bill rate do not have a significant effect on either the investment-grade CDX spread or the high-yield CDX spread.

The findings firstly report that the employment conditions play a significant role in determining the CDX spread. The growth of total nonfarm payroll, a macroeconomic indicator that to the best of my knowledge has not been previously explored in the CDS spread pricing literature, has a significantly negative effect on the CDX spread. In addition, in the analysis, the growth of industrial production does not have a significantly effect on the CDX spread. This suggests that the growth of total nonfarm payroll may be more powerful in explaining the CDX spread than the output growth as measured by industrial production growth.

A potential reason for the significance of the total nonfarm payroll growth is that compared with other macroeconomic variables, the growth of total nonfarm payroll may be an early indicator of companies' future performance and default risk. The increases in the total nonfarm payroll indicates that companies increase hiring and plan to expand business in the future, therefore they are less likely to default in the future. As a result, the growth of total nonfarm payroll affects the CDX spread that is regarded as a measure of overall default risk.

The adjusted R square is 37.57% for the investment-grade CDX spread and 58.26% for the high-yield CDX spread. The higher adjusted R square for the high-yield CDX spread indicates that macroeconomic level variables have more explanatory power in explaining the total variation in the high-yield CDX spread.

Adjusted R squares in this section are larger compared with findings by some empirical literature, such as Ericsson, Jacobs, and Oviedo (2009). One potential reason for the lower adjusted R square in Ericsson, Jacobs, and Oviedo (2009) is that only the risk-free rate measure is used in their analysis. The risk-free rate measure alone cannot fully capture the macroeconomic conditions and therefore it is able to explain only a small share of variation of the change of the CDS spread.

Finally, Table 3.8 reports a higher adjusted R square for the high-yield CDX spread than for investment-grade CDX spread. One reason for differences in adjusted R squares is that the macroeconomy affects the high-yield CDX spread more than the investment-grade CDX spread. The macroeconomy can first affect the high-yield CDX spread through affecting the default probability of high-yield companies. A report released by S&P Global Rating shows that investment-grade default rate is low and remain stable from 1987 to 2016 while high-yield default rate is comparatively higher and exhibits a countercyclical pattern. The countercyclical pattern of the high-yield default rate may cause the CDX high-yield spread rely on the macroeconomic level more than the CDX investment-grade spread does.

Another reason relates to the financing and investment strategy of high-yield companies. Campello, Graham, and Harvey (2010) suggest that high-yield companies show a higher propensity to link the availability of external financing to the ability to pursue attractive projects. Campello, Graham, and Harvey (2010) show that, during the crisis when the availability of external funds is limited, high-yield companies tend to postpone investment and cut more technology, marketing, and employment expenditures more than investment-grade companies do. The financing and investment strategy of high-yield companies indicates that the performance and default probability of high-yield companies are significantly affected by the macroeconomic level through the funding channel, which may help to explain the higher adjusted R square for the high-yield CDX spread.

In summary, the results indicate that the growth of total nonfarm payroll, the economic indicator that has not been previously studied in the CDS pricing literature, has a significantly negative effect on the CDX spread. The analysis also empirically establishes the importance of macroeconomic level variables in determining the CDX spread by showing that macroeconomic level variables can jointly explain roughly 40% to 60% of total variation in the CDX spread, which is comparatively larger than studies that focus on the single-name CDS spread change and employ only a single variable or a limited set of macroeconomic indicators. Finally, by conducting the analysis on the investment-grade CDX spread and the high-yield CDX spread separately, shows that macroeconomic level variables attribute a larger share of variation in the high-yield CDX spread than in the investment-grade CDX spread.

3.4.1.2 Diagnostic Tests for Regression (3.1)

After running Regression (3.1), this chapter conducts the Breusch-Godfrey serial correlation LM test and Engle's ARCH heteroskedasticity test to detect the existence of autocorrelation and heteroskedasticity in the residuals of Regression (3.1).

Results for the Breusch-Godfrey serial correlation LM test are reported in the Panel A of Table 3.9. The null hypothesis for the Breusch-Godfrey serial correlation LM test is that there is no first-order autocorrelation in the residuals of Regression (3.1). The p-value is less than 0.05, therefore the null hypothesis should be rejected at 95% confidence level.

Panel B of Table 3.9 shows the results of Engle's ARCH heteroskedasticity test for the residuals of Regression (3.1) using investment-grade CDX spread and high-yield CDX spread as the dependent variable respectively. The null hypothesis is that the regression residuals are homoscedastic with the same variance across time. The p-value is less than 0.05, therefore the null hypothesis should be rejected at 95% confidence level. As a result, there are autocorrelation and heteroskedasticity in the residuals of Regression (3.1). Regression (3.1) use Newey-West standard errors to obtain robust t-statistics, adjusting for autocorrelation and heteroskedasticity in the residuals of Regression (3.1).

Given the fact that there are several outliers in the macroeconomic volatility series, a Chow test, introduced by Chow (1960), was undertaken to test for parameter stability. The sample was divided into two sub-samples, with each sub-sample containing 47 observations. The null hypothesis is that there is no structural break in the data, defined arbitrarily on the basis of a pre- and post-January 2013 divide. Panel A of Table 3.10 reports the results for Chow test on Regression (3.1) in relation to investment-grade CDX spread and high-yield CDX spread as dependent variables. The results indicate that the null hypothesis of no structural break is rejected, with a p-value smaller than 0.01. The results therefore suggest that outliers may affect parameter constancy in the analysis and the reliability of estimation results of Regression (3.1).[8] However, the power of the Chow test is limited. Candelon and Lutkepohl (2001) suggest that the Chow test is prone to a small sample problem, with rejection of the null as a consequence. In the current study, this is likely to be an issue in relation to the test because of the small size of the two sub-samples.

[8] It is possible that the same considerations influence the results in Table 4.9 in Chapter 4.

TABLE 3.8 MACROECONOMIC CONDITION AND VOLATILITY VARIABLES AND CDX SPREADS

	Panel A: CDX IG		Panel B: CDX HY	
	(a)	(b)	(c)	(d)
Constant	100.25***	84.40***	593.42***	428.55***
	(16.38)	(7.07)	(15.92)	(6.21)
IP	2.26	4.31	6.88	28.38
	(0.44)	(1.09)	(0.22)	(1.39)
NonF	-92.00***	-75.99***	-898.13***	-741.26***
	(-4.14)	(-4.60)	(-5.88)	(-7.75)
CPI	5.19	7.98	31.64	60.16
	(0.59)	(0.91)	(0.69)	(1.25)
RF	-1.53	-19.82	-19.51	-178.23
	(-0.05)	(-0.69)	(-0.11)	(-1.03)
IPVol		59.05***		534.56***
		(3.59)		(5.58)
NonFVol		99.72		223.51
		(1.35)		(0.48)
CPIVol		-77.91		-119.73
		(-0.57)		(-0.16)
RFVol		158.82		1597.71*
		(1.06)		(1.84)
Adjusted R square	0.3757	0.4272	0.5826	0.6556
No. observations	94	94	94	94

Notes: This table reports results of Regression (3.1) and Regression (3.2). The columns (a) and (c) report results of Regression (3.1) using CDX IG and CDX HY as the dependent variable respectively. The columns (b) and (d) reports results of Regression (3.2) using CDX IG and CDX HY as the dependent variable respectively. The dependent variables are CDX IG and CDX HY. CDX IG and CDX HY are spreads for the investment-grade CDX and high-yield CDX respectively; IP is the growth of industrial production; NonF is the growth of total nonfarm payroll, CPI is the growth of consumer price index; and RF is the 3-month Treasury Bill rate. IPVol, NonFVol, CPIVol, and RFVol are volatility measures for IP, NonF, CPI, and RF respectively. CDX IG and CDX HY spreads are measured in basis points; IP, NonF, CPI, RFand RFVol are measured in percentage; IPVol, NonFVol, and CPIVol are measured in squared percentage. IP, NonF and CPI are values at month t-1. The CDX IG, CDX HY, RF, IPVol, NonFVol, CPIVol, and RFVol are values at month t. The sample period is from March 2009 to December 2016. The estimation is carried out by using Newey-West standard errors to control for autocorrelation and heteroskedasticity. T-statistics are given in parenthesis. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

TABLE 3.9 RESULTS FOR BREUSCH-GODFREY SERIAL CORRELATION LM TEST AND ENGLE'S ARCH HETEROSKEDASTICITY TEST

	Panel A: Breusch-Godfrey Test		Panel B: Engle's ARCH Heteroskedasticity Test	
	F Statistics	P-value	F Statistics	P-value
CDX IG Regression (3.1)	3.41	0.00	24.68	0.00
CDX HY Regression (3.1)	1.91	0.02	9.14	0.00
CDX IG Regression (3.2)	2.84	0.00	43.36	0.00
CDX HY Regression (3.2)	1.73	0.04	42.15	0.00

Notes: The Panel A of Table 3.9 shows the Breusch-Godfrey serial correlation LM test for the Regression (3.1) and Regression (3.2) using investment-grade CDX spread and high-yield CDX spread as the dependent variable respectively. Panel B of Table 3.9 shows the results of Engle's ARCH heteroskedasticity test on the Regression (3.1) and Regression (3.2) using investment-grade CDX spread and high-yield CDX spread as the dependent variable respectively. The sample is from March 2009 to December 2016.

TABLE 3.10 CHOW BREAKPOINT TEST

	Panel A: Regression (3.1)		Panel B: Regression (3.2)	
	CDX IG	CDX HY	CDX IG	CDX HY
F statistics	13.49	9.34	8.18	6.64
P value	0.00	0.00	0.00	0.00

Notes: The Table 3.10 shows the results for the Chow test. The sample is from March 2009 to December 2016.

3.4.2 MACROECONOMIC LEVEL AND VOLATILITY VARIABLES AND THE CDX SPREAD

3.4.2.1 Regression (3.2) Results

This section will explore the joint effect of macroeconomic level variables and macroeconomic volatility variables on the CDX spread. To this end, regression (3.2) is estimated separately for the investment-grade CDX spread and the high-yield CDX spread as the dependent variable and results are reported in Column (b) and Column (d) of Table 3.8, respectively.

After introducing macroeconomic volatility variables to the regression, the growth of total nonfarm payroll remains significant while the growth of industrial production, consumer price inflation and the 3-month Treasury Bill rate remain insignificant.

The volatility of industrial production growth has a significantly positive effect on the investment-grade CDX spread and high-yield CDX spread at the 99% confidence level. The sign of coefficient is as expected, and it is consistent with the findings of Baum and Wan (2010). The volatility of total nonfarm payroll growth and the volatility of consumer prices inflation have insignificant effects on the investment-grade CDX spread and the high-yield CDX spread. The effect of the volatility of 3-month Treasury Bill rate varies across Column (b) and (d). The volatility of 3-month Treasury Bill rate has an insignificant effect on the investment-grade CDX spread but significantly positive effect on the high-yield CDX spread at 90% confidence level. The significantly positive sign of the volatility of 3-month Treasury Bill rate is in line with the expectation and it is consistent with the results in Kim and Stock (2014) who document a positive effect of the risk-free rate volatility on the bond credit spread.

It is interesting to compare the effect of the volatility of industrial production growth with the findings by Baum and Wan (2010). The findings show the positive relationship between the CDX spread and the volatility of industrial production growth are consistent with the findings of Baum and Wan (2010) that use the single-name CDS spread. Furthermore, the results here differ from those in Tang and Yan (2010) who find an insignificant relationship between the customized market average CDS spread and the volatility of industrial production growth modelled with the autoregressive model, which may indicate that the conditional variance modelled by GARCH as in the present analysis may be a better measure of the macroeconomic volatility.

The different effects of the volatility of 3-month Treasury Bill rate on the investment-grade CDX spread and high-yield CDX spread have not been explored before but can be explained by the work of Diamond (1991) that finds that low-rated firms have no choice but be forced to borrow short-term debt due to the higher probability of failing to support long-term debt with insufficient funding. Consequently, high-yield companies have a greater exposure to variations in the short-term risk-free rate and, therefore, their CDS spreads are affected to a greater extent by the volatility of short-term risk-free rate.

After introducing macroeconomic volatility variables into the regression, the adjusted R square for the investment-grade CDX spread increases from 37.57% to 42.72% and the adjusted R square for the high-yield CDX spread increases from 58.26% to 65.56%. The adjusted R square increases after adding macroeconomic volatility variables, indicating that macroeconomic volatility variables contain new important information that is relevant for pricing the investment-grade CDX spread and high-yield CDX spread.

Compared with Annaert *et al*. (2013) and Tang and Yan (2010), this section studies separately the explanatory power of the macroeconomic volatility group of variables and macroeconomic level variables. As a result, this section makes a contribution to the literature by showing that adding macroeconomic volatility variables help improving the model's explanatory power beyond that of the macroeconomic level variables.

The adjusted R square is larger than the R-square of 15.23% in Annaert *et al.* (2013) for the joint effect of macroeconomic level variables and macroeconomic volatility variables on the single-name CDS spread. One theory that can potentially explain the lower adjusted R square in Annaert *et al.* (2013) is the modern portfolio theory that is introduced by Markowitz (1952). The CDX is a basket of single name CDS contracts. As a result, the construction of the CDX diversifies the firm-specific risk component in the spread, making macroeconomic determinants to attribute a larger proportion of the CDX spread. Another potential reason for the larger adjusted R square in this study, as mentioned in Section 3.4.1, is that the analysis here employs a broader selection of macroeconomic level and macroeconomic volatility variables, enabling the model to explain a greater share of the variation in the CDS spread.

Furthermore, the adjusted R square in this section can be more directly related to the finding by Tang and Yan (2010) who study the market-average CDS spread, which is calculated for a combined basket of the investment-grade and high-yield single-name CDS spreads. They obtain an adjusted R square of 0.46 which is comparable with the adjusted R-square of 0.43 for investment-grade CDX but considerably lower than adjusted R-square of 0.66 for high-yield CDX in this study. It is likely that this considerably higher explanatory power for high yield CDX in the present study is due to studying a more comprehensive set of macroeconomic level and volatility variables, with some of those found important here but omitted from consideration in Tang and Yan (2010). However, a separate estimation of their model for high-yield and investment-grade CDX would be required for a more conclusive comparison.

Finally, Table 3.8 shows that macroeconomic level variables together with macroeconomic volatility variables can explain more variations in the high-yield CDX spread than in the investment-grade CDX spread. This finding is consistent with the higher explanatory power of macroeconomic levels variables for the high-yield CDX spread reported in Section 3.4.1 for which this section provides potential explanations.

In summary, results from Regression (3.2) indicate that apart from macroeconomic level variables, macroeconomic volatility variables, such as the volatility of industrial production growth and the volatility of short-term interest rate, also play significant part in determining the CDX spread. By comparing the explanatory power of the model with both macroeconomic levels and volatility variables to a model with macroeconomic level variables only, the analysis suggest that macroeconomic volatility variables are able to explain a notable additional share of variation in the CDX spread, beyond that explained by macroeconomic level variables.

Furthermore, this section contributes to the literature by highlighting that CDS credit quality plays a role in determining the impact of macroeconomic variables on the CDX spread. In particular, macroeconomic level and volatility variables jointly have a greater explanatory power for the high-yield CDX spread than for the investment-grade CDX spread. Also, the effect of certain macroeconomic variables, namely, the volatility of the 3-month Treasury Bill rate is only found significant for high-yield CDX spread but not the investment-grade CDX spread.

3.4.2.2 Diagnostic Tests for Regression (3.2)

After running Regression (3.2), the Breusch-Godfrey serial correlation LM test and Engle's ARCH heteroskedasticity test and detect the existence of autocorrelation and heteroskedasticity in Regression (3.2).

Results for the Breusch-Godfrey serial correlation LM test and Engle's ARCH heteroskedasticity test are reported in the Panel A and Panel B of Table 3.9 and show that there are autocorrelation and heteroskedasticity in the residuals of Regression (3.2). As a result, Regression (3.2) use Newey-West standard errors to obtain robust t-statistics, adjusting for autocorrelation and heteroskedasticity in the residuals of Regression (3.2).

Finally, this section runs the Chow test to test for parameter stability. Similar to the Chow test in Section 3.4.1.2, the sample was divided into two sub-samples, with each sub-sample containing 47 observations. The null hypothesis is that there is no structural break in the data. Panel B of Table 3.10 reports the results for Chow test on Regression (3.2) in relation to investment-grade CDX spread and high-yield CDX spread as dependent variables. The p-value is smaller than 0.01, which thereby reject the null hypothesis of no structural break and suggest that outliers may affect parameter constancy in the analysis and the reliability of estimation results of Regression (3.2).

3.4.3 RELATIVE IMPORTANCE ANALYSIS

In Section 3.4.1 and 3.4.2, the effect of macroeconomic level and volatility variables on CDX spreads of different credit ratings is explored. This section expands this analysis by comparing the relative importance of macroeconomic level variables and macroeconomic volatility variables. The analysis results are reported in Table 3.11.

The results show that macroeconomic level variables contribute 75.81% and macroeconomic volatility variables contribute the remaining 24.19% of the explained variation in the investment-grade CDX spread. For the high-yield CDX spread, macroeconomic level variables can explain marginally higher proportion, 77.47%, of explained variation and macroeconomic volatility variables can explain 22.53% of explained variation.

Marginal contributions made by macroeconomic level variables and macroeconomic volatility are both positive and sizable, suggesting that both variable groups are of importance in explaining the CDX spread. This finding provides supportive empirical evidence for the theoretical model of Tang and Yan (2006), by showing that both macroeconomic level and volatility variables have significant explanatory power in explaining the CDX spread. Furthermore, this analysis may provide useful insights for empirical CDS studies such as Lesplingart, Majois, and Petitjean (2012) that do not control for macroeconomic conditions and volatility and Ericsson, Jacobs and Oviedo (2009) that considers macroeconomic level but omits macroeconomic volatility variables when pricing the CDS spread.

This section shows that macroeconomic level variables make a relatively greater contribution than macroeconomic volatility variables in explaining the CDX spread. This finding can be related to Annaert *et al.* (2013) who find the stock market index return, their market-based measure of economic conditions, can explain more variation in the single-name CDS spread than the volatility of stock index return. However, the finding in this section cannot be compared with the finding by Annaert *et al.* (2013) directly because the two studies include different types of independent variables. Annaert *et al.* (2013) focus on indirect measures such as the stock market index return and its volatility, capturing the overall stock market performance and market volatility while this section focuses on economic output, employment and other variables that directly capture the state of the macroeconomy.

There is one potential reason that can explain why macroeconomic level variables can make greater marginal contribution than macroeconomic volatility variables in explaining the CDS spread. Several papers, such as Ramey and Ramey (1995), report that economic volatility significantly decreases economic growth. As a result, macroeconomic volatility variables can affect the CDX spread both directly and also indirectly via macroeconomic level variables, with their indirect impact not reflected in the reported measures.

In summary, Section 3.4.3 examines the relative importance of macroeconomic level and macroeconomic volatility groups of variables by comparing their marginal contribution to the explained variation in the CDX spread. The results show that both macroeconomic level variables and macroeconomic volatility variables play important parts in explaining the total variation in the CDX spread. However, this section shows that macroeconomic level variables jointly contribute more in explaining the total variation in the CDX spread by showing that macroeconomic level variables contribute around 75% of explained variation in the CDX spread while macroeconomic volatility variables contribute around 25% of explained variation in the CDX spread. The distribution of marginal contributions made by macroeconomic level and volatility groups of variables is similar for the CDS spread of investment-grade and high-yield credit quality.

TABLE 3.11 RELATIVE IMPORTANCE OF MACROECONOMIC LEVEL VARIABLES AND MACROECONOMIC VOLATILITY VARIABLES

	CDX IG	CDX HY
Marginal Contribution (Macro Condition)	0.7581	0.7747
Marginal Contribution (Macro Volatility)	0.2419	0.2253

Note: This table reports the marginal contributions of macroeconomic condition variables and macroeconomic volatility variables. CDX IG and CDX HY are spreads for the investment-grade CDX and high-yield CDX respectively. Macro Condition category contains the growth of industrial production, the growth of total nonfarm payroll, the growth of consumer price index, and the 3-month Treasury Bill rate. Macro Volatility category contains the volatility of the growth of industrial production, the volatility of the growth of total nonfarm payroll, the volatility of the growth of consumer price index, and the volatility of the 3-month Treasury Bill rate. The sample period is from March 2009 to December 2016.

3.4.4 SENSITIVITY ANALYSIS

Section 3.4.1 and Section 3.4.2 provide the analysis of how macroeconomic level variables and macroeconomic volatility variables affect the CDX investment-grade spread and the CDX high-yield spread. The analysis shows that the regression coefficients for some independent variables differ notably for CDX of investment grade and high-yield credit quality. However, the coefficient values can be misleading measures for comparing the sensitivity of the CDX investment-grade spread and the CDX high-yield spread to various macroeconomic determinants because their magnitudes differ substantially. In particular, Table 3.5 shows that the mean value of the investment-grade CDX spread is 93.33 whereas it is 520.60 for high-yield CDX spread.

In order to compare the sensitivity of dependent variables to independent variables, adjusted for differences in the dependent variables' magnitude, the elasticity is calculated. The elasticity of an independent variable is constructed using its slope coefficient in Regression

(3.2) divided by the mean of dependent variable and then multiplied by the mean of independent variable. Using this construction method, the elasticity measures the proportional change of the dependent variable due to the proportional change in the independent variable. To interpret the meaning of elasticity in a straightforward manner, this section uses the elasticity of the total nonfarm payroll growth to provide an example. The elasticity of total nonfarm payroll growth of -0.0745 in Panel A of Table 3.12 suggests that if the total nonfarm payroll growth increases by 100%, the investment-grade CDX spread will decrease by 7.45%. Elasticities of the investment-grade CDX spread and the high-yield CDX spread to macroeconomic level and volatility variables are reported in Table 3.12.

The growth of industrial production, consumer price inflation, 3-month Treasury Bill rate, the volatility of nonfarm payroll growth, the volatility of consumer price inflation has no significant effects on the CDX spread. Comparing sensitivities of statistically insignificant variables cannot provide useful information, so that these variables are omitted from the discussion below.

The elasticity of the CDX high-yield spread for the growth of total nonfarm payroll at -0.0745 is approximately twice as large as the elasticity of -0.1303 for the investment-grade CDX spread, suggesting that the high-yield CDX spread is twice as sensitive as the investment-grade CDX spread to the growth of total nonfarm payroll.

The elasticity of the high-yield CDX spread for the volatility of industrial production growth is 0.1651 which is approximately 1.5 times as large in absolute value as the elasticity of 0.2680 for the investment-grade CDX spread, suggesting that the high-yield CDX spread is 1.5 times as sensitive as the investment-grade CDX spread to the volatility of industrial production growth.

The volatility of 3-month Treasury Bill rate is significant in determining the high-yield CDX spread but insignificant in determining the investment-grade CDX spread. In line with this result, the absolute value of the elasticity of the investment-grade CDX spread is approximately two-times smaller than that of the high-yield CDX spread, indicating that the high-yield CDX spread is more sensitive to the volatility of 3-month Treasury Bill rate. This finding, together with similar findings for other variables, provides consistent evidence that the high-yield CDX spread is about 1.5 to 2-times more sensitive to macroeconomic level variables and macroeconomic volatility variables relative to the investment-grade CDX spread.

A higher sensitivity of the high-yield CDX spread to macroeconomic level variables and macroeconomic volatility variables is consistent with earlier findings from Sections 3.4.1 and 3.4.2. A potential explanation put forward in those sections is that the investment strategy of high-yield companies relies more on external funding than that of investment-grade companies do. As a result, the higher sensitivity to the countercyclical external funding causes the risk of default of high-yield companies and the CDX high-yield spread to be more sensitive to the macroeconomy.

TABLE 3.12 ELASTICITY MEASURES FOR MACROECONOMIC VARIABLES

	Panel A: CDX IG	Panel B: CDX HY
IP	0.0069	0.0081
NonF	-0.0745***	-0.1303***
CPI	0.0121	0.0164
RF	-0.0232	-0.0374
IPVol	0.1651***	0.2680***
NonFVol	0.0111	0.0045
CPIVol	-0.0333	-0.0092
RFVol	0.0265	0.0479*

Notes: This table reports results elasticity of independent variables in Regression (3.2). The values reported in the table are the elasticities that measure the proportional percentage change of the dependent variable due to the proportional percentage change in the independent variable. The Panel A reports results of Regression (3.2) using CDX IG as the dependent variable. The Panel B reports results of Regression (3.2) using CDX HY as the dependent variable. CDX IG and CDX HY are spreads for the investment-grade CDX and high-yield CDX respectively; IP is the growth of industrial production; NonF is the growth of total nonfarm payroll, CPI is the growth of consumer price index; and RF is the 3-month Treasury Bill rate; IPVol, NonFVol, CPIVol, and RFVol are volatility measures for IP, NonF, CPI, and RF respectively. CDX IG and CDX HY spreads are measured in basis points; IP, NonF, CPI, RFand RFVol are measured in percentage; IPVol, NonFVol, and CPIVol are measured in percentage square. IP, NonF and CPI are values at month t-1. The CDX IG spread, CDX HY spread, RF, IPVol, NonFVol, CPIVol, and RFVol are values at month t. The sample period is from March 2009 to December 2016. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

3.5 ROBUSTNESS CHECK

To establish the robustness of findings and further explore the importance of economic output growth on the CDX spread, a real gross domestic product (GDP) measure of growth was used in place of industrial production growth as the overall state of the economy.

Real GDP represents the constant price, market value of all goods and services produced in the United States each period. The series is available quarterly and two interpolation methods are applied to convert the quarterly Real GDP to monthly values. A linear interpolation method crudely assigns the quarterly value to the first month of the quarter with the real gross domestic product value in remaining months of the quarter treated as intermediate points on a straight-line interpolation connecting the values for first month of consecutive quarters.

An alternative interpolation method follows the procedure introduced by Chow and Lin (1971). This approach constructs disaggregated values for monthly real GDP based upon an estimated relationship between quarterly real GDP growth and the quarterly rate of growth of advanced retail sales. The latter variable is available at both quarterly and monthly frequency with disaggregation proceeding on the assumption that the relationship estimated between quarterly real GDP and quarterly advanced retails sales growth holds equivalently at the monthly frequency. The detailed interpolation procedure is in Appendix A.

Real GDP growth in month t is defined as the logarithmic-difference between real GDP in month t and the corresponding value in month t-1. For convenience, this thesis will refer to the monthly-interpolated value of real GDP growth based on the linear interpolation method as GDP hereafter, whilst real GDP growth based upon the Chow-Lin method will be referred to as GDP_Sales reflecting the influence of advanced retail sales in its construction.

Volatility measures for both GDP and GDP_Sales are constructed using a GARCH modelling approach, with the results for the exercise reported in Table 3.13. The volatility of the GDP and GDP_Sales are referred to as GDPVol and GDP_SalesVol hereafter.

As alternative economic output growth measures, GDP and GDP_Sales are expected to have a negative effect on the CDX spread. In line with our previous discussion, GDPVol and GDP_SalesVol are each expected to have a positive effect on the CDX spread.

The results of augmented Dickey-Fuller unit root tests for stationarity of GDP, GDP_Sales, GDPVol, and GDP_SalesVol are reported in Table 3.14. The null hypothesis of the unit root test is that a unit root is present in the time series. P-values reported in the Table 3.14 for GDP, GDP_Sales, GDPVol, and GDP_SalesVol are each smaller than 0.05, which suggests that the null hypothesis be rejected at the 95% confidence level. As a result, GDP, GDP_Sales, GDPVol, and GDP_SalesVol are stationary.

Descriptive statistics for the series are reported in Table 3.15. GDP_Sales has a slightly larger maximum, lower minimum and larger standard deviation than the corresponding GDP measure derived from linear interpolation. Similarly, GDP_SalesVol is more volatile than GDPVol. Figure 4 also shows these differences in a more straightforward way. One potential reason for the difference is that the Chow-Lin method imports noise from the monthly advanced retail sales data.

Table 3.16 reports pair-wise correlations between CDX spreads and the macroeconomic variable for the period from March 2009 to December 2016. In the majority of cases these correlation coefficients are consistent with expectations. One noteworthy finding is that the correlation between GDP and GDP_Sales is relatively low at 0.24. This moderate correlation, together with the coefficient on advanced retail sales reported in Table A.3 in Appendix A, suggest that although advanced retail sales are an important proxy for GDP, they are not perfect correlated. This finding is consistent with the view that output movements and growth in the United States also originate from other sources in addition to retail sales. A further reason for the moderate correlation is that the advanced retail sales measure represents a survey-based economic indicator, derived from responses to a questionnaire administered to 5500 firms in the United States. This is more narrowly based than real GDP itself which is a nation-wide indicator of economic activity. Low correlations between independent variables generally mitigate concern regarding potential for multicollinearity in the multivariate regressions reported in the thesis.

TABLE 3.13 GARCH MEASURES OF MACROECONOMIC VOLATILITY FROM 2009M3 TO 2016M12

	GDP	GDP_Sales
Constant	0.1630***	0.3205***
(Mean equation)	(20.0717)	(14.1607)
Constant	0.0050***	0.0375***
(Variance equation)	(6.1285)	(8.5187)
ARCH (1)	0.0736*	0.3169**
	(1.8242)	(2.9250)
Log likelihood	70.4927	8.2468
No. Obs	94	94

Notes: The dependent variables for each panel are GDP, GDP_Sales. AR=Autoregressive; MA=Moving Average; ARCH=Autoregressive Conditional Heteroskedasticity; Mean equation=GARCH conditional mean equation; Variance equation=GARCH conditional variance equation. All dependent variables are sampled on a monthly basis. The sample period is from March 2009 to December 2016. T-Statistics are given in parentheses. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

TABLE 3.14 UNIT ROOT TEST

Variables	t-Statistics	p-value
GDP	-5.61	0.02
GDP_Sales	-11.00	0.00
GDPVol	-4.54	0.04
GDP_SalesVol	-8.93	0.00

Notes: The table shows the unit root test on GDP, GDP_Sales, GDPVol, and GDP_SalesVol. The null hypothesis is that there is a unit root in time series data. GDP is the growth of real gross domestic production that is constructed using linear method; GDP_Sales is the growth of real gross domestic production that is linearly interpolated using advanced retail sales; GDPVol, GDP_SalesVol are the volatility of GDP, GDP_Sales respectively. The sample period is from March 2009 to December 2016.

TABLE 3.15 SUMMARY STATISTICS OF DEPENDENT AND INDEPENDENT VARIABLES

	Mean	Med	Max	Min	Std. Dev.	N	Skew	Kurt	JB Prob
GDP	0.17	0.18	0.43	-0.13	0.13	94	-0.09	2.30	0.35
GDP_Sales	0.32	0.34	1.07	-0.72	0.24	94	-0.90	7.22	0.00
GDPVol	0.02	0.01	0.05	0.01	0.01	94	1.13	2.89	0.00
GDP_SalesVol	0.06	0.04	0.38	0.04	0.04	94	5.29	35.58	0.00

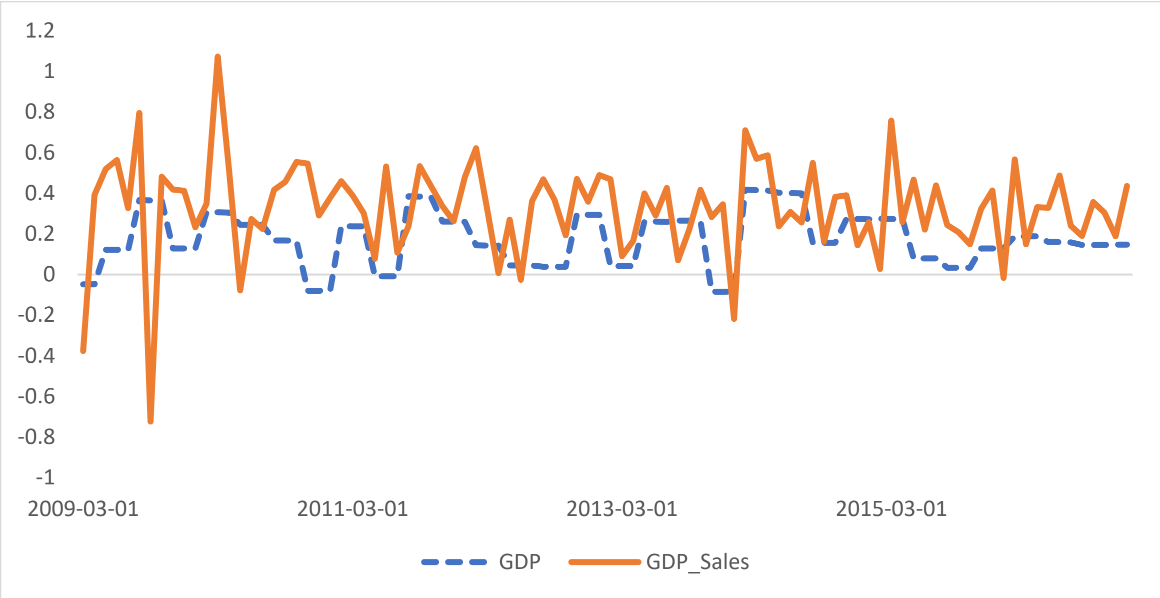
Notes: GDP is the growth of Real Gross Domestic Product that is constructed using linear method; GDP_Sales is the growth rate of Real Gross Domestic Product that is interpolated using Advanced Retail Sales growth in a Chow-Lin procedure for non-stationary variables; GDPVol, GDP_SalesVol are the volatility of GDP, GDP_Sales respectively. GDP and GDP_Sales, are measured as a percentage; GDPVol and GDP_SalesVol are measured in percentage square. The Mean, Med, Max, Min, Std. Dev, N, skew, and Kurt represent the mean, median, maximum, minimum, standard deviation, number of observations of variables, skewness, and kurtosis of the series: JB Prob is the p-value for the Jarque–Bera normality test.

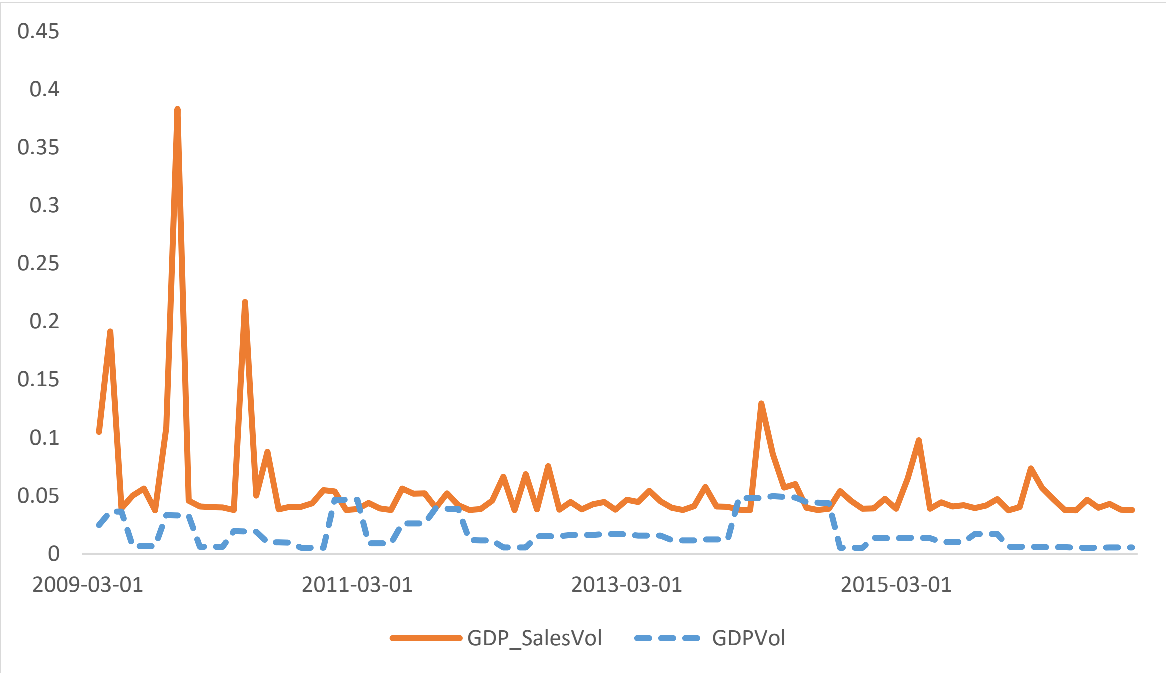
TABLE 3.16 PAIR-WISE CORRELATION OF DEPENDENT AND INDEPENDENT VARIABLES

	CDX IG	CDX HY	GDP	GDP_Sales	NonF	CPI	RF	GDPVol	GDP_SalesVol	NonFVol	CPIVol	RFVol
CDX IG	1.00											
CDX HY	0.94	1.00										
GDP	-0.20	-0.18	1.00									
GDP_Sales	-0.21	-0.19	0.24	1.00								
NonF	-0.65	-0.78	0.30	0.28	1.00							
CPI	0.10	0.10	-0.13	0.14	-0.14	1.00						
RF	0.10	0.13	-0.20	-0.02	-0.20	0.10	1.00					
GDPVol	0.05	0.03	0.03	-0.03	-0.05	0.08	-0.33	1.00				
GDP_SalesVol	0.21	0.27	0.09	-0.36	-0.33	-0.01	-0.01	0.22	1.00			
NonFVol	0.28	0.27	-0.06	-0.12	-0.33	-0.03	0.08	-0.05	0.12	1.00		
CPIVol	0.23	0.35	-0.11	-0.12	-0.45	-0.09	-0.03	-0.09	0.19	0.03	1.00	
RFVol	0.15	0.18	-0.24	-0.14	-0.22	0.05	0.55	-0.21	0.02	0.04	-0.03	1.00

Notes: CDX IG and CDX HY are spreads for the investment-grade CDX and high-yield CDX respectively. GDP is the growth of real gross domestic production that is constructed using linear method; GDP_Sales is the growth of Real GDP that is derived from a Chow-Lin interpolation using Advanced Retail Sales; NonF is the growth of total nonfarm payroll and CPI is the growth of consumer price index; RF is the 3-month Treasury Bill rate; GDPVol, GDP_SalesVol, NonFVol, CPIVol and RFVol are the volatility of GDP, GDP_Sales, NonF, CPI, RF respectively. GDP, GDP_Sales, NonF and CPI are values at time t-1 while RF, GDPVol, GDP_SalesVol, NonFVol, CPIVol and RFVol are values at time t. The sample period is from March 2009 to December 2016.

Figure 4 monthly GDP growth and its volatility





Note: The graph shows monthly GDP growth and its volatility. GDP is constructed using a linear interpolation method whereas GDP_Sales growth is derived from a Chow-Lin procedure using Advanced Retail Sales; GDPVol and GDP_SalesVol are the corresponding volatility measures.

To further test the robustness of the results, Regression (3.1) and Regression (3.2) were re-estimated with the growth rate of industrial production replaced by the alternative economic growth measures, the results being reported in Table 3.17. The results re-estimating Regression (3.1) indicate that GDP and GDP_Sales have an insignificant effect on the investment-grade CDX spread and high-yield CDX spread, consistent with the effect of the industrial production growth reported earlier. In the re-estimated relationship, macroeconomic condition variables explain around 38% of total variation in the investment-grade CDX spread and 58% of the total variation in the high-yield CDX spread. The adjusted R squares from these regressions are similar to the adjusted R squares from similar regressions (Regression 3.1) in the main analysis Section 3.5.1, supporting the earlier findings based upon industrial production growth as a measure of the economic output growth.

Table 3.18 reports the results of Regression (3.2) re-estimation. In general, the re-estimation results are similar to the findings reported in Table 3.11. Economic growth, measured by either GDP or GDP_Sales, has no significant effects on the CDX spread. The volatility of economic growth measured using either GDPVol or GDP_SalesVol, has a significantly positive effect on the CDX spread.

The insignificant effect of economic growth and the significant positive effect for output growth, suggest that the three alternative measures of aggregate output growth in the economy as well as their respective volatility measures have similar explanatory power.

Finally, the Chow test is conducted to test for parameter stability. Table 3.19 reports results of the Chow test. The results indicate that the null hypothesis of no structural break is rejected, with a p-value smaller than 0.01. These results suggest that outliers in alternative measures of aggregate output growth may affect parameter constancy.

TABLE 3.17 MACROECONOMIC CONDITION VARIABLES AND CDX SPREADS

	Panel A: CDX IG		Panel B: CDX HY	
	GDP	GDP_Sales	GDP	GDP_Sales
Constant	103.61***	103.85***	588.94***	608.35***
	(15.88)	(15.54)	(15.14)	(15.40)
Economic Output Growth	-5.94	-11.76	30.53	-48.84
	(-0.26)	(-1.53)	(0.22)	(-0.95)
NonF	-89.11***	-87.08***	-898.13***	-879.99***
	(-4.19)	(-4.34)	(-5.61)	(-5.68)
CPI	5.21	7.49	32.90	41.14
	(0.57)	(0.88)	(0.71)	(0.91)
RF	-4.38	-3.94	-18.49	-30.82
	(-0.15)	(-0.13)	(-0.11)	(-0.16)
Adjusted R square	0.3744	0.3866	0.5827	0.5859
No. observations	94	94	94	94

Notes: This table reports results of Regression (3.1). The dependent variable and explanatory variables are on a monthly basis. Panel A reports results of Regression (3.1) using CDX IG as the dependent variable. Panel B reports results of Regression (3.1) using CDX HY as the dependent variable. CDX IG and CDX HY are spreads for the investment-grade CDX and high-yield CDX respectively; GDP is the monthly growth of real gross domestic production that is constructed using linear method; GDP_Sales is the growth of gross domestic production that is linearly interpolated using advanced retail sales; NonF is the growth of total nonfarm payroll, CPI is the growth of consumer price index; and RF is the 3-month Treasury Bill rate. CDX IG and CDX HY spreads are measured in basis points; GDP, GDP_Sales, NonF, CPI and RF are measured in percentage. GDP, GDP_Sales, NonF and CPI are values at month t-1. The CDX IG, CDX HY, the RF is the value at month t. The estimation is carried out by using Newey-West standard errors to control for autocorrelation and heteroskedasticity. The sample period is from March 2009 to December 2016. T-statistics are given in parenthesis. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

TABLE 3.18 MACROECONOMIC CONDITION AND VOLATILITY VARIABLES AND CDX SPREADS

	Panel A: CDX IG		Panel B:CDX HY	
	GDP	GDP_Sales	GDP	GDP_Sales
Constant	101.95***	103.65***	570.24***	564.63***
	(8.36)	(8.25)	(5.94)	(7.26)
Economic Output Growth	-9.51	-10.71	-3.39	-26.33
	(-0.41)	(-0.69)	(-0.03)	(-0.65)
NonF	-89.03***	-87.92***	-873.60***	-857.53***
	(-4.45)	(-4.15)	(-5.74)	(-5.28)
CPI	4.82	7.30	39.78	42.59
	(0.54)	(0.92)	(0.88)	(1.02)
RF	-23.29	-19.66	-203.07	-177.80
	(-0.78)	(-0.64)	(-1.16)	(-0.99)
Economic growth volatility	54.87***	52.04***	509.16***	508.68***
	(3.09)	(3.25)	(4.65)	(3.27)
NonFVol	142.35	137.22	631.69	598.18
	(1.48)	(1.48)	(0.95)	(0.92)
CPIVol	-58.62	-61.41	-65.78	65.28
	(-0.42)	(-0.43)	(-0.07)	(0.07)
RFVol	134.06	220.46	1623.71*	2414.68*
	(0.86)	(1.08)	(1.79)	(1.80)
Adjusted R square	0.4237	0.4301	0.6173	0.6184
Number of observations	94	94	94	94

Notes: This table reports results of Regression (3.2). The dependent variable and explanatory variables are on a monthly basis. Panel A reports results of Regression (3.2) using CDX IG as the dependent variable. Panel B reports results of Regression (3.2) using CDX HY as the dependent variable. CDX IG and CDX HY are spreads for the investment-grade CDX and high-yield CDX respectively; GDP is the monthly growth of real gross domestic production that is constructed using linear method; GDP_Sales is the growth of real gross domestic production that is linearly interpolated using personal consumption expenditure; NonF is the growth of total nonfarm payroll, CPI is the growth of consumer price index; and RF is the 3-month Treasury Bill rate; GDPVol, GDP_SalesVol, NonFVol, CPIVol, and RFVol are volatility measures for GDP, GDP_Sales, NonF, CPI, and RF respectively. CDX IG and CDX HY are measured in basis points; GDP, GDP_Sales, NonF, CPI, RF and RFVol are measured in percentage; GDPVol, GDP_SalesVol, NonFVol, and CPIVol are measured in percentage square. GDP, GDP_Sales, NonF and CPI are values at month t-1. The CDX IG, CDX HY, RF, GDPVol, GDP_SalesVol, NonFVol, CPIVol, and RFVol are values at month t. The estimation is carried out by using Newey-West standard errors to control for autocorrelation and heteroskedasticity. T-statistics are given in parenthesis. The sample period is from March 2009 to December 2016. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

TABLE 3.19 CHOW TEST

	Panel A: CDX IG				Panel B: CDX HY			
	GDP		GDP_Sales		GDP		GDP_Sales	
	F Statistics	P value	F Statistics	P value	F Statistics	P value	F Statistics	P value
Regression (3.1)	11.52	0.00	12.85	0.00	8.69	0.00	8.90	0.00
Regression (3.2)	7.09	0.00	7.58	0.00	6.49	0.00	6.06	0.00

Notes: This table reports the results for Chow test. Panel A reports results using CDX IG as the dependent variable. Panel B reports results using CDX HY as the dependent variable. The economic output growth measure in the first and third columns is GDP and the economic output growth measure in the second and fourth columns is GDP_Sales. CDX IG and CDX HY are spreads for the investment-grade CDX and high-yield CDX respectively; GDP is the monthly growth of real gross domestic production that is constructed using linear method; GDP_Sales is the growth of real gross domestic production that is linearly interpolated using advanced retail sales. The sample period is from March 2009 to December 2016.

3.6 CONCLUSION

This chapter explores the relationship between the CDX spread and macroeconomic determinants by incorporating both macroeconomic level and volatility variables that are highlighted by theoretical and empirical studies.

The research period is from March 2009 to December 2016. This chapter used spreads of two CDS indices in North America market, investment-grade CDX and high-yield CDX as the dependent variable. The growth of industrial production index and the growth of total nonfarm payroll are employed as economic indicators to capture the output and employment conditions of the aggregate economy. The consumer price inflation is used to capture the inflation condition. 3-month Treasury Bill rate is used to capture the risk-free rate. Measures of macroeconomic volatility employed in the analysis are constructed using the ARMA-GARCH model for the growth of industrial production index, the growth of total nonfarm payroll and consumer price inflation. The 3-month Treasury Bill rate volatility is measured using the standard deviation of daily observations within a given month for the 3-month Treasury Bill rate. The analysis uses multivariate time-series regressions using Newey-West standard errors to control for autocorrelation and heteroskedasticity.

This chapter makes several contributions to the literature. First, it investigates how macroeconomic level variables, representing multiple dimensions of the macroeconomy, influence the CDX spread. The growth of industrial production, the growth of total nonfarm payroll, the consumer price inflation and 3-month Treasury Bill rate are used to capture the economic output, employment, inflation and the risk-free rate. The respective analysis in this chapter identifies the growth of total nonfarm payroll, an indicator of employment conditions in the aggregate economy, as a new important determinant of the CDX spread, not previously examined in the CDS pricing literature. The total nonfarm payroll growth is found to have a significantly negative effect on the CDX spread of both investment-grade and high-yield credit quality. This may be because employment conditions serve as an early indicator of firms' future performance and, as such, of their future risk of default, suggesting that employment related variables may be of relevance to other theoretical and empirical CDS pricing studies.

Furthermore, the regression results show that the explanatory power of macroeconomic level variables is jointly larger compared with findings in Ericsson, Jacobs, and Oviedo (2009) for single-name CDS. The higher explanatory power found in this chapter is likely to be due to a broader selection of macroeconomic level variables that include an important employment indicator, omitted in these studies. However, it is important to note that the explanatory power of the CDX-based model in this study may have been also boosted because firm-specific risk, reflected in single-name CDS spreads in Ericsson, Jacobs, and Oviedo (2009), has been diversified away in the present study, making the CDX spread influenced to a greater extent by economy-wide factors.

The second novel contribution is the related finding that macroeconomic level variables can explain a greater share of variation in the high-yield CDX spread relative to investment-grade CDX spread. A greater explanatory power of macroeconomic level variables for the high-yield CDX spread might because high-yield companies rely more on external funding which, in turn, is known to be highly countercyclical, making the high-yield CDX spreads more exposed to business cycle variations.

Third, the chapter examines the effect of the macroeconomic volatility variables capturing various sources of macroeconomic uncertainty that have been largely overlooked in the previous CDS literature. The analysis provides evidence that the volatility of industrial production growth has a significantly positive effect on the CDX spread. Also, the volatility of the 3-month Treasury Bill rate has a significantly positive effect on the high-yield CDX spread but it is insignificant for the investment-grade CDX spread. The adjusted regression

R square increases notably after adding macroeconomic volatility variables, suggesting their importance in determining the CDX spread. Macroeconomic level variables and macroeconomic volatility variables can jointly explain roughly 40% of the total variation in the CDX investment-grade spread and 65% of the total variation in the CDX high-yield spread.

The fourth contribution arises from the comparison of the relative importance of macroeconomic level and macroeconomic volatility groups of variables in explaining the investment-grade and high-yield CDX spreads. The macroeconomic level variables are more important, jointly accounting for approximately 75% of explained variation in the investment-grade CDX spread and the high-yield CDX spread. The macroeconomic volatility variables account for the remaining 25% of explained variation in both the CDX investment-grade spread and the CDX high-yield spread. A potential explanation for a lower relative impact of the volatility variables stems from Ramey and Ramey (1995), who show that macroeconomic volatility influences macroeconomic level variables, so that the marginal contribution of macroeconomic level variables may reflect some contribution from macroeconomic volatility variables.

The finding emphasising the importance of both macroeconomic level and volatility variables for determining the CDS spreads is of importance to CDS pricing studies like Ericsson, Jacobs and Oviedo (2009) that omit macroeconomic volatility variables from consideration altogether or Lesplingart, Majois, and Petitjean (2012) that does not consider neither macroeconomic level variables nor macroeconomic volatility variables when pricing the CDS spread.

The final, fifth contribution, arises from the sensitivity analysis that explores whether the investment-grade CDX spread and the high-yield CDX spread differ in their sensitivities to macroeconomic variables. The analysis shows that the high-yield CDX is substantially more sensitive than the high-yield CDX to both macroeconomic level and volatility variables. In particular, its sensitivity to the total nonfarm payroll growth, the volatility of industrial production growth, and the volatility of 3-month Treasury Bill rate is 1.5 to 2-times greater than the investment-grade CDX spread sensitivity to these variables. This result is consistent with other analysis parts in this chapter. Such sensitivity analysis that accounts for the substantial difference in the absolute values of the investment-grade and high-yield CDX, has not been previously carried out.

Building on the empirical findings of this chapter, the next empirical chapter will extend the analysis by turning from the CDX spread to the single-name CDS spread. Consequently, the focus of the next chapter is to explore how macroeconomic factors influence the single-name CDS spread. In contrast to the CDX index spreads, representing diversified portfolios, single-name CDS spreads are affected by firm-specific characteristics in addition to macroeconomic variables. This is an important factor that differentiates the variable of interest and the analysis in the next chapter.

4. MACROECONOMIC AND FIRM-SPECIFIC DETERMINANTS OF SINGLE-NAME CDS SPREADS

4.1 INTRODUCTION

Results in Chapter 3 show that macroeconomic level and volatility variables can jointly explain 42% to 65% of the total variation in the CDX index spread. The CDX is the average weighted basket of single-name CDS. According to the modern portfolio theory introduced by Markowitz (1952), the firm-specific risk associated with each CDS spread is likely to be diversified away, leaving systematic risk, such as macroeconomic risk priced in the CDX index spread. In contrast, the single-name CDS is written on an individual firm and its spread should reflect both firm-specific characteristics and macroeconomy. This difference between the CDS index and single-name CDS provides motivations for this chapter to extend the analysis in the previous chapter to study to how macroeconomic variables affect the spread on a different type of a CDS instrument, namely, the single-name CDS.

Although results of the Chapter 3 highlight the importance of the macroeconomy in determining the CDS index spread, some variables, such as the growth of industrial production, that have been indicated as important in some theoretical studies, such as Tang and Yan (2006) and empirical studies, such as Tang and Yan (2010) are found insignificant. One potential reason is that the CDS index represents a basket of single name CDS contracts that are written on companies that are from both cyclical industry sectors (e.g. consumer discretionary, financials, and materials sectors) and defensive industry sectors (e.g. consumer staples, energy, healthcare, and utilities sectors). The performance and default risk of companies in the CDX index might be affected differentially by macroeconomic indicators, therefore making the effects of macroeconomic indicators on the aggregated CDS index, less pronounced.

As a result, extended analysis of how macroeconomic variables affect single-name CDS spreads, with firm heterogeneity being taken into account, is necessary. This chapter will use single-name CDS spreads to explore how the macroeconomy affects the spread of a CDS contract written on a given firm. If macroeconomic variables are found to explain CDS spreads significantly, this could help, address at least in part, the credit spread puzzle. This is the first aim of this chapter.

The second aim is motivated by a number of recent theoretical models that attempt to address one of key assumptions made by traditional structural models that firms default when the asset value falls below the debt value. In particular, Anderson and Sundaresan (1996) and Tang and Yan (2006) among others introduce alternative structural models that reflect the importance of cash flow and its volatility in determining firms' default by re-defining financial distress as the situation where cash flow cannot cover current interest-payment obligations. As suggested by these models, the cash flow, overlooked in traditional structural models, may play an important role in determining debt pricing and credit spreads. Although several empirical papers, such as Baum and Wan (2010) have attempted to incorporate the cash-flow variables into their analysis, they use indirect measures such as return on equity or return on asset to capture the firms' profitability, with these measures not specifically capturing the cash flow. There is limited empirical evidence on how cash flow and its volatility affect CDS spreads, and the only exception is Tang and Yan (2010). Consequently, the second aim of this chapter is to fill the gap in literature by empirically investigating the role of cash flow and its volatility in pricing the single-name CDS spread.

Unlike the Chapter 3 where the analysis is applied to a basket of CDS contracts, this chapter uses single-name CDS contracts written on individual firms. The sample includes U.S. dollar denominated CDS contracts that are obtained from Bloomberg for the period from February 2009 to December 2016, representing 197 single-name CDS contracts, with 18105 monthly CDS spreads quotes. The analysis further splits the whole sample into investment grade and high yield sub-samples. The investment grade sub-sample contains 13116 quotes of 154 single-name CDS contracts that are issued on companies that have investment grade ratings and high yield sub-sample contains 4989 quotes of 75 single-name CDS contracts that are issued on company debt that have high yield ratings. [9]

The dataset represents a strongly balanced monthly panel. Panel data regressions with fixed effects are used to explore the joint effect of firm-specific and macroeconomic variables on the CDS spread. The dependent variable is the CDS spread. Firm-specific independent variables used are the leverage, the operating cash flow over total assets, and operating cash flow volatility. Following from the previous chapter, industrial production growth, total nonfarm payroll growth, consumer price inflation and the 3-month Treasury Bill rate are used as independent variables to capture macroeconomic levels. Similar volatility measures as those in Chapter 3 are used as independent variables to capture the macroeconomic volatility.

The chapter therefore makes contributions to the literature by exploring the following questions:

(1) How do macroeconomic variables, to be more specific, macroeconomic level variables and macroeconomic volatility measures, affect single-name CDS spread?
(2) Do investment-grade and high yield CDS spreads respond differently to firm-specific or macroeconomic variables?
(3) Does cash flow and cash flow volatility variables help explain CDS spreads, beyond the commonly used firm-specific variables?

The chapter reports the following findings:

[9] This thesis refers to Moody's credit rating systems. A bond is considered investment grade if its credit rating is Aaa, Aa1, Aa2, Aa3, A1, A2, A3, Baa1, Baa2, or Baa3. A bond is considered high yield if its credit rating is Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca, or C.

Macroeconomic level variables are significant determinants of the CDS spread. More specifically, the industrial production growth has a significantly negative effect on the high-yield CDS spread and total nonfarm payroll growth has a significantly negative effect on the whole-sample CDS spread and high-yield CDS spread.

Macroeconomic volatility variables are also significant determinants of the CDS spread. The volatility of industrial production growth and the volatility of 3-month Treasury Bill rate are found to have a significantly positive effect on the whole-sample, investment-grade and high-yield CDS spread. The volatility of the total nonfarm payroll has a significant positive effect on the investment-grade CDS spread.

The relative importance analysis shows that firm-specific variables contribute to more than 90% of the explained variation in the CDS spread, which is notably greater than marginal contributions made by macroeconomic variables. The relative importance analysis further shows that among macroeconomic variables, variables capturing macroeconomic uncertainty jointly explain at least as much or more variation in the single-name CDS spread relative to macroeconomic level variables.

The sensitivity analysis results also show that high-yield single name CDS spreads tend to be more sensitive to both firm-specific and macroeconomic variables than investment-grade CDS spread. In particular, high-yield CDS spreads are found to exhibit greater sensitivity to firm leverage, industrial production growth volatility and 3-month Treasury Bill rate volatility. The only two exceptions are operating cash flow volatility and nonfarm payroll volatility to which the investment-grade CDS are more sensitive.

The effect of cash flow volatility variables depends on the CDS credit quality. Cash flow volatility has a significantly positive effect on the investment-grade CDS spread but has no significant effect on the high-yield CDS spread.

The remainder of this chapter is organized as follows. Section 4.2 details the firm-specific and macroeconomic variables used in the study, explaining how variables are constructed. The expected relationships between dependent and independent variables are also outlined in Section 4.2. Section 4.3 describes the dataset and methodology applied in the analysis, while analytical results and discussion is provided in Section 4.4. Section 4.5 gives a brief comparison of findings for the CDX spread and the CDS spread. Finally, Section 4.6 summarizes the whole chapter and presents the concluding remarks.

4.2 VARIABLE SELECTION

This section lists the dependent variable, macroeconomic independent variables, and firm-specific independent variables. At the end of this section, an overview of the independent variables with descriptions and predicted signs is provided in Table 4.1.

4.2.1 DEPENDENT VARIABLE

The single-name corporate CDS spread is used as the dependent variable in this chapter and is referred to as CDS spread, hereafter. The CDS spread is available on a daily basis and the monthly values are represented as the average of daily close-of-market spread value over the corresponding month, consistent with extant literature focusing on the macroeconomic effects such as Tang and Yan (2010), Coro, Dufour, and Varotto (2013), and Kim, Park, and Park (2015).

4.2.2 MACROECONOMIC VARIABLES

This chapter employs macroeconomic variables that are motivated and used in the Chapter 3. The industrial production index growth (IP), the total nonfarm payroll growth (NonF), the consumer price index growth (CPI), and 3-month Treasury Bill rate (RF) are used to capture the condition with regards to aggregate economic output, employment, inflation and risk-free interest rate respectively. The conditional variance of IP (IPVol), NonF (NonFVol), CPI (CPIVol), along with monthly standard deviation of RF (RFVol) are used to capture the volatility of economic output, employment, inflation and the risk-free rate respectively.

4.2.3 FIRM-SPECIFIC VARIABLES

Operating Cash Flow over Total Asset (CF)

This chapter follows studies, such as Fitzpatrick and Ogden (2011), to capture the net cash flow in the firm using the ratio of operating cash flow over total asset.

The operating cash flow over total assets is defined as:

$$CF = \frac{Operating\_Cashflow}{Total\_Asset}$$

A negative relationship between the CDS spread and operating cash over total asset is expected to hold.

Cash flow volatility (CFVol)

Apart from measuring the firm's ability to generate cash flow, this chapter also employs a measure of uncertainty about the firm's cash flow by using the cash flow volatility. This chapter adopts the following method of Minton and Schrand (1999), Molina (2005), and Tang and Yan (2010), expressing cash flow volatility as:

$$CVCF = 100 \times \frac{standard\_deviation\_of\_OCF}{|mean\_of\_OCF|}$$

where

CVCF is the cash flow volatility;

OCF is the operating cash flow;

standard deviation of OCF is the standard deviation of the operating cash flow over the past 3 years.

A positive relationship is expected to hold between the cash flow volatility and the CDS spread.

The cash flow volatility measure proposed here differed from the volatility measures employed elsewhere in the thesis. As the operating cash flow data comes from the firm's income statement and is available monthly therefore the within-month standard deviation that is applied to construct the 3-month Treasury Bill rate volatility cannot be used here.

In addition, the GARCH model that is applied for estimating volatility of real activity and inflation variables, is not appropriate to capture the volatility in the operating cash flow either because of its computational complexity. Applying GARCH models to firm-level data means that 197 GARCH models ought to be built for firm-level operating cash flow series. Furthermore, due to ae large number of firms, there is a possibility where operating cash flow data from some firms does not fit GARCH model.

Finally, there is not much theoretical or empirical guidance on how to model operating cash flow volatility. The work of Minton and Schrand (1999), Molina (2005), and Tang and Yan (2010), uses the rolling variance of operating cash flow, which inspires this thesis to follow their method. Although the rolling-window volatility is a better measure to proxy the operating cash flow volatility in this chapter, yet it is subject to an econometric problem. Harri and Brorsen (1998) and Britten-Jones and Neuberge (2010) suggest that using rolling-window with overlapping of observations creates autocorrelations[10] which can lead to misleading estimates of the confidence intervals. Limited volatility proxies for operating cash flow and the weakness of the rolling-window volatility measure throw lights on the future research topic on exploring the optimal volatility proxies for cash flow.

Leverage (LEV)

In this chapter, the firm leverage is constructed using a common method which has been also employed in Collin-Dufresne, Goldstein, and Martin (2001), and Tang and Yan (2010), amongst others. For each firm on which the single name CDS contract is written, its leverage is calculated as:

[10] This thesis attempts to account for this autocorrelation using robust standard errors.

$$\frac{Book\_Value\_of\_Debt}{Book\_Value\_of\_Debt + Market\_Value\_of\_Equity}$$

where the book value of debt is the sum of book value of short-term and long-term debt. The market value of the equity is calculated as the monthly stock price multiplies the monthly number of shares outstanding.

The leverage is expected to have a positive relationship with the CDS spread.

Table 4.1 summarizes all independent variables, including macroeconomic variables and firm specific variables, and lists expected relationships between the dependent variable and independent variables.

TABLE 4.1 SUMMARY OF THE ASSUMED RELATIONSHIPS BETWEEN THE DEPENDENT AND INDEPENDENT VARIABLES

Independent Variables	Predicted Sign
Macroeconomic Variables	
IP	-
NonF	-
CPI	+/-
RF	-
IPVol	+
NonFVol	+
CPIVol	+
RFVol	+
Firm-specific Variables	
LEV	+
CF	-
CFVol	+

Notes: The table shows a summary of the expected signs for the relationship between CDS spreads and macroeconomic level, macroeconomic volatility, and firm-specific variables. IP is the growth of industrial production; NonF is the growth of total nonfarm payroll; CPI is the growth of consumer price index; RF is the 3-month Treasury Bill rate; IPVol, NonFVol, CPIVol and RFVol are the volatility of IP, NonF, CPI, RF respectively. LEV is the leverage; CF is the ratio of operating cash flow and total asset; CFVol is the operating cash flow volatility

4.3 DATA DESCRIPTION AND METHODOLOGY

4.3.1 DATA DESCRIPTION

The dataset covers the period from March 2009 to December 2016 and is compiled from two data sources: the Federal Reserve Economic Database (FRED) and Bloomberg. FRED provides macroeconomic indicators that will be used in this chapter and these indicators include the industrial production index, the total nonfarm payroll, the consumer price inflation, the 3-month Treasury Bill rate. All macroeconomic indicators provided by FRED are available on a monthly basis.

Bloomberg provides the daily last quote on the spread of the single-name U.S. dollar denominated credit default swap time stamped with New York time. The sample reference entities on which sample credit default swaps are written are public-listed U.S.-based companies and have either investment-grade or high-yield[11] credit ratings. Furthermore, monthly firm-specific information, including the book value of debt, the book value of asset, the market value of equity, and the operating cash flow, is also obtained from Bloomberg to construct firm-specific variables that are mentioned in the Data Variables section.

The 5-year CDS contracts has been considered as the most liquid CDS contracts by empirical studies (e.g. Meng and Gwilym, 2008) and their spreads contain less liquidity premium compared with CDS spreads of other maturities, therefore have been used to test the explanatory power of firm-specific variables and macroeconomic variables in empirical literature (e.g. Tang and Yan, 2008; Baum and Wan, 2010; Tang and Yan, 2010). As a result, this chapter employs the 5-year CDS spread as the dependent variable.

Single-name credit default swap contracts that have either fewer than 25-month observation or more than 25-month missing observations are excluded from the dataset, which has,

[11] This thesis refers to Moody's credit rating systems. A bond is considered investment-grade if its credit rating is Aaa, Aa1, Aa2, Aa3, A1, A2, A3, Baa1, Baa2, or Baa3. A bond is considered high yield if its credit rating is Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca, or C.

among the remaining data, left very little illiquidity of concern. Table B.1 of Appendix B shows a table that summarizes the number of firms and the number of missing daily CDS spread quotes during the research period. 155 of 197 remaining companies have no missing daily CDS spread quotes while 42 companies have some missing CDS spread quotes.

In addition, reference entities that belong to the financial sector are excluded. European Bank Federation (2010) defines financial firms, especially banks, as financial intermediaries between borrowers and lenders. This implies that banks tend to have high optimal leverage ratios. The average leverage (measured as the ratio of debt to asset) of U.S. banks, as estimated by Gornall and Strebulaev (2015), has ranged from 87% to 95% over the past 80 years while the average leverage of public U.S. non-financials has ranged from 20% to 30%. Adrian and Shin (2010) and DeAngelo and Stulz (2013) among others further suggest that issuing debt is one key element of banks' business because banks can profit by producing liquidity to financially constrained firms via debt service. Furthermore, Berg and Gider (2017) also indicate that, compared with non-financial companies, the diversification in banks' asset portfolio leads to lower bank's asset volatility which in turn enables banks to pursue higher leverage with safety. Above literature indicates that financial institutions tend to have higher leverage than non-financial institutions and the meaning and values of the leverage in financial sector substantially differ from those in other sectors. As a result, the reference entities that are in financial sector are removed from the dataset.

Furthermore, utilities are usually government monopolies or private-owned companies that are highly regulated by public utilities commissions. Due to differences in the corporate governance of the utilities sector and other industry sectors, the reference entities that are in the utility sector are also excluded.

Applying above criteria produces a whole sample that covers both investment-grade and speculative grade entities. The whole sample represents a strongly balanced panel data set and investment-grade and high-yield sub-samples also represent strongly balanced panel data sets. Table 4.2 provides an overview of the sample, showing that these criteria leaves single-name CDS contracts that are written on 197 companies and 18105 monthly CDS spreads quotes in total. Among the whole sample, there are 154 CDS contracts with 13116 investment-grade CDS spread quotes and 75 CDS contracts with 4989 high-yield CDS spread quotes. Some CDS contracts may enter both sub-samples because their credit ratings change from investment-grade (high-yield) to high-yield (investment-grade) during the sample period. The changes on the rating of CDS contracts, causes the number of CDS contracts in the whole sample to be smaller than the sum of CDS contracts in two sub-samples.

Table 4.3 details the descriptive statistics for the whole sample and two sub-samples. Panel A shows the descriptive statistics for the whole sample. The scale of CDS spreads ranges from 1.01 basis points to 8921.87 basis points, with a standard deviation of 337.48. Panel B and C show the descriptive statistics for investment-grade sub-sample and high-yield sub-sample respectively. Notable differences in values can be identified across the investment-grade and the high-yield sub-samples. In the first place, high-yield CDS have a mean of 426.65 basis points which is more than 4 times larger than that of investment-grade CDS (83.14 basis points). Furthermore, the standard deviation of high-yield CDS is 558.78 basis points while the standard deviation of investment-grade CDS is roughly 8-fold lower at 77.09 basis points. The descriptive statistics reported in Table 4.3 suggest that the high-yield CDS spread is higher and more volatile than the investment-grade CDS spread.

In addition, differences exist in firm-specific variables in Panel B and C. LEV has a lower mean value (21.61%) in the investment-grade sub-sample than that (46.06%) in the high-yield sub-sample. LEV also has the standard deviation of 11.79% for the investment-grade sub-sample while its standard deviation for the high-yield sub-sample is almost twice as high at 22.09%. Similarly, CFVol has a lower mean value of 0.80% for investment sub-sample than the mean value of 4.55% for high-yield sub-sample. Furthermore, CF for investment-grade sub-sample has a mean value of 2.95% and the standard deviation of 2.47%. On the other hand, CF for the high-yield sub-sample has a smaller mean value (1.66%) but a higher standard deviation (3.21%) than that in investment-grade sub-sample. The higher standard deviation of CF is consistent with the observed higher mean value of CFVol in the high-yield sub-sample, implying that the operating cash flow in the high-yield companies is more volatile than that in the investment-grade sub-sample. Table 4.3 shows that high-yield companies have higher leverage, and lower and more volatile cash flow which is consistent with implications from the structural models.

Furthermore, a time-series of cross-section mean of firm-specific variables are calculated and platted in Figure 5 to show the time variability of firm-specific variables from March 2009 to December 2016. Panel A reports the firm-specific variables that are from the whole sample. Panel B compares the difference between firm-specific variables with different credit qualities. Panel B shows that firm variables with different credit qualities exhibit similar trends as time passes but differ significantly in absolute scales. Investment-grade CDS spread, leverage, and operating cashflow volatility are comparatively lower than that of high-yield sub-sample. On the other hand, investment-grade operating cashflow over total asset is comparatively higher but less volatile than that of high-yield sub-sample. Patterns shown by Figure 5 further support descriptive statistics reported in Table 4.3

Pair-wise correlations between the CDS spread and macroeconomic and firm-specific variables for the whole sample, the investment-grade sub-sample, and the high-yield sub-sample are reported in Panel A, B, and C of Table 4.4. In the Table 4.4, the cross-sectional average firm variables are calculated and correlations between them and macroeconomic variables are reported, respectively. The correlations in each panel are consistent with the hypotheses from the previous section. Among all firm-specific variables, LEV has the strongest linear correlation with the CDS spread while CFVol has the weakest linear correlation with the CDS spread in the three panels. As for macroeconomic condition variables, NonF has the highest correlation with the CDS spread. Furthermore, overly high correlations between explanatory variables are not observed in either whole sample or sub-samples, indicating that multicollinearity issues are unlikely in this analysis.

Finally, a unit root test is conducted on the dependent and independent variables to test the stationarity and to eliminate the issue of spurious regression. This chapter adopts the Fisher-type unit root test that is introduced by Maddala and Wu (1999) and extended by Choi (2001). Compared with previous panel data unit root tests, such as Im–Pesaran–Shin test and Levin–Lin–Chu test, the Fisher-type unit root test are more flexible because it assumes the number of companies to be finite and that time series spans for the companies are different. These assumptions are consistent with the characteristics of the data, as reported in Table 4.2 and Table 4.3.

The null hypothesis for the Fisher-type unit root test is that there is a unit root in each companies' data. Then the test assumes $G_{i,t}$ as a one-sided Dickey and Fuller's statistic for the ith company. The asymptotic p-value for the $G_{i,t}$ test is defined as

$$p_i = F\left(G_{i,t}\right) \qquad \text{Equation (4.1)}$$

where F(•) denotes the distribution function that corresponds to the random variable $G_{i,t}$. Two test statistics can be proposed use the p-value and are defined as follows:

$$P = -2\sum_{i=1}^{N} \ln\left(p_i\right) \qquad \text{Equation (4.2)}$$

$$Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \Phi^{-1}\left(p_i\right) \qquad \text{Equation (4.3)}$$

where $\Phi(\bullet)$ is the standard normal cumulative distribution function.

Equation (4.2) is called the inverse chi-square test statistics and Equation (4.3) is called the inverse normal test statistics. As in Coro, Dufour, Varotto (2013), two test statistics, the inverse normal and the inverse logit, are considered and reported in Chapter 4. The null hypothesis of the test is that the panel data has a unit root. Table 4.5 reports Fisher-type unit root test results. Panel A, B and C are for Fisher-type unit root results for the whole sample, investment-grade sub-sample and high-yield sub-sample respectively. As the table shows, p-values for the dependent variable and independent variables are all below 0.1 using both test statistics. As a result, the null hypothesis of there is a unit root in each panel data series can be rejected. Results of the Fisher-type unit root test show that the dependent variable and independent variables are stationary therefore no transformation needs to be done on the data.

TABLE 4.2 NUMBER OF FIRMS AND CDS SPREAD QUOTES IN THE DATA SAMPLE.

Credit Quality	No. of firms	No. CDS spread quotes
Whole Sample	197	18105
Investment-grade	154	13116
High-yield	75	4989

Notes: This table shows summary statistics for the single-name CDS spread. To be consistent with Chapter 3, this chapter focuses on the U.S. dollar denominated single-name CDS spread from March 209 to December 2016. The data is on monthly basis.

TABLE 4.3 SUMMARY STATISTICS OF DEPENDENT AND INDEPENDENT VARIABLES

Panel A: Whole sample

Variables	No. Obs	Mean	Std. Dev	Min	Max
CDS	18105	177.82	337.48	1.01	8921.87
LEV	18105	28.07	18.57	0.00	99.22
CF	18105	2.60	2.75	-27.13	26.44
CFVol	18105	1.83	23.44	0.10	2448.97

Panel B: Investment-grade sub-sample

	No. Obs	Mean	Std. Dev	Min	Max
CDS	13116	83.14	77.09	1.01	1931.84
LEV	13116	21.61	11.79	0.42	88.28
CF	13116	2.95	2.47	-16.89	26.44
CFVol	13116	0.80	3.64	0.10	396.80

Panel C: High-yield sub-sample

Variables	Obs	Mean	Std. Dev	Min	Max
CDS	4989	426.65	558.78	7.56	8921.87
LEV	4989	45.06	22.09	0.00	99.22
CF	4989	1.66	3.21	-27.13	22.27
CFVol	4989	4.55	44.15	0.10	2448.97

Notes: The table reports descriptive statistics for CDS spreads and firm-specific variables in the whole sample, investment-grade and high-yield sub-samples. LEV is the leverage; CF is the ratio of operating cash flow and total asset; CFVol is the operating cash flow volatility. CDS are measured in basis point; LEV, CF, and CFVol are measured in percentage. The sample period is from March 2009 to December 2016. Obs, Mean, Std.Dev, Min, and Max in the first row represent the number, mean, standard deviation, maximum, minimum of observations of variables.

TABLE 4.4 PAIR-WISE CORRELATION OF DEPENDENT AND INDEPENDENT VARIABLES

Panel A: Whole Sample

	CDS	LEV	CF	CFVol	IP	NonF	CPI	RF	IPCV	NonFVol	CPIVol	RFVol
CDS	1.00											
LEV	0.93	1.00										
CF	-0.12	0.16	1.00									
CFVol	0.10	0.11	0.04	1.00								
IP	-0.21	-0.18	0.01	0.03	1.00							
NonF	-0.65	-0.77	-0.10	0.03	0.25	1.00						
CPI	0.06	0.05	-0.11	0.15	0.01	-0.05	1.00					
RF	0.26	0.34	0.13	0.12	-0.18	-0.16	0.09	1.00				
IPCV	0.53	0.51	0.15	-0.01	-0.28	-0.43	-0.08	0.17	1.00			
NonFVol	0.23	0.22	-0.08	-0.04	-0.02	-0.29	-0.04	0.07	0.21	1.00		
CPIVol	0.29	0.36	0.04	-0.10	-0.15	-0.41	-0.12	-0.06	0.22	0.01	1.00	
RFVol	0.22	0.22	0.12	-0.04	-0.13	-0.05	0.03	0.54	0.17	0.03	-0.08	1.00

TABLE 4.4 – CONTINUED

Panel: B Investment-grade sample

	CDS	LEV	CF	CFVol	IP	NonF	CPI	RF	IPCV	NonFVol	CPIVol	RFVol
CDS	1.00											
LEV	0.70	1.00										
CF	-0.11	0.09	1.00									
CFVol	0.30	0.10	0.15	1.00								
IP	-0.16	-0.25	0.01	-0.01	1.00							
NonF	-0.41	-0.78	-0.07	-0.05	0.25	1.00						
CPI	0.01	-0.02	-0.10	0.07	0.01	-0.05	1.00					
RF	0.18	0.32	0.05	-0.12	-0.18	-0.16	0.09	1.00				
IPCV	0.39	0.55	0.14	-0.02	-0.28	-0.43	-0.08	0.17	1.00			
NonFVol	0.20	0.20	-0.07	-0.01	-0.02	-0.29	-0.04	0.07	0.21	1.00		
CPIVol	0.09	0.41	0.03	-0.09	-0.15	-0.41	-0.12	-0.06	0.22	0.01	1.00	
RFVol	0.22	0.27	0.07	-0.08	-0.13	-0.05	0.03	0.54	0.17	0.03	-0.08	1.00

TABLE 4.4 – CONTINUED

Panel C: High-yield Sample

	CDS	LEV	CF	CFVol	IP	NonF	CPI	RF	IPCV	NonFVol	CPIVol	RFVol
CDS	1.00											
LEV	0.91	1.00										
CF	0.15	0.13	1.00									
CFVol	0.42	0.43	0.02	1.00								
IP	-0.26	-0.14	0.01	-0.01	1.00							
NonF	-0.68	-0.65	-0.18	-0.30	0.25	1.00						
CPI	0.05	0.10	-0.09	0.19	0.01	-0.05	1.00					
RF	0.22	0.22	0.31	-0.03	-0.18	-0.16	0.09	1.00				
IPCV	0.56	0.40	0.18	0.15	-0.28	-0.43	-0.08	0.17	1.00			
NonFVol	0.19	0.13	-0.02	-0.03	-0.02	-0.29	-0.04	0.07	0.21	1.00		
CPIVol	0.34	0.32	0.01	0.13	-0.15	-0.41	-0.12	-0.06	0.22	0.01	1.00	
RFVol	0.19	0.10	0.23	-0.09	-0.13	-0.05	0.03	0.54	0.17	0.03	-0.08	1.00

Notes: The table reports pair-wise correlation between CDS spreads, macroeconomic and firm-specific variables in the whole sample, investment-grade and high-yield sub-samples. LEV is the cross-sectional average leverage; CF is the cross-sectional average operating cash flow over total asset; CFVol is the cross-sectional operating cash flow volatility. IP is the growth of industrial production; NonF is the growth of total nonfarm payroll, CPI is the growth of consumer price index; and RF is the 3-month Treasury Bill rate; IPVol, NonFVol, CPIVol, and RFVol are volatilities of IP, NonF, CPI, and RF. CDS are measured in basis point; LEV, CF, CFVol, IP, NonF, CPI, RF, and RFVol are measured in percentage. IPVol, NonFVol, and CPIVol are measured in squared percentage. LEV, CF, CFVol, IP, NonF and CPI are values at month t-1. The CDS, RF, IPVol, NonFVol, CPIVol, and RFVol are values at month t. The sample period is from March 2009 to December 2016.

TABLE 4.5 PANEL DATA UNIT ROOT TEST

Panel A: Whole sample

	Inverse normal		Inverse logit	
	Test Statistics	p-value	Test Statistics	p-value
CDS	-54.56	0.00	-95.98	0.00
LEV	-32.74	0.00	-42.78	0.00
CF	-46.57	0.00	-63.55	0.00
CFVol	-6.66	0.00	-17.93	0.00

Panel B: Investment-grade sub-sample

	Inverse normal		Inverse logit	
	Test Statistics	p-value	Test Statistics	p-value
CDS	-30.97	0.00	-54.67	0.00
LEV	-12.94	0.00	-18.16	0.00
CF	-38.36	0.00	-51.84	0.00
CFVol	-15.25	0.00	-19.26	0.00

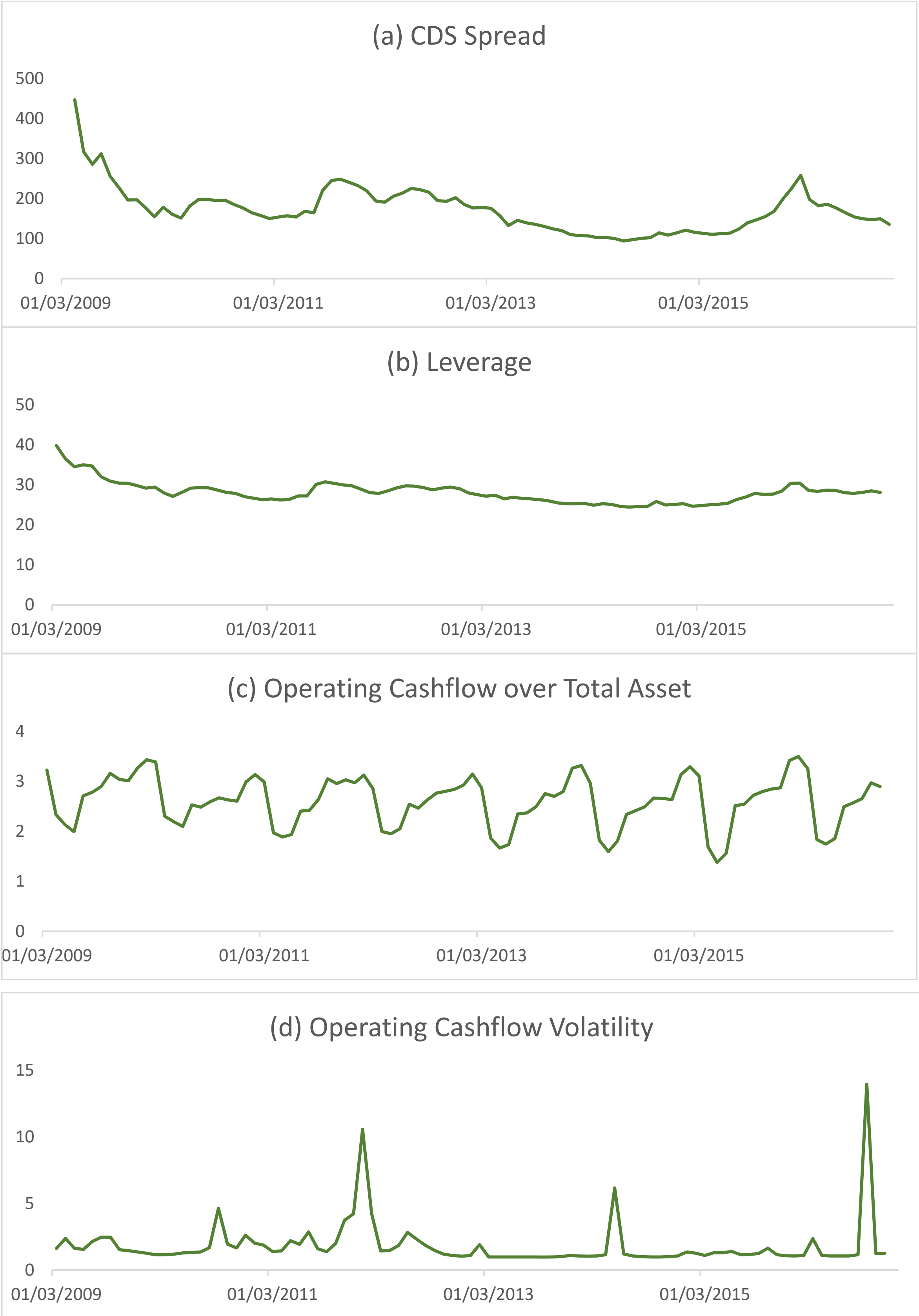
Panel C: High-yield sub-sample

	Inverse normal		Inverse logit	
	Test Statistics	p-value	Test Statistics	p-value
CDS	-25.69	0.00	-50.62	0.00
LEV	-7.39	0.00	-11.72	0.00
CF	-21.13	0.00	-28.07	0.00
CFVol	-14.56	0.00	-31.61	0.00

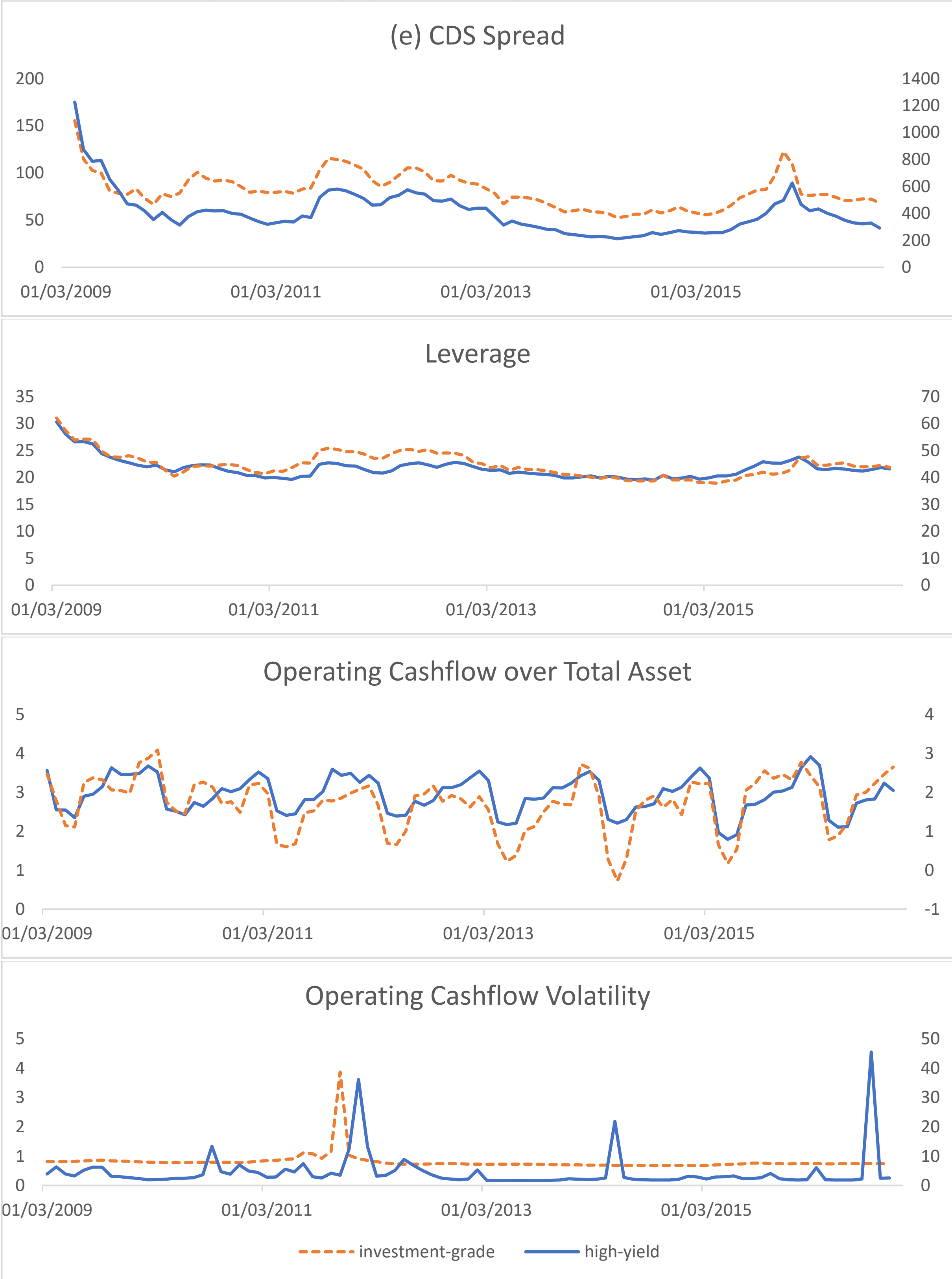
Notes: The table reports results of Fisher-type unit root test for CDS spreads and firm-specific variables from the whole sample, investment-grade sub-sample, and high-yield sub-sample. Two test statistics, inverse normal and inverse logit, are considered in the table. LEV is the leverage; CF is the ratio of operating cash flow over total asset; CFVol is the operating cash flow volatility. CDS are measured in basis point; LEV, CF, CFVol are measured in percentage. The sample period is from March 2009 to December 2016.

FIGURE 5 CROSS-SECTIONAL AVERAGE FIRM-SPECIFIC VARIABLES

Panel A Whole sample



Panel B Investment-grade and High-yield Sub-sample



Note: This figure shows cross-sectional average firm-specific variables. Panel A reports whole sample firm-specific variables; Panel B reports firm-specific variables from investment-grade and high-yield sub-samples. CDS spreads is measured in basis points; leverage, operating cash flow over total asset, operating cash flow volatility are measured in percentage. The left and right vertical axis show values for the investment-grade and the high-yield sub-samples respectively. The sample period is from March 2009 to December 2016.

4.3.2 METHODOLOGY

As mentioned in Section 4.2.3, a summary of expected relationships between dependent and independent variables is reported in Table 4.1. To test expected relationships between single-name CDS spreads and macroeconomic variables, and firm-specific variables, this chapter begins by studying the effect of macroeconomic condition variables on the single-name CDs spread by running a panel data regression. The Regression (4.1) will be constructed and estimated to explain how firm-specific variables influence the single-name CDS spread:

$$CDS_{i,t} = \alpha_i + \beta_1 IP_{t-1} + \beta_2 NonF_{t-1} + \beta_3 CPI_{t-1} + \beta_4 RF_t + \varepsilon_{i,t} \qquad \text{Regression (4.1)}$$

where i=1, …, N indexes firms, t=1, …, T denotes time in months.

Regression (4.2) will be conducted by adding macroeconomic volatility variables to Regression (4.1), to explore the joint effect of macroeconomic condition ad volatility variables on single-name CDS spreads:

$$\begin{aligned} CDS_{i,t} = {} & \alpha_i + \beta_1 IP_{t-1} + \beta_2 NonF_{t-1} + \beta_3 CPI_{t-1} + \beta_4 RF_t + \beta_5 IPVol_t + \beta_6 NonFVol_t + \beta_7 CPIVol_t \\ & + \beta_8 RFVol_t + \varepsilon_{i,t} \end{aligned}$$

Regression (4.2)

where i=1, …, N indexes firms, t=1, …, T denotes time in months.

Finally, the Regression (4.3) will be conducted by adding firm-specific variables to Regression (4.2), to explore the joint effect of macroeconomic condition variables and firm-specific variables on single-name CDS spreads.

$$\begin{aligned} CDS_{i,t} = {} & \alpha_i + \beta_1 IP_{t-1} + \beta_2 NonF_{t-1} + \beta_3 CPI_{t-1} + \beta_4 RF_t + \beta_5 IPVol_t + \beta_6 NonFVol_t + \beta_7 CPIVol_t \\ & + \beta_8 RFVol_t + \beta_9 LEV_{i,t-1} + \beta_{10} CF_{i,t-1} + \beta_{11} CFVol_{i,t-1} + \varepsilon_{i,t} \end{aligned}$$

Regression (4.3)

where i=1, …, N indexes firms, t=1, …, T denotes time in months.

Two models, the fixed effect model and the random effect model, can be used when running Regression (4.1), (4.2), and (4.3). The intercept value for an individual company in Regression (4.3) can be expressed as a random variable with a mean value α

$$\alpha_i = \alpha + \mu_i \qquad \text{Equation (4.4)}$$

where μ_i is a random error term representing the company-specific characteristics, with a mean value of zero and a variance of σ_μ^2 . If the error term, μ_i, in Regression (4.3) are correlated with independent variables, then using the random effect model will result in inconsistent estimation of the regression coefficients. This thesis will apply Hausman test which tests whether error terms are correlated with independent variables and whether the random effect model can give consistent regression estimates.

Results of Hausman test for Regression (4.3), the whole regression, is reported in Table 4.6, with the whole sample and sub-samples being tested separately. The null hypothesis is that the estimator given by the random effect model is an efficient and consistent estimator of true parameters. Table 4.6 shows that p value for each row is smaller than 0.01, which suggests a rejection of the null hypothesis at 99% confidence level. As a result, the random effect model cannot provide efficient and consistent estimators and the fixed effect model should be applied in the later empirical analysis.

Furthermore, the Wooldridge test, proposed by Wooldridge (2002), is conducted on Regression (4.3) to detect the presence of serial correlations in residuals. This thesis adopts this test because this test can be applied on the fixed effect models, balanced and unbalanced panel data compared with other panel data serial correlation tests.

To more easily detail the technical information regarding to the Wooldridge test, Regression (4.3) is re-written as in vector form:

$$CDS_{i,t} = \alpha_i + X_{i,t}\beta + \varepsilon_{i,t} \qquad \text{Equation (4.5)}$$

where $X_{i,t}$ is the (1×11) vector of macroeconomic and firm-specific variables that are involved in Regression (4.3). Then doing the first differencing to remove the firm-specific effect α_i and get Regression (3.3) in first-differences:

$$\Delta CDS_{i,t} = \Delta X_{i,t}\beta + \Delta\varepsilon_{i,t} \qquad \text{Equation (4.6)}$$

where Δ is the first-difference operator.

Wooldridge test uses $\Delta\varepsilon_{i,t}$ from Equation (4.6). The rationale behind the Wooldridge test is that if $\varepsilon_{i,t}$ in Equation (4.5) is not correlated, then $Corr\left(\Delta\varepsilon_{i,t}, \Delta\varepsilon_{i,t-1}\right) = -0.5$. The null hypothesis of the Wooldridge test is that there is no first-order serial correlations in Regression (4.3) residuals. The p-values in Table 4.7 for the whole sample and two sub-samples are less than 0.01, which are strong rejections on the null hypothesis at 99% confidence level. One potential reason for the existence of serial correlation, as mentioned in Section 4.2.3, is the use of the rolling standard deviation for the volatility of cash flows.

Furthermore, this thesis also applies the modified Wald test that is designed for group-wise heteroskedasticity in the residuals of a fixed-effect regression model. The estimator of the ith cross-sectional company's error variance is given by:

$$\sigma_i^2 = T_i^{-1}\sum\nolimits_{t=1}^{T_i}\varepsilon_{i,t}^2 \qquad \text{Equation (4.7)}$$

where T_i is the length sample period; $\varepsilon_{i,t}$ is the firm-specific and time-specific error term in Regression (4.3).

The estimated variance of σ_i^2 is given by:

$$V_i = T_i^{-1}\left(T_i - 1\right)^{-1}\sum\nolimits_{t=1}^{T_i}\left(\varepsilon_{i,t}^2 - \sigma_i^2\right)^2 \qquad \text{Equation (4.8)}$$

The modified Wald test statistic, defined as

$$W = \sum\nolimits_{i=1}^{N}\frac{\left(\sigma_i^2 - \sigma^2\right)^2}{V_i} \qquad \text{Equation (4.9)}$$

will be distributed as $\chi^2\left(N\right)$ under the null hypothesis. The null hypothesis specifies that

$\sigma_i^2 = \sigma^2$ for i = 1, . . ., N, where N is the number of companies. P values in Table 4.8 are smaller than 0.01 for the whole sample and subsamples. As a result, the null hypothesis is rejected at 99% confidence level and there is heteroskedasticity across different companies.

Serial correlations and group-wise heteroskedasticity in the linear panel data model biases the standard errors therefore lead to less efficient coefficient estimators. As a result, the t-statistics of coefficients in Regression (4.3) are adjusted using panel robust standard errors [12]because of the existence of heteroskedasticity and autocorrelation in residuals.

[12] However, this may not be sufficient to treat the symptoms of the autocorrelation introduced by the design of the variable representing operating cash flow volatility.

TABLE 4.6 PANEL REGRESSION HAUSMAN TEST

	Chi Statistics	P-value
Whole Sample	33.08	0.00
Investment-grade Sub-sample	290.01	0.00
High-yield Sub-sample	39.93	0.00

Notes: This table shows the results of Hausman on Regression (4.3) using the whole sample and 2 sub-samples. The null hypothesis is that difference in coefficients are not systematic and random effects exists in the regression. The sample period is from March 2009 to December 2016.

TABLE 4.7 WOOLDRIDGE TEST FOR AUTOCORRELATION IN PANEL REGRESSION

	F Statistics	P-value
Whole Sample	57.503	0.00
Investment-grade Sub-sample	409.297	0.00
High-yield Sub-sample	50.348	0.00

Notes: This table shows the results of Wooldridge test on Regression (4.3) using the whole sample and 2 sub-samples. The null hypothesis of the Wooldridge test is that there are no first-order serial correlations in residuals. The sample period is from March 2009 to December 2016.

TABLE 4.8 MODIFIED WALD TEST FOR HETEROSKEDASTICITY

	Chi Statistics	P-value
Whole Sample	2100000	0.00
Investment-grade Sub-sample	630000	0.00
High-yield Sub-sample	250000	0.00

Notes: This table shows results of the Modified Wald test on Regression (4.3) using the whole sample and 2 sub-samples. The null hypothesis is that the regression disturbances are homoscedastic with the same variance across time and individuals. The sample period is from March 2009 to December 2016.

Furthermore, in order to assess the relative importance of various variable groups, firm-specific variables, macroeconomic condition variables, and macroeconomic volatility variables, this chapter applies an instructive method that is used by Düllmann and Sosinska (2007) and Annaert *et al*. (2013). The marginal contribution of nth group of variables mc_n to the total explained R square in the Regression (4.3) is expressed as:

$$\frac{R^2 - R_n^2}{\sum_{n=1}^{3}\left(R^2 - R_n^2\right)}$$

where R^2 is the explained R square in Regression (4.3); R_n^2 is the explained R square of the regression with nth group of variables being removed.

Finally, sensitivity analysis is conducted to compare the elasticity of the investment-grade and high-yield CDS spread to firm-specific variables and macroeconomic variables. The elasticity is constructed following the methodology also adopted in the Chapter 3 by dividing the slope coefficient of independent variables by the mean of the dependent variable and multiplying by the mean of the relevant independent variable. The elasticity is interpreted as the proportional change of the dependent variable due to the proportional change in the independent variable. For a given independent variable, the dependent variable with larger elasticity is more sensitive to the independent variable.

Using this method, one can obtain the elasticity that accounts for differences in absolute values of dependent variables, making the elasticity comparable across the investment-grade and high-yield CDS. Furthermore, following the same method used in the Chapter 3 effectively enables to the comparison of the sensitivity analysis results in this chapter to the results reported in Chapter 3.

4.4 EMPIRICAL RESULTS

The empirical analysis in Section 4.4.1 starts by exploring the relationship between the single-name CDS spread and macroeconomic condition variables and continues with exploring the relationship between the single-name CDS spread and both macroeconomic condition and volatility variables. Section 4.4.2 analyses the joint effects of firm-specific variables, macroeconomic condition variables and macroeconomic volatility variables on the single-name CDS spread. Section 4.4.3 studies the marginal contributions of macroeconomic condition, macroeconomic volatility, and firm-specific groups of variables to the explained variation in the CDS spread. Finally, Section 4.4.4 conducts sensitivity analysis to test whether investment-grade and high-yield CDS spreads have different sensitivities to macroeconomic variables and firm-specific variables.

4.4.1 MACROECONOMIC LEVEL AND VOLATILITY DETERMINANTS OF SINGLE-NAME CDS SPREADS

The empirical analysis of macroeconomic-variable effects on the CDS spread starts with estimating Regression (4.1) and the results are reported in Table 4.9.

Column (1) of Panel A reports estimated results for Regression (4.1) focusing on the effect of macroeconomic condition variables on the whole sample only, with the results for investment-grade CDS and high-yield CDS separately reported in column (1) of Panels B and C, respectively. The table shows that the growth rate of industrial production has a significantly negative effect on the CDS spread at 95% confidence level in the entire sample and also the two sub-samples. This result is in line with the implication of the theoretical model by Tang and Yan (2006) and also with empirical findings by Tang and Yan (2010).

Total nonfarm payroll growth has a significantly negative effect on the whole sample CDS spread and also two sub-sample CDS spread, all at 99% confidence level. The negative effect of the total nonfarm payroll growth is consistent with the expectation and with the findings in Chapter 3.

The growth of consumer prices index and 3-month Treasury Bill rate are insignificant in determining either the whole sample CDS spread or the sub-sample CDS spread.

Finally, the R squares in Column (1) of Panels A, B and C suggests that macroeconomic level variables can explain 2.64%, 2.84% and 7.24% of total variation in the CDS in the whole sample, investment-grade sub-sample and high-yield sub-sample CDS spreads, respectively. One reason for the higher explained variation in the high-yield CDS spread is related to the discussion in Section 3.4.1 of Chapter 3. Default probability of high-yield companies changes dramatically when macroeconomy changes while the default probability of investment-grade companies does not show the same degree of time-variation over the business cycle. This, at least in part, may be related to investment-grade companies not relying as much as high-yield companies on the external funding that tends to become costly or even unavailable during recessions. As a result, macroeconomic conditions account for a larger share of variation in the high-yield CDS spread than in the investment-grade CDS spread.

The second step of the empirical analysis is to explore the joint effect of macroeconomic condition and volatility variables on CDS spreads by running Regression (4.2). The results for the whole sample, the investment-grade sub-sample, and the high-yield sub-sample are reported in the Column (2) of Panel A, B, and C in Table 4.9 respectively.

Industrial production growth volatility has a significantly positive effect on the whole sample CDS spread, the investment-grade CDS spread, and the high-yield CDS spread at 99% confidence level, in line with findings in Baum and Wan (2010), and Tang and Yan (2010). The positive sign indicates that the more volatile economic output growth is associated with a higher CDS spread of both high yield and investment grade quality.

A notable finding is that total nonfarm payroll growth volatility is insignificant in determining the whole sample CDS and the high-yield CDS spread but has a significantly positive effect on the investment-grade CDS spread at 90% confidence level. A potential explanation is related to the work of Kaplan and Zingales (1997) and Cleary (1999) that firms with high creditworthiness are more affected by cash flow volatility relative to less-creditworthy firms because, in contrast to high-yield firms, investment projects of investment-grade companies are more sensitive to internal funding, such as cash flow. Consequently, more volatile cash flow may prevent investment-grade companies from making investments. This suggests that a higher uncertainty in nonfarm payroll may be indicative of a higher uncertainty about the firms' business growth prospects that, it turn, makes the firms' operating cash flows also more uncertain.

In addition, 3-month Treasury rate volatility has a significantly positive effect on the whole sample and both sub-sample CDS spreads, which is consistent with the finding by Kim and Stock (2014) that study the bond credit spread whereas inflation volatility is insignificant in all three samples.

Regarding macroeconomic condition variables, industrial production growth loses its significance in the augmented regressions for the whole sample and investment-grade sub-sample. The growth of total nonfarm payroll retains its significance across all sub-samples whereas measures of inflation and risk-free rate remain insignificant.

Furthermore, in line with the variable significance results, the regression R square increases, even though only very moderately, after adding macroeconomic volatility variables to the regression. The increase in the R square suggests that macroeconomic volatility variables help explaining some additional variation in CDS spreads, beyond that is explained by macroeconomic level variables.

In summary, the analysis of the joint effect of economic condition and volatility variables on CDS spreads show that the nonfarm payroll growth has a significantly negative effect on CDS spreads in the whole sample and the two sub-samples whereas industrial production growth is only important for high-yield CDS. Among the volatility variables, industrial production growth volatility and 3-month Treasury rate volatility have a significantly positive effect in the whole sample and both sub-samples. Total nonfarm payroll growth volatility has a significantly positive effect on the investment-grade CDS spread but has an insignificant effect on the whole sample CDS spread and high-yield CDS spread. Finally, macroeconomic level and volatility variables jointly account for a larger share of variation of the high-yield CDS spread than in investment-grade CDS spread.

TABLE 4.9 MACROECONOMIC AND FIRM-SPECIFIC VARIABLES AND CDS SPREADS

	Panel A: Whole Sample			Panel B: Investment-grade Sub-sample			Panel C: High-yield Sub-sample		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Constant	192.19***	118.13***	-201.77***	84.83***	69.02***	-29.76***	472.59***	249.03***	-486.39***
	(27.12)	(9.34)	(-4.84)	(56.65)	(27.14)	(-2.67)	(19.97)	(5.75)	(-4.16)
IP	-8.97**	-0.32	-4.53	-2.92**	-0.94	-0.82	-20.54**	-4.35**	-22.17**
	(-2.22)	-0.09	(-1.5)	(-2.02)	(-0.70)	(-0.77)	(-2.43)	(2.34)	(-2.13)
NonF	-299.70***	-232.16***	-52.47*	-59.69***	-46.67***	0.67	-916.52***	-716.15***	-211.37*
	(-4.69)	(-4.86)	(-1.77)	(-5.19)	(-4.90)	(0.09)	(-4.44)	(-4.67)	(-1.91)
CPI	13.52	26.22	10.32	0.53	2.89	1.22	46.42	88.09	11.05
	(1.62)	(1.54)	(1.53)	(0.16)	(0.86)	(0.57)	(1.63)	(1.45)	(0.48)
RF	96.84	20.81	-29.36	35.68	4.98	-6.18	215.13	24.39	-58.07
	(1.32)	(0.61)	(-1.16)	(0.78)	(0.54)	(-0.75)	(1.48)	(0.20)	(-0.73)
IPVol		187.55***	99.98***		45.86***	21.82***		554.53***	322.35***
		(5.06)	(3.68)		(6.64)	(4.45)		(4.63)	(3.34)
NonFVol		31.09	91.56		50.84*	86.32***		75.46	9.56
		(0.40)	(1.29)		(1.94)	(3.55)		(0.32)	(0.04)
CPIVol		226.75	-13.34		-31.09	-16.29		860.02	397.14
		(1.19)	(-0.08)		(-1.17)	(-0.35)		(1.28)	(0.65)
RFVol		1009.74***	419.68**		407.88***	146.65*		2519.74***	1907.84***

TABLE 4.9 CONTINUED

	Panel A: Whole Sample			Panel B: Investment-grade Sub-sample			Panel C: High-yield Sub-sample		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
		(3.85)	(2.14)		(3.57)	(1.86)		(2.75)	(2.71)
LEV			12.59***			5.04***			17.83***
			(9.77)			(10.29)			(8.29)
CF			-1.61			-0.38			-5.49
			(-1.31)			(-1.62)			(-1.47)
CFVol			0.07			0.37***			0.08
			(1.08)			(4.44)			(1.38)
R square	0.0264	0.0306	0.4314	0.0284	0.0371	0.2287	0.0724	0.0850	0.4014
No. obs	18105	18105	18105	13116	13116	13116	4989	4989	4989
No. Groups	197	197	197	154	154	154	75	75	75

Note: This table reports coefficients of Regression (4.1), (4.2), and (4.3) estimated using the panel data fixed effect model, clustering at the firm level. The dependent variable and explanatory variables are on a monthly basis. The column (1) in Panel A, B, and C report results of Regression (4.1) using the whole sample and 2 sub-samples. The Column (2) of Panel A, B, and C report results of Regression (4.2) using the whole sample and 2 sub-samples. The Column (3) of Panel A, B, and C report results of Regression (4.3) using the whole sample and 2 subsamples. LEV is leverage; CF is the ratio of operating cash flow over total asset; CFVol is the operating cash flow volatility. IP is the growth of industrial production; NonF is the growth of total nonfarm payroll, CPI is the growth of consumer price index; RF is the 3-month Treasury Bill rate; IPVol, NonFVol, CPIVol, and RFVol are volatilities of IP, NonF, CPI, and RF. CDS are measured in basis point; LEV, CF, CFVol, IP, NonF, CPI, RF, and RFVol are measured in percentage. IPVol, NonFVol, and CPIVol are measured in squared percentage. LEV, CF, CFVol, IP, NonF and CPI are values in month t-1. The CDS spread, RF, IPVol, NonFVol, CPIVol, and RFVol are values in month t. The t-statistics are computed using standard errors robust for serial autocorrelation and heteroskedasticity. Associated t-statistics are given in parenthesis. The sample period is from March 2009 to December 2016. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

4.4.2 MACROECONOMIC LEVEL, MACROECNOMIC VOLATILITY, FIRM-SPECIFIC DETERMINANTS OF CDS SPREADS

The next step of the empirical analysis is to explore the joint effect of macroeconomic condition variables, macroeconomic volatility variables, and firm-specific variables, on the CDS spread. Regression (4.3) results for the whole sample, investment-grade sub-sample, and high-yield sub-sample are reported in Column (3) of Panel A, B, and C of Table 4.9.

Leverage has a significantly positive effect on the whole sample CDS and both sub-sample CDS spread at 99% confidence level, which is consistent with the prediction of the structural models and empirical literature (e.g. Ericsson, Jacobs, and Oviedo, 2009; and Tang and Yan, 2010).

The firm's cash flow, measured by the percentage of operating cash flow over total asset, does not have a significant effect on neither the whole sample CDS spread, nor the sub-sample CDS spread. The insignificant effect of cash flow measure conflicts with findings by Tang and Yan (2010) that find the cash flow measure has a significantly negative effect on the CDS spread. A potential explanation for the difference in the results maybe because Tang and Yan (2010) use pre-crisis period data while this chapter uses post-crisis data. Another potential explanation is that, although operating cash flow over total asset has been commonly used in the literature, it cannot fully capture the cash flow condition of the firm compared with other cash flow measures. This explanation encourages future studies to explore more appropriate cash flow measures.

Another noteworthy finding of this section highlights the importance of cash flow volatility in determining the investment-grade CDS spread at 99% confidence level. The positive sign of the cash flow volatility is consistent with the Tang and Yan (2006) structural model. However, this section finds that the cash flow volatility is insignificant in determining the high-yield CDS spread. Kaplan and Zingales (1997) and Cleary (1999) offer a possible explanation by showing that companies with high creditworthiness are extremely sensitive to cash flow measure as it affects their ability to make investments relative to high-yield companies. This different sensitivity, although is not reflected in the cash flow measure, is reflected in the cash flow volatility measure.

After introducing firm-specific variables, the growth of total nonfarm payroll loses its significance in explaining the investment-grade CDS spread. The effect of macroeconomic variables remains largely unchanged in the whole sample and high-yield sub-sample.

Furthermore, the R square in Column (3) of Panels A, B, and C suggest that macroeconomic variables and firm-specific variables can jointly explain 43.14%, 22.87% and 40.14% of total variation in the whole sample, the investment-grade and the high-yield CDS spread respectively. The R-square values are relatively higher than the corresponding values from regression (4.2) with macroeconomic variables only, indicating that firm-specific variables explain an additional, large share of variation in the whole sample CDS spread, investment-grade CDS spread and the high-yield CDS spread.

The R squared of 43.14% for the whole-sample in this analysis is larger than R squares of 36% reported in a related study of single-name CDS spreads by Baum and Wan (2010). This can be because this analysis uses more macroeconomic measures that capture various dimensions of macroeconomy as opposed to measures of economic output growth and volatility only employed in Baum and Wan (2010). However, the R square for the whole-sample CDS spread is somewhat smaller here than 53.70% reported by Tang and Yan (2010). The higher R square in Tang and Yan (2010) might be because they use time dummies in their analysis to capture all the time-series variation attributed by macroeconomic conditions. However, time dummies can capture not only overall macroeconomic conditions but also other market-wide factors such as market liquidity, that are not directly related to macroeconomic conditions. In addition, their dummy-based measures cannot be directly interpreted or linked to specific macroeconomic risk factors.

Finally, another noteworthy finding in this section is that firm-specific variables can explain a greater share of variation in the high-yield CDS spread than the variation in the investment-grade CDS spread, with this result largely driven by firm leverage.

This result can be explained by high-yield firms typically having a considerably higher leverage levels due to a higher level of indebtedness relative to investment-grade firms, with high leverage signalling greater default risk. In particular, in this data sample, the average leverage of 45.06% of the high yield CDS is notably higher than the average leverage of 21.61% in the investment-grade sample.

In summary, the results show that leverage has a significantly positive effect on the whole sample and the sub-sample CDS spread. Cash flow volatility has a significantly positive effect on the investment-grade CDS spread whereas the effect of the cash flow measure is insignificant. Finally, firm-specific variables explain additional variation in the CDS spread in addition to macroeconomic variables.

4.4.3 RELATIVE IMPORTANCE ANALYSIS

This section begins by presenting the results of the relative importance analysis that compares the marginal contributions of macroeconomic condition and volatility variables to the explained R square in Regression (4.2). The analysis results are reported in Table 4.10. Panel A, B, and C report the results for the whole sample, the investment-grade sub-sample, and the high-yield sub-sample, respectively.

The Panel A shows macroeconomic level variables and macroeconomic variables contribute, respectively, 68.42% and 31.58% to the explained R square in the whole sample, with very similar result reported in Panel C for high-yield CDS. The contribution of the macroeconomic condition variables is only moderately higher relative to that of volatility variables while using the investment-grade CDS spread. These results are generally consistent with the regression R squares reported in Table 4.9 for regressions that include macroeconomic condition variables only in column (1) and both macroeconomic condition and volatility variables in column (2), both without firm-level variables.

The reason for higher marginal contribution made by macroeconomic condition variables relative to volatility variables is that macroeconomic volatility can affect the CDS spread both directly and also indirectly via macroeconomic level variables, with their indirect impact not reflected in the reported measures.

Next, the relative importance analysis is conducted for the firm-specific, macroeconomic level, and macroeconomic volatility groups of variables by comparing the marginal contributions of each variable group. Panels A, B, and C of Table 4.11 report results for the whole sample CDS spread, the investment-grade CDS spread, and high-yield CDS spread respectively.

Table 4.11 shows that firm-specific variables are the largest marginal contributor, attributing more than 95% of the explained variation in the CDS spread. On the other hand, macroeconomic level group of variables as a group contribute only 0.25%, 0.00%, and 1.94% to explained variation in the whole sample CDS spread, the investment-grade CDS spread, and the high-yield CDS spread respectively. Macroeconomic volatility group of variables makes only slightly greater contribution of 0.37%, 1.54%, and 2.15% to explained variation in the whole sample, and the investment-grade and high-yield sub-samples, respectively.

A high relative importance of firm-specific variables is consistent with Tang and Yan (2010) that find firm-specific variables explain approximately 10 times as large total variation in the CDS spread as macroeconomic variables do.

One potential reason for a considerably higher marginal contribution of the firm-specific groups of variables is that, as suggested by Korajczyk and Levy (2003) and Hackbarth, Miao and Morellec (2006), macroeconomic variables may influence the CDS spread not only directly but also through the firm-specific variables. As a result, some of the explanatory power of macroeconomic variables may be absorbed by firm-specific variables, particularly, leverage. The results of Regression (4.2) and (4.3) in Table 4.9 are consistent with this explanation. The results show that even though Regression (4.3) has leverage as the only significant firm-specific variable, its R square is around 14 times higher than that of Regression (4.2). This maybe a future research topic because, to the best of my knowledge, there is no systematic analysis on how macroeconomic level variables of multiple dimensions affect the firm leverage.

In summary, the macroeconomic level group of variables makes a greater marginal contribution relative to the macroeconomic volatility group of variables. Among the three variable groups, firm-specific variables jointly make a considerably greater marginal contribution to the explained variation in the whole sample CDS spread, the investment-grade, and the high-yield CDS spread than macroeconomic level and volatility variables do.

TABLE 4.10 COMPARISON OF RELATIVE IMPORTANCE OF MACROECONOMIC LEVEL AND VOLATILITY VARIABLES

	Panel A: Whole Sample	Panel B: Investment-grade Sub-sample	Panel C: High-yield Sub-sample
	(a)	(b)	(c)
MC (Macro Condition)	0.6842	0.5058	0.6613
MC (Macro Volatility)	0.3158	0.4942	0.3387

Notes: This table shows the marginal contributions made by macroeconomic level and volatility variables to the explained variation in the CDS spread in Regression (4.2). Panel A, B, and C report results using the whole sample CDS spread, investment-grade CDS spread, and high-yield CDS spread. The sample period is from March 2009 to December 2016.

TABLE 4.11 COMPARISON OF RELATIVE IMPORTANCE OF FIRM-SPECIFIC, MACROECONOMIC CONDITION, AND MACROECONOMIC VOLATILITY VARIABLES

	Panel A Whole Sample	Panel B Investment-grade	Panel C High-yield
MC(Firm)	0.9938	0.9846	0.9591
MC (Macro Condition)	0.0025	0.0000	0.0194
MC (Macro Volatility)	0.0037	0.0154	0.0215

Notes: This table shows the marginal contribution made by firm-specific variables, macroeconomic level variables, and macroeconomic volatility variables to the explained variation in the CDS spread in Regression (4.3). Panel A, B, and C report results using the whole sample CDS spread, investment-grade CDS spread, and high-yield CDS spread. The sample period is from March 2009 to December 2016.

4.4.4 SENSITIVITY ANALYSIS

The absolute value of the regression coefficient reported in the previous analysis cannot reveal the relative sensitivity of the investment-grade and the high-yield CDS spread to various determinants because the magnitudes of the investment-grade CDS spread and the high-yield CDS spread differ considerably. In particular, Table 4.3 shows that the mean value of the investment-grade CDS spread is 83.14 whereas it is 426.65 for high-yield CDS spread. The elasticities for CDS from the investment-grade and high-yield sub-samples are reported in Panel A and B of Table 4.12.

Next, the elasticity of the industrial production growth volatility is used as an example for interpreting the meaning of elasticity in a straightforward manner. The elasticity of industrial production growth volatility of 0.0682 in Panel A of Table 4.12 suggests that the investment-grade CDX spread will increase by 6.82% if the industrial production growth volatility increases by 100%.

The cash flow measure, consumer prices inflation, 3-month Treasury Bill rate, and the volatility of consumer prices inflation are insignificant in both samples, therefore these variables are omitted from the discussion below.

With regards to macroeconomic level group of variables, the industrial production growth and the total nonfarm payroll growth are significant determinants for the high yield CDS spread but not for the investment grade CDS spread. The notably larger absolute values of the elasticities for these two variables for the high-yield CDS relative to the investment-grade CDS spread provide additional evidence suggesting that the high-yield CDX spread is considerably more sensitive than the investment-grade CDX spread to variations in the industrial production growth and the total nonfarm payroll growth.

Turning to macroeconomic volatility variables, the elasticity of industrial production growth volatility for the high-yield CDS spread is approximately 3 times as large as that of the investment-grade CDS spread. This result is consistent with Baum and Wan (2010). The elasticity of 3-month Treasury rate volatility for the investment-grade CDS spread is also approximately 3 times as large as that for the high-yield CDS spread, suggesting the high-yield CDS spread is more sensitive to the volatility of 3-month Treasury Bill rate. The reason why high-yield CDS spreads are more sensitive to macroeconomic variables are detailed in Section 3.4.4 and Section 4.4.1.

The volatility of total nonfarm payroll growth is significant in determining the investment-grade CDS spread but insignificant in determining the high-yield CDS spread. In line with this result, the absolute value of the elasticity of the investment-grade CDS spread is considerably larger than that of the high-yield CDX spread, indicating that the investment-grade CDX spread is more sensitive to the volatility of total nonfarm payroll growth. A potential reason why the volatility of total nonfarm payroll growth matters for the investment-grade CDS spread but not for high-yield CDS spread is discussed in Section 4.4.1.

The elasticity of leverage for the investment-grade CDS spread is smaller than the elasticity 1.88 for high-yield CDS spread. This result suggests that high-yield CDS spread is more sensitive to the leverage than the investment-grade CDS spread. This is aligned with the results in Section 4.4.2, with a potential explanation also offered in this section.

The volatility of cash flow is significant in determining the investment-grade CDS spread but insignificant in determining the high-yield CDS spread. In line with this result, the absolute value of the elasticity of the investment-grade CDS spread is considerably larger than that of the high-yield CDX spread. A potential explanation of why the volatility of cash flow is a significant determinant of the investment-grade CDS spread but not of the high-yield CDS spread is offered in Section 4.4.3.

In summary, this section finds that compared with the investment-grade CDS spread, the high-yield CDS spread tends to be more sensitive to the firm-specific and macroeconomic volatility variables. The exceptions are the volatility of operating cash flow and the volatility of total nonfarm payroll growth to which the investment-grade CDS is more sensitive.

TABLE 4.12 SENSITIVITY ANALYSIS ON EFFECTS OF FIRM-SPECIFIC AND MACROECONOMIC DETERMINANTS

	Panel A Investment-grade	Panel B High-yield
IP	-0.0013	-0.0071**
NonF	0.0007	-0.0400*
CPI	0.0021	0.0037
RF	-0.0080	-0.0153
IPVol	0.0682***	0.1984***
NonFVol	0.0107***	0.0002
CPIVol	-0.0557	0.0371
RFVol	0.0267*	0.0687***
LEV	1.3097***	1.8825***
CF	-0.0135	-0.0214
CFVol	0.0035***	0.0008

Notes: This table reports elasticities of independent variables in Regression (4.3) estimated using the panel data fixed-effect model, clustering at the firm level. The values reported in the table are the elasticities that measure the proportional percentage change of the dependent variable due to the proportional percentage change in the independent variable._The dependent variable and independent variables are on a monthly basis. The Panel A reports results of Regression (4.3) using the investment-grade CDS spread as the dependent variable. The Panel B reports results of Regression (4.3) using the high-yield CDS spread as the dependent variable. IP is the growth of Industrial Production; NonF is the growth of Nonfarm Payroll; CPI is the growth of Consumer Price Index; and RF is the 3-month Treasury Bill rate; IPVol, NonFVol, CPIVol, and RFVol are volatilities of IP, NonF, CPI, and RF; LEV is leverage; CF is the ratio between operating cash flow and total asset; CFVol is the operating cash flow volatility. The t-statistics are computed using standard errors robust for serial autocorrelation and heteroskedasticity. The sample period is from March 2009 to December 2016. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

4.5 RELATING KEY FINDINGS FOR SINGLE-NAME CDS AND CDX SPREADS

The analyses in Chapter 3 and Chapter 4 both show that macroeconomic variables have significant effects on CDX index spreads and single-name CDS spreads. However, there are also some differences in how macroeconomic determinants influence CDX and CDS spreads.

The CDX index analysis in Chapter 3 shows that the total nonfarm payroll growth has a significantly negative effect on both the investment-grade and high-yield CDX spread. The volatility of industrial production growth has a significantly positive effect on both investment-grade and high-yield CDX spread. The volatility of 3-month Treasury Bill rate has a significantly positive effect on the high-yield CDX spread but has no significant effect on the investment-grade CDX spread.

The analysis of single-name CDS in Chapter 4 shows that the industrial production growth and the total nonfarm payroll growth has a significantly negative effect on the high-yield CDX spread. The volatility of industrial production growth and the volatility of 3-month Treasury Bill rate have a significantly positive effect on both investment-grade and high-yield CDX spread. The volatility of total nonfarm payroll growth has a significantly positive effect on the investment-grade CDS spread but has no significant effect on the high-yield CDS spread.

Results from Chapter 3 and Chapter 4 show that more macroeconomic variables play a role in determining the single-name CDS spread. Similar results can be found from Tang and Yan (2010) that find some macroeconomic variables that are significant in determining single-name CDS lose their significance for the aggregate customized market average CDS spread. Results from Chapter 3 and Chapter 4, together with the findings by Tang and Yan (2010) indicate firm heterogeneity might play a role in the firm-level CDS pricing analysis.

In Chapter 3, macroeconomic level variables together with macroeconomic volatility variables jointly explain 43% of total variation in the investment grade CDX spread and 66% of total variation in the high-yield CDX spread. However, explanatory power of macroeconomic variables reported in Chapter 4 for single-name CDS spread is comparatively smaller than the explanatory power of macroeconomic variables reported in Chapter 3. The reason for this difference is that CDX includes companies that are affected differentially by macroeconomic conditions, therefore making the effects of macroeconomic indicators on the aggregated CDS index, less pronounced. As a result, this difference further demonstrates the role of the firm heterogeneity played in how macroeconomic level and volatility variables affect the CDS spread.

Furthermore, the analysis in Chapter 3 shows that macroeconomic level variables jointly contribute to around 75% of explained variation in the investment-grade CDX spread and the high-yield CDX spread, indicating that macroeconomic level variables are of greater relative importance in explaining the CDX index spread than macroeconomic volatility variables that attribute the remaining 25% of the explained variation. Chapter 4 finds that when only two macroeconomic variable group are considered (without firm-level variables), macroeconomic level variables also make a larger marginal contribution to the explained variation in the single name CDS spread relative to the macroeconomic volatility variables but their marginal contribution is lower and differs notably at 50.58% and 66.13% for investment-grade and high-yield CDS spreads. This difference in marginal contributions serves as another evidence of firm heterogeneity playing a role in how macroeconomic level and volatility variables affect the CDS spread.

In addition, Chapter 3 and Chapter 4 both find that high-yield spreads tend to be more sensitive to the macroeconomic level variables and macroeconomic volatility variables than investment-grade spreads. This finding applies to all macroeconomic level and volatility variables found significant in explaining the CDX index spread and all macroeconomic level and most macroeconomic volatility variables found significant for explaining the single-name CDS spread. As discussed in Section 4.4.1, this may be because the financing and investment strategy of high-yield companies indicates that the performance and default probability of high-yield companies are significantly affected by the macroeconomic level through the funding channel.

The only exception relates to the investment-grade single-name CDS spreads that are more sensitive than high-yield single-name CDS spreads to the total nonfarm payroll growth volatility. This is potentially because, as previously discussed in Section 4.4.1, total nonfarm payroll growth volatility may be indicative of uncertainty about future firms' cash flow to which investment-grade firms' are more sensitive.

4.6 CONCLUSION

This chapter extends the analysis in Chapter 3 by exploring the determinants of the single-name CDS spread. By incorporating both firm-specific and macroeconomic variables that are highlighted by theoretical and empirical studies, this chapter conducts an extended analysis on how single-name CDS spread is affected by firm-specific, macroeconomic level, macroeconomic volatility variables.

This dataset in this chapter contains 5-year U.S. dollar denominated single-name CDS contracts that are written on 197 companies. Macroeconomic level variables used in the analysis include industrial production growth, total nonfarm payroll growth, consumer price inflation, and 3-month Treasury Bill rate. Macroeconomic volatility variables are based on macroeconomic level variables and are constructed following the same method as that used in Chapter 3. In addition, a commonly used firm-specific variable, leverage, is used to capture firms' relationship between the asset and debt values. The ratio of operating cash flow over total asset and the volatility of operating cash flow are used to capture the cash flow level and volatility in the firm.

The analysis in this chapter makes several contributions to the literature.

The first contribution is delivered by incorporating within the CDS pricing model macroeconomic variables capturing various dimensions of the economy, including both level variables and volatility variables, and conducting an extended analysis on how macroeconomic level and volatility variables affect the single-name CDS spread.

The findings first highlight the importance of a number of macroeconomic level and volatility determinants, some of which have not been previously analysed in the CDS context. This result has useful implications by informing future research of the determinants of CDS spreads.

The first such novel variable is the total nonfarm payroll growth which is shown to have a significantly negative effect on the CDS spread. This chapter is also the first one to study how the volatility of the nonfarm payroll growth and the volatility of 3-month Treasury Bill rate affect the single-name CDS spread, finding both volatility variables important in explaining the single-name CDS spread. Other significant variables, the industrial production growth and volatility of industrial production growth, have been previously studied in Baum and Wan (2010) and Tang and Yan (2010) and also found significant for determining single-name CDS.

Furthermore, by conducting research separately on the investment-grade sub-sample and high-yield sub-sample, the analysis in this chapter shows that the effect of some macroeconomic variables differs for CDS spreads with different credit qualities. In particular, the industrial production growth and the total nonfarm payroll growth have a significantly negative effect on the high-yield CDS spread but both variables have insignificant effect on the investment-grade CDS spread. One explanation for this finding is that the investment of high-yield companies relies more on external funding than investment-grade companies do and external funding changes dramatically when macroeconomic level changes. As a result, macroeconomic level variables may be affecting high-yield companies more than investment-grade companies via the external investment funding channel.

In addition, the analysis shows that the volatility of total nonfarm payroll growth has a significantly positive effect on the investment-grade CDS spread but it is insignificant for determining the high-yield CDS spread. A potential explanation may be that investment grade spreads respond more than high yield spreads to the non-farm payroll volatility because a higher uncertainty in nonfarm payroll indicates a more volatile operating cash flows that have larger effect on the investment-grade companies' investment decisions.

With regards to the effect of the firm-specific variables, the related contribution highlights the importance of cash flow volatility in determining the CDS spread and documents the difference in its effect on investment-grade CDS spread and high-yield CDS spread. Cash flow volatility is found to have a significantly positive effect on the investment-grade CDS spread but an insignificant effect on the high-yield CDS spread. The positive sign is consistent with Tang and Yan (2010). The difference may because the investment decisions of investment-grade companies are more sensitive to their cash flow, with high cash flow volatility indicating greater internal funding risks.

In addition, this chapter also makes contribution by comparing the relative importance of different variable groups in determining the single-name CDS spread.

Even though firm-specific variables attribute a considerably greater share of variation in the CDS spread relative to the macroeconomic group of variables, macroeconomic variables are nevertheless important in explaining the single-name CDS spread. This result applies to the whole sample, investment-grade sub-sample and high-yield sub-sample, highlighting the importance of accounting for both macroeconomic fundamentals and macroeconomic uncertainty when modelling single name CDS in future research.

The relative importance analysis results further show that among the macroeconomic variables, macroeconomic volatility group of variables is at least as important as macroeconomic level group of variables in explaining the variation in the high-yield CDS spreads and more important than the macroeconomic level group of variables in explaining the investment-grade CDS spreads. Surprisingly, for investment-grade CDS, macroeconomic level variables are found unimportant. This may be because, as Korajczyk and Levy (2003) document, macroeconomic level variables play a significant role in firm's decisions regarding their capital structure and investments. This can also explain a relatively high marginal contribution to the regression R-square made by firm-specific variables because some effect of macroeconomic level variables may be absorbed by firm-specific variables, leverage in particular, lowering the marginal contribution of macroeconomic level variables.

Finally, the analysis in this chapter contributes to the literature by conducting the sensitivity analysis that compares the sensitivity of the investment-grade CDS spread and the high-yield CDS spread to various firm-specific and macroeconomic determinants. The analysis covers a broad set of macroeconomic variables, including fundamentals levels and volatility, which contrasts with Baum and Wan (2010), the only other known study to implement a similar analysis, in that they only study sensitivities of the CDS spread to macroeconomic volatility, with a focus on volatility of economic output. The chapter finds that the sensitivity of the CDS spread to various firm-specific and macroeconomic determinants varies with credit quality. In particular, high-yield CDS spread is more sensitive to leverage compared with the investment-grade CDS spread. This considerably greater sensitivity of the high-yield CDS to leverage is also reflected in the notably higher R-square statistic of the high-yield CDS regression employing firm-specific variables only relative to the corresponding regression R-square for the investment-grade CDS. A higher leverage indicates high-yield firms are more likely to reach their default threshold, therefore CDS buyers and sellers may pay particularly attention to high-yield firms' leverage position when pricing high-yield CDS spreads. However, investment-grade CDS spread is found to be more sensitive to the volatility of operating cash flow, which might be caused by the investment-grade companies' investment decisions being more sensitive to their cash flow.

In addition, the analysis provides further evidence of the high-yield CDS spread being more sensitive to macroeconomic level variables. As noted earlier, none of the macroeconomic level variables is significant in explaining the investment-grade CDS spreads. With regards to the macroeconomic volatility variables, the high-yield CDS spread is found to be also more sensitive to the volatility of industrial production and the volatility of the 3-month Treasury rate when compared to the investment-grade CDS spread. However, the investment-grade CDS spread is more sensitive to the volatility of the total nonfarm payroll growth. A possible explanation is that macroeconomic level variables and some macroeconomic volatility variables to which the high-yield CDS spread is more sensitive can affect high-yield companies more via the external funding channel. In contrast, the volatility of total nonfarm payroll growth potentially influences the investment-grade CDS spread more via the internal funding channel.

5. MACROECONOMIC ANNOUNCEMENTS AND CDX SPREADS

5.1 INTRODUCTION

Macroeconomy is an essential determinant in pricing single-name CDS spreads and CDS indices spreads. This argument has been supported by theoretical models, empirical analysis in the previous two empirical chapters of this thesis in addition to the previous empirical literature. In the previous two chapters, macroeconomic variables that capture the level and volatility of different U.S. economy dimensions are investigated on how they influence the credit default swap spread at the index level and at the firm level. Several macroeconomic variables, such as total nonfarm payroll growth, and industrial production growth volatility, are found to have significant effects on both the CDS index spread and the single-name CDS spread. Although there are theoretical and empirical studies focusing on the linkage between macroeconomy and the CDS spread, there is no existing research on how the CDS market reacts to the macroeconomic news announcements, more specifically, to the unexpected component of macroeconomic news announcements.

Several markets, such as stock market, corporate bond market, and Treasury bond market have been empirically examined on how they react to macroeconomic news releases. For example, Flannery and Protopapadakis (2002), and Kim, McKenzie, and Faff (2004) find that positive unexpected components in the announcements on consumer price inflation, and producer price inflation significantly decrease stock prices. Another strand of literature (e.g. McQueen and Roley, 1993; Boyd, and Jagannathan, and Hu, 2005) focuses on effects of macroeconomic announcements during different phrases of the business cycle. This literature shows that good news in macroeconomic announcements actually decrease stock price in expansions period while increase stock price in recessions. Furthermore, Bomfim (2000), Nikkinen and Sahlström (2004), and Rangel (2011) amongst others find that stock market volatility changes significantly before/on/after macroeconomic news announcement days. Extensive papers, such as Jones, Lamont, and Lumsdaine (1998), Balduzzi, Elton and Green (2001), and Boelli and Urga (2015) focus on government bond market. This stream of empirical research detects significant relationships between regional government bond markets and both regional and foreign macroeconomic news announcements. Several empirical papers, such as Huang and Kong (2005), and Barragan (2017), find that unexpected macroeconomic announcements, such as total nonfarm payroll, significantly affect the change of corporate bond indices spread. Stock market, government bond market, and corporate bond market have been previously investigated in the literature. However, whether and how macroeconomic news announcements influence the CDS market is a potential and unexplored topic.

The previous literature highlights that markets do not react to the macroeconomic indicator values itself, but to the disparity between actual macroeconomic news and expected news. This chapter is based on the previous 2 chapters and further extends the research by studying how unexpected macroeconomic announcements the CDX spread. To the best of the knowledge, this chapter is the first research that explores the relationship between the CDS market and unexpected macroeconomic news. It adds a different angle to the existing research that focuses on the CDS pricing. Moreover, this chapter extends the macroeconomic announcements literature by investigating whether macroeconomic announcements affect the credit derivatives markets, namely the CDS market. The chapter uncovers the importance of macroeconomic news announcements in influencing the CDX spread, which has implications for both financial institutions, market regulators, and economic policy makers.

This chapter aims to improve the current understanding of how macroeconomy, more specifically macroeconomic news announcements, affect CDX spread. As a result, this chapter focuses on the research question of whether and how various macroeconomic news announcements influence the CDX spread.

To address this research questions, this chapter uses daily spreads of two CDS indices, CDX.NA.IG and CDX.NA.HY, from Bloomberg Professional. 13 U.S. macroeconomic indicators included in this chapter are the gross domestic product, industrial production, total nonfarm payroll, unemployment rate, consumer price index, consumer sentiment, target Federal Fund rate, advanced retail Sales, durable goods new orders, capacity utilization, ISM Manufacturing index, ISM Non-Manufacturing index, and trade balance. Actual macroeconomic news releases, together with their estimated values, are obtained from Bloomberg Professional. The standardised macroeconomic surprise is constructed using the method that is introduced by Balduzzi, Elton, and Green (2001). The standardised surprise in macroeconomic announcement is constructed in this chapter aims to capture the standardised unexpected component in macroeconomic news release. The empirical analysis is conducted, based on daily data spanning from March 2009 to December 2016. Univariate and multivariate regressions are estimated to explore the individual and joint effects of standardised macroeconomic surprises on CDX spread changes. Whether standard errors are adjusted for serial autocorrelations and heteroskedasticity depends on results of Breusch-Godfrey serial correlation LM test and ARCH test.

The key findings from this chapter reveal that macroeconomic news announcements have significant effect on the CDX market. The univariate analysis is first conducted to isolate the impact of each macroeconomic announcement separately. To this end, each CDS index is regressed on each macroeconomic announcement separately, using only announcement day observations.

The univariate analysis results first show that standardised surprises in the total nonfarm payroll, advanced retail sales and trade balance have a significantly negative effect on the CDX spread. Total nonfarm payroll, advanced retail sales and trade balance are indicators for the U.S. economy. Higher-than-expected values suggest that the economy is growing, which is associated with a lower firm default rate, leading to a lower CDX spread.

In addition, the ISM Manufacturing index has a significantly negative effect on the high-yield CDX spread but does not have significant effect on the investment-grade CDX spread change. This might because high-yield companies are more sensitive to macroeconomic conditions.

Total nonfarm payroll is the macroeconomic announcement with the most profound effect on the CDX because the percentage-change in the CDX spread due to 1-unit of standardized surprise in total nonfarm payroll is the largest among all macroeconomic announcements. This may be because apart from affecting the firm's default probability directly, total nonfarm payroll may influence the CDX spread indirectly by affecting the risk-free rate through influencing yields on Treasuries.

At the next step, this chapter uses a multivariate approach to examine the overall explanatory power of macroeconomic announcements in the CDX spread. A multivariate regression with all macroeconomic announcements is run, using data from both announcement days and non-announcement days.

Similar to results from the univariate analysis, standardised surprises in the total nonfarm payroll, advanced retail sales, the ISM Manufacturing index and trade balance have a significantly negative effect on the CDX spread change. Total nonfarm payroll is the most profound macroeconomic announcement among all macroeconomic announcements.

One noteworthy finding reported is that standardized surprises in industrial production growth have a significantly positive effect on the CDX spread change. The unexpected positive effect of industrial production growth standardized surprises might be explained by the arguments raised by McQueen and Roley (1993), and Boyd, Jagannathan, and Hu (2005). Positive macroeconomic surprises during the business cycle expansion results in fear of an overheating economy. As a result, this fear leads to a higher expected future default rate, which increases the CDX spread. In a recession, a positive macroeconomic surprise indicates the end of the downturn, which in turn increases the expected future default probability and reduces the CDX spread.

The structure of this chapter is organized as follows. Section 5.2 provides the literature review discussing the effects of macroeconomic announcements on determining different markets. This section also details commonly used macroeconomic indicators and lists various methods of constructing unexpected macroeconomic news. Section 5.3 details the CDS data and macroeconomic indicators that are under consideration in this chapter. The unexpected macroeconomic news will be constructed in this section and research sample statistics will also be reported in section 5.3. Section 5.4 describes the methodology that is applied to the analysis. Empirical results and discussion are reported in section 5.5. Finally, a conclusion is provided in section 5.6.

5.2 LITERATURE REVIEW

This section provides an outline of existing literatures that relates to the impact of macroeconomic announcement. Whilst there is no paper that explores the reaction of the credit default swap market to the release of macroeconomic news, there is abundant empirical evidence that other several markets, such as stock market, money market, and corporate bond market, show significant reactions to some macroeconomic news announcements. This section will explore macroeconomic new announcements that are studied in the literature and the effects of macroeconomic news announcements on these financial markets will be detailed.

This chapter is broadly related to 2 strands of literature. First, this chapter is linked to the literature that focuses on how macroeconomy affects credit/CDS spreads. Secondly, this chapter contributes to the literature that focuses on effects of macroeconomic news announcements on various financial markets.

5.2.1 THE RELATIONSHIP BETWEEN THE MACROECONOMY AND THE CDS SPREAD

There is well-established theoretical research on how the macroeconomy affects the credit/CDS spread. Chapter 2 provided a thorough review of this strand of literature. This strand of literature contains a number of theoretical studies. For example, Tang and Yan (2006) incorporate economic output growth and economic output growth volatility into the risky bond pricing model. The model of Tang and Yan (2006) indicates a negative relationship between the credit spread and the economic output growth but a positive relationship between the credit spread and the economic output growth volatility. David (2008) studies the effect of inflation on pricing the corporate bond and find that the current inflation can change the bond price by changing investors' risk preference.

Furthermore, there is a vast amount of empirical literature studying how the macroeconomy affect the credit/CDS spread. Ericsson, Jacobs, and Oviedo (2009) report a significantly negative relationship between the CDS spread and the risk-free rate. Tang and Yan (2010) and amongst others find a significant negative relationship between the single-name CDS spread and the growth of industrial production. Some recent empirical studies (e.g. Baum and Wan, 2010; Tang and Yan, 2010) report significantly positive relationships between the single-name CDS spread and the volatility of industrial production.

5.2.2 MACROECONOMIC NEWS ANNOUNCEMENT AND STOCK MARKET

The Gordon growth model introduced by Gordon and Shapiro (1956) provide an explanation on how macroeconomic news affect the stock price. Using the Gordon growth model, the current price of a stock is given by:

$$P_0 = \sum_{t=1}^{n} \frac{D_t}{\left(1+k_t\right)^t} \qquad \text{Equation (5.1)}$$

where P_0 is the current price of the stock;

D_t is the expected future cash flow;

k_t is the discount rate.

Equation (5.1) suggests that the macroeconomic news can affect investors' expectation on the future macroeconomy therefore affect the price of a stock by changing investor's expectation on future cash flows or by changing the discount factor.

The Gordon growth model suggests that stock prices reflect expected information. The unexpected component of macroeconomic news is the source of determining price changes therefore is the main research topic of the existing literature. The literature regarding how stock market reacts to macroeconomic news announcements are abundant, and ample evidence demonstrates that stock markets react to macroeconomic releases with precious response depending on the phase of the business cycle.

McQueen and Roley (1993) for example, study the effect of macroeconomic news announcement on the daily S&P 500 return for the period from September 1, 1977 to May 31, 1988, the monthly percentage change in industrial production, the unemployment rate, the monthly percentage change in total nonfarm payroll, merchandise trade deficit, the monthly percentage in change in consumer and producer price index, and the monthly percentage change in M1. The paper defines the unexpected news of a macroeconomic indicator as the difference between its actual and expected values and finds that good news of some macroeconomic announcements (e.g. higher-than-expected industrial production growth, lower-than-expected unemployment rate, higher-than-expected merchandise trade deficit) significantly lowers the stock price during expansions while good news does not affect stock price significantly during recessions.

Boyd, Jagannathan, and Hu (2005) in contrast focus on the release of news of unemployment rate and study its effects on daily S&P 500 return from January 1, 1962 to December 31, 1995. Boyd, Jagannathan, and Hu (2005) define the good news as the real unemployment rate increases less than the forecasted unemployment rate and define the bad news as the real unemployment rate increases more than the forecasted unemployment rate. The paper finds that the stock price decreases on the good news but increases on bad news during the business cycle expansion. This finding is consistent with McQueen and Roley (1993).

Anderson *et al.* (2007) study the impact of 25 macroeconomic news announcements on the tick-by-tick S&P 500 future prices from July 1, 1998 to December 31, 2002. The paper constructs a standard news surprise following Balduzzi, Elton and Green (2001)[13]. Anderson *et al.* (2007) show that positive standard news surprises of the nonfarm payroll, and producer price index decreases S&P 500 future prices in expansions while positive standard news surprises of the nonfarm payroll and durable goods orders increase S&P 500 future prices

[13] Balduzzi, Elton and Green (2001) defines the macroeconomic surprise as the difference between real economic indicator value and expected economic indicator value and then standardize the macroeconomic surprises by its sample period standard deviation.

during contractions. The effects of positive news surprises on the stock price during expansions and recessions are line with McQueen and Roley (1993) and Boyd, Jagannathan, and Hu (2005).

The dependence of stock prices on the business cycle, as reported by McQueen and Roley (1993) Boyd, Jagannathan, and Hu (2005), and Anderson *et al.* (2007) is caused by asymmetric reactions of cash flow and discount rate to macroeconomic news announcements. As the Gordon growth model suggests, the stock price is priced as the sum of discounted future cash flows. McQueen and Roley (1993), and Boyd, Jagannathan, and Hu (2005) document that a positive macroeconomic surprise in a business cycle expansion results in fear of an overheating economy therefore policymakers increase real interest rates with stock price decreasing as a consequence. In a recession, a positive macroeconomic surprise indicates the end of the downturn thus leading to the expectation of higher future cash flows and higher stock prices.

Another stream of literature focuses on the reaction of stock market to macroeconomic news releases without considering business conditions. Flannery and Protopapadakis (2002) study the effects of 17 series of macroeconomic news announcements on a weighted U.S. stock index[14] return using daily data from January 1, 1980 to December 31, 1996. The macroeconomic surprise is constructed following the method suggested by Balduzzi, Elton and Green (2001). Flannery and Protopapadakis (2002) report news surprises, defined as the difference between actual news and expected news, of consumer price inflation and producer price inflation decreases stock index.

Kim, McKenzie, and Faff (2004) measure macroeconomic surprises as the difference between actual and expected macroeconomic values and study how daily Dow Jones Index

[14] The weighted stock index is a value-weighted stock index that is constructed using NYSE index, AMEX index and NASDAQ.

returns react to macroeconomic surprises in a period spanning 2nd January 1983 to 31st December 1998. Six macroeconomic indicators are incorporated in the study, including nominal foreign international trade balance, gross domestic product, unemployment rate, retail sales growth, consumer price, and producer price index. The study obtains similar results to Flannery and Protopapadakis (2002) and shows that there is a positive response in the Dow Jones Index if consumer price and producer price inflation are below expectation.

Birz (2011) studies the effect of both the expected and the unexpected components in macroeconomic news on the stock market. Birz (2011) collects headlines of GDP, unemployment, retail sales, and durable goods on 389 U.S. newspapers from January 1, 1991 to April 30, 2004. Newspaper headline count are regarded as a proxy measure of investors' expectation on the macroeconomy. Positive headlines in relation to GDP are found to increase the S&P 500 return while negative GDP headlines are found to decrease S&P 500 returns. Birz (2011) measures the macroeconomic surprise using the difference between actual and expected macroeconomic news release following McQueen and Roley (1993), Boyd, Jagannathan, and Hu (2005). However, in contrast with the significant effects of macroeconomic news on stock index returns that are found in McQueen and Roley (1993), and Kim, McKenzie, and Faff (2004), Birz (2011) fails to find any significant relationship between macroeconomic surprises and the S&P 500 returns.

5.2.3 MACROECONOMIC NEWS ANNOUNCEMENTS AND THE TREASURY MARKET

There is also empirical evidence that macroeconomic announcements affect the Treasury market.

Balduzzi, Elton and Green (2001) capture the effect of unexpected macroeconomic news in the Treasury market by standardizing the difference between the real economic indicator and its expected value using its sample period standard deviation. The data set contains 17 macroeconomic news announcements and intraday prices for the 3-month bill, 2-year, 10-

year, and 30-year Treasury notes spanning the period from July 1, 1991 to September 29, 1995. The paper shows that positive surprises to durable goods orders, housing starts, initial jobless claims, total nonfarm payroll, producer price index, consumer confidence, NAPM index, and new home sales significantly decrease prices of 4 Treasury instruments 30-minutes after announcements are released. Positive surprises of other macroeconomic announcements also have negative effects, but these are more limited, affecting only one or two T-bond.

Anderson *et al.* (2007) finds that positive news to GDP, nonfarm payroll employment, durable goods orders, producer price index, and initial unemployment claims significantly lower the price of U.S. 30-year Treasury bond.

Ouadghiri, Mignon, and Boitout (2016) also study the effects of macroeconomic news announcements on intraday prices for 2-year and 10-year U.S. Treasury bonds spanning a period from January 1, 2007 to July 11, 2011. Macroeconomic news surprise is constructed following Balduzzi, Elton, and Green (2001) and find that positive surprises to the consumer confidence consumer price index, Core CPI, total nonfarm payroll change, new home sales reduce bond prices significantly 15-minute after the macroeconomic news is released.

More recent papers turn to the topic of spillover effects of macroeconomic news and explore how U.S. macroeconomic news announcements affect government bond markets internationally, notably the Eurozone market. For example, Boelli and Urga (2015) examine the spread of 10-year government bonds of Belgium, France, Germany, Italy, the Netherlands and Spain over the period 2nd January 2009 to 31st May 2012 using high frequency tick-by-tick data. The paper models the movement, jump and co-jumps in government bond spreads using a Tobit-GARCH model and defines standardised macroeconomic surprises following Balduzzi, Elton, and Green (2001) and amongst others. Boelli and Urga (2015) suggest that spreads of government bond issued by 5-EU countries are not only affected its domestic news announcements (e.g. industrial production, business confidence, and gross domestic production) but are affected by European-area news announcements (e.g. introductory statement, industrial production) and U.S. news announcements (e.g. total nonfarm payroll, Chicago PMI, and consumer confidence).

5.2.4 MACROECONOMIC NEWS ANNOUNCEMENTS AND CORPORATE BOND MARKET

Apart from the literature that explores how macroeconomic announcements affect equity, Treasury bond, and sovereign bond markets, there are also several studies analysing the relationship between macroeconomic announcements and the corporate bond market.

Kim, McKenzie, and Faff (2004) study how macroeconomic announcements affect the U.S. bond return over the period beginning from January 2, 1986 to December 31, 1998. The paper shows that there is a positive response to the bond return if consumer price inflation and producer price inflation are higher than expectations or retail sales growth is lower than the expectation.

Huang and Kong (2005) is the first paper to study the effect of macroeconomic announcements on the corporate credit spread. The paper selects 11 economic indicators, including the Federal Open Market Committee (FOMC) Target, industrial production, capacity utilization, gross domestic product, unemployment rate, total nonfarm payroll, consumer price index, producer price index, consumer confidence, National Association of Purchasing Managers (NAPM) index, and advanced retail sales, to capture different dimensions of the U.S. economy. Huang and Kong (2005) construct macroeconomic news surprises following Balduzzi, Elton, and Green (2001), and use daily Bank of America Merrill Lynch corporate bond indices spreads from January 1, 1997 through to June 31, 2003. Huang and Kong (2005) find that investment-grade spreads are insensitive to macroeconomic new announcements but that positive surprises to total nonfarm payroll, NAPM index, advanced retail sales, and consumer confidence have negative effects on high-yield spreads.

In a follow-up study, Barragan (2017) uses daily Bank of America Merrill Lynch US Corporate bond index spreads from January 1, 1997 to December 31, 2016. This paper uses gross domestic product, industrial production, unemployment rate, advanced retail sales, nonfarm payrolls, government budget, consumer price index, ISM Manufacturing index, ISM Non-Manufacturing index, and Michigan consumer confidence, to capture movements of macroeconomy. As with Huang and Kong (2005), the paper finds that macroeconomic surprises rarely have significant effects on high-rated spreads (e.g. AAA, AA, and BBB). However, for low-rated spreads, a negative relationship is found between credit spreads and positive surprises in the ISM Manufacturing index, total nonfarm payroll changes, and unemployment rate. The negative relationship between macroeconomic surprises and the credit spread and sensitivity of differentially-rated credit spreads to macroeconomic surprises are consistent with the findings by Huang and Kong (2005).

Apart from the aforementioned empirical papers, another strand of the literature focuses on the effects of monetary policy on credit spreads. For example, Beckworth, Moon, Toles (2010) study how monetary policy announcements affect credit spreads. Using data from January 1, 1959 to June 31, 2008 and conducting the analysis within a VAR framework, the paper finds that a positive monetary policy shock results in a decrease in the spread between Moody's BAA and AAA bond yields with the monetary shock accounting for 42% of the variation in corporate bond yield spreads after 9 months. Cenesizoglu and Essid (2010) use the Federal Fund rate as an indicator of monetary policy and study how its announcements affect monthly average yields on Moody's seasoned+ BAA, A, AA and AAA rated bonds. The paper uses monthly data from May 1989 to December 2008 and defines the monetary shock as the difference between real monthly average Federal Fund rate and the 30-day Federal fund future price. Using linear regression, the paper finds credit spreads increase following negative surprises in the Federal Fund rate in recessions. Javadi, Nejadmalayeri, and Krehbiel (2017) focus on the linkage between Federal Open Market Committee actions and U.S. corporate credit spreads using daily data from August 13, 2002 to December 16, 2012. The paper shows higher or lower than expected Federal Fund rate lower credit spreads and that this effect is stronger for high-yield and short-maturity bonds. On the other hand, credit spreads are positively affected if the real Federal Fund rate equals to its the expected value. Furthermore, during periods when conventional monetary policy was ineffective, quantitative easing announcements also have negative effects on credit spreads for investment-grade, high-yield, short-term and long-term credit spreads

5.2.5 SUMMARY

This section summarizes a broad strand of the literature to which this chapter relates. Theoretical and empirical literature highlights the importance of different dimensions of macroeconomy, such as economic activity, and inflation, in determining credit/CDS spreads. Furthermore, this section details empirical evidence that macroeconomic news announcements significantly affect the equity market, Treasury bond market, and corporate bond market. Commonly used macroeconomic indicators are identified and the effects of macroeconomic announcements, such as total nonfarm payroll, consumer price index, and producer price index, on financial markets are described.

Although there are several studies (Tang and Yan, 2006; Annaert *et al*., 2013; Baum and Wan, 2010; Tang and Yan, 2010; Coro, Dufour and Varotto, 2013) on how macroeconomic condition and volatility affect CDS spreads, there is a dearth of papers documenting how the CDS market reacts to macroeconomic news announcements. As a result, the relationship between macroeconomic announcements and CDS market needs further exploration. This chapter aims to fill this gap.

5.3. DATA DESCRIPTION

5.3.1 CREDIT DEFAULT SWAP INDEX SPREAD

This chapter examines daily end-of-day spreads of investment-grade CDX and high-yield CDX. The CDX spread data used in this chapter is the same as the data used in Chapter 3. The original data is provided by Markit and is obtained from Bloomberg for the period spanning from March 3, 2009 to December 31, 2016. Macroeconomic news is usually released in the morning or afternoon; hence the end of the day spread is more likely to capture the CDS market's reaction to macroeconomic news announcements.

The investment-grade CDX index is constituted from the 125 most liquid North American CDS contracts with investment-grade credit ratings while the high-yield CDX involves the 100 liquid North American CDS contracts with high-yield credit ratings. The investment-grade CDX and the high-yield CDX roll-over every 6 months with any constituents that cannot meet the criteria being removed from the index and newly qualified CDS contracts added to the index to keep the number of constituents unchanged. To remove the roll-over effect on the CDX spread, the roll-over adjusted spread of the investment-grade CDX index and the high-yield CDX index are used in this chapter.

The daily change of the CDX spread on day t is defined as the logarithmic-difference between the CDX spread on day t and the CDX spread on day t-1, with summary statistics for the daily changes of the CDX spread reported in Table 5.1. The statistics indicate that the change of the CDX investment-grade spread and CDX high-yield spread have similar mean, standard deviation, minimum, maximum, skewness, and kurtosis. Furthermore, the last column of Table 5.1 also reports the Jarque–Bera normality test. The probabilities of 0.00 reject the null hypothesises where investment-grade and high-yield CDX spread changes are normally distributed.

Figure 6 graphs the investment-grade CDX spread and high-yield CDX spread. Figure 6 shows that the investment-grade CDX spread and high-yield CDX spread have a big difference in the absolute scale. However, the evolution dynamics of two CDX spread series are similar.

Figure 7 graphs the daily change of the investment-grade CDX spread and the high-yield CDX spread. Figure 7 shows that daily changes of investment-grade CDX spread and high-yield CDX spread also have similar patterns across time, with high-yield series having more extreme outliers. The figure shows 2 series have patterns of heteroskedasticity with two major volatility clustering during the research period. The volatility clustering spanning from April 2010 to July 2010 may have been caused by Standard & Poor's downgrading Greece's sovereign credit rating to junk status therefore triggering more volatile movements in the CDS market. The second volatility clustering spanning from July 2011 to December 2011 and may have arisen due to the CDS market reflecting the contagion of the worsening of the European sovereign debt crisis and the markets' fear of the U.S. sovereign credit rating being downgraded because of the debt-ceiling crisis of the United States.

TABLE 5.1 STATISTICS SUMMARY OF CDX SPREAD CHANGES

CDX	No. Obs	Mean	Std. Dev	Min	Max	Skew	Kurt	JB Prob
CDX IG	2044	-0.05	2.48	-17.36	20.28	0.14	7.41	0.00
CDX HY	2044	-0.07	2.34	-13.76	15.23	0.09	6.07	0.00

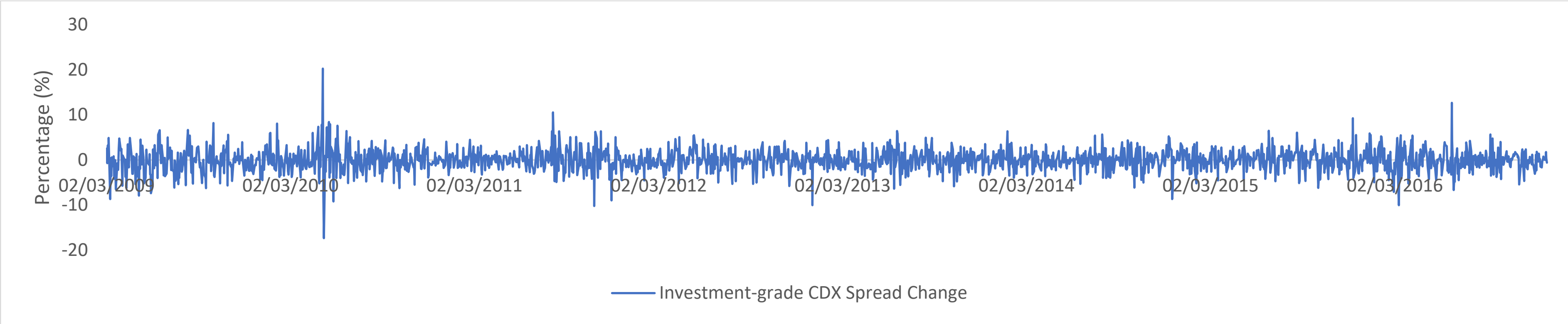
Notes: This table reports descriptive statistics for the change of CDX spreads, spanning from March 3, 2009 to December 31, 2016. CDX IG and CDX HY represents the investment-grade CDX spread change and high-yield CDX spread change. CDX IG and CDX HY are measured in percentage. No.Obs, Mean, Std.Dev, Min, Max, Skew, and Kurt represent the number, mean, standard deviation, minimum, maximum, skewness, and kurtosis. JB Prob is the test probability for the Jarque–Bera normality test.

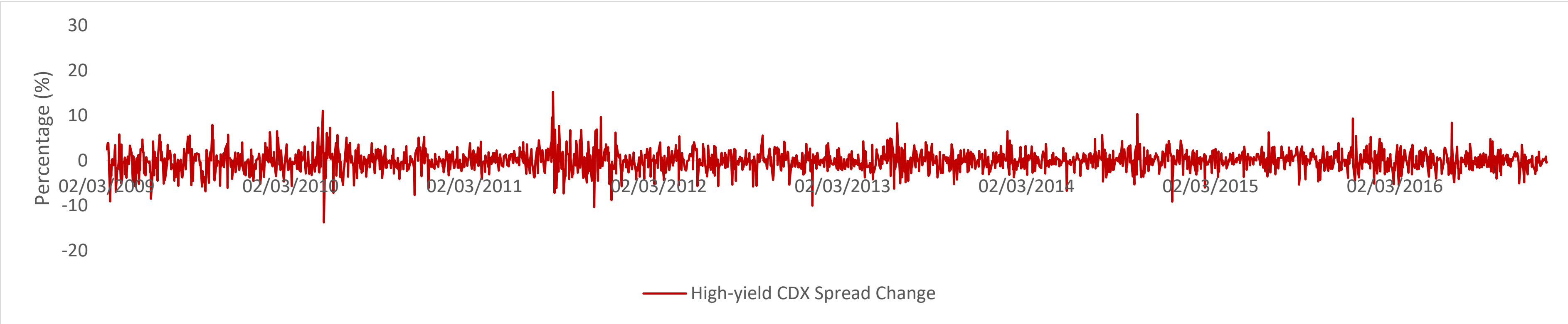
FIGURE 6 DAILY INVESTMENT-GRADE CDX SPREAD AND HIGH-YIELD CDX SPREAD

Data Source: Bloomberg Professional

Notes: This figure represents the daily investment-grade CDX spread and high-yield CDX spread from March 3, 2009 to December 31, 2016. The left vertical axis is measured in basis points and shows the values for the investment-grade CDX spread. The right vertical axis is measured in basis points and shows the values for the high-yield CDX spread.

FIGURE 7 DAILY INVESTMENT-GRADE CDX SPREAD CHANGES AND HIGH-YIELD CDX SPREAD CHANGES





Data Source: Bloomberg Professional
Notes: This figure represents the daily investment-grade CDX spread change and high-yield CDX spread change from March 3, 2009 to December 31, 2016. The y axis is measured in percentage.

5.3.2 MACROECONOMIC NEWS ANNOUNCEMENTS AND FORECASTING DATA

Macroeconomic News Release Data

The data on macroeconomic news releases consists of 13 series of macroeconomic announcements that correspond mainly to variables identified by the literature that reports empirical evidence of their importance in affecting equity, Treasury bond, and corporate bond markets. Thirteen macroeconomic announcements include: gross domestic product, industrial production, total nonfarm payroll, unemployment rate, consumer sentiment, consumer price index, Federal Fund rate upper target, advanced retail sales, durable goods new orders, capacity utilization, ISM Manufacturing index, ISM Non-Manufacturing index, and trade balance. For all macroeconomic indicators, their actual values are released by its original data release source using the Eastern Daylight Time and are provided by Bloomberg.

Gross domestic product, a widely used measure of U.S. output, is the market value of the goods and services produced by labour and property located in the United States. Gross domestic product is a quarterly economic indicator and is released by the Bureau of Economic Analysis of the Commerce Department. The first report of gross domestic product, called the advance report, is released at 8:30 A.M. on the last business day of January, April, July and October (one month after the previous quarter). Because some information is not available immediately, the gross domestic product data is revised in subsequent preliminary and final reports that are released one and two months after the advance report release. This chapter records the advance, preliminary and final reports of the seasonally adjusted quarter-to-quarter growth of gross domestic product (GDP).

Industrial production is an economic indicator that measures real output for all facilities located in U.S. manufacturing, mining, and electric, and gas utilities (excluding those in U.S. territories). Industrial production is a monthly economic indicator and is released by the Board of Governors of the Federal Reserve System. Industrial production is released at 9:15

A.M. in the middle of month. This chapter uses seasonally adjusted month-to-month growth of industrial production (IP) as a macroeconomic indicator.

Total nonfarm payroll and unemployment rate are the main indicators of U.S. labour market condition that have been regarded as 'the king of announcements' by Gilbert *et al.* (2010) with their release found to have significant effects on multiple financial markets in the literature. Total nonfarm, commonly known as total nonfarm payroll, is a measure of the number of U.S. workers in the economy that excludes proprietors, private household employees, unpaid volunteers, farm employees, and the unincorporated self-employed. The unemployment rate represents the number of unemployed as a percentage of the labour force. Nonfarm payroll and unemployment rate (UR) are published by the U.S. Bureau of Labour Statistics on the first Friday of a month at 8:30 a.m. This chapter uses published month-to-month change in total nonfarm payroll (NP) and the seasonally adjusted unemployment rate (UR) to capture labour market movement over the sample.

The consumer price index and producer price index are two indicators that are published by the U.S. Bureau of Labour Statistics to describe U.S. inflation. The consumer price index is published at 8:30 a.m. in the middle of the month with producer price index being published one or two days earlier. The consumer price index and producer price index are also pronounced macroeconomic announcements that have been empirically shown to influence stock and bond markets. Due to the unavailability of the forecasting value of producer price index from Bloomberg after January 2014, this chapter only considers published the seasonally adjusted month-to-month change on consumer price index (CPI) as the inflation measure.

The Federal Fund target rate (RF) is the main indicator of U.S. monetary policy. The Federal Open Market Committee (FOMC) holds eight pre-determined meetings annually to review and make decisions on the Federal Fund rate. The meeting usually lasts for 2 days and the target Federal Fund rate is released in the afternoon of the second meeting day.

Advanced retail sales measures monthly sales of goods to consumers at retail outlets in U.S. Advanced retail sales is released by Federal Reserve Bank of St. Louis at 8.30 A.M. in the middle of the month. This chapter considers the role of the seasonally month-to-month percentage change of advanced retail sales (ARS) at the CDS market.

Durable goods new orders record monthly new orders received from more than 4,000 manufacturers of durable goods, which are generally defined as higher-priced capital goods orders with a useful life of three years or more, such as cars, semiconductor equipment and turbines. The figure is released by Census Bureau of the U.S. Department of Commerce at the end of the month at 8:30 a.m. This chapter examine seasonally adjusted month-to-month change on Durable Goods New Orders (DG).

Capacity utilization is the percentage of resources used by corporations and factories to produce goods in manufacturing, mining, and electric and gas utilities for all facilities located in the United States. It is usually released together with industrial production by the Board of Governors of the Federal Reserve System at 9:15 a.m. in the middle day of the month.

This chapter also adopt trade balance (TB) as one of macroeconomic indicators. Trade balance measures the difference between the value of a country's exports and imports for a given period, accounting for the largest component of a country's balance of payments. The monthly figure is released by U.S. Bureau of the Census at the beginning of the month at 8:30 a.m.

Except for the Federal Fund rate, all macroeconomic announcements are available monthly. The advanced release of gross domestic product in quarter t is released one month after the quarter t, and its preliminary and final releases are released in the subsequent two months successively. Apart from gross domestic Product, values of the rest of the macroeconomic announcements at month t are released at month t+1. A summary of macroeconomic announcements is reported in Table 5.2.

Macroeconomic News Forecasts Data

Bloomberg provides macroeconomic forecasts by a number of economists from reputable institutions a few days before each announcement day. This chapter does not choose the forecast generated by particular economists, discarding forecasts from other economists, because discarded forecasts can contain useful information about the future that is not reflected in the chosen forecast. As a result, Bates and Granger (1969) argue for a combined forecast when alternative forecasts are available.

Bessler and Brandt (1981) Brandt and Bessler (1983) and several subsequent studies report that the simple average of alternative forecasts often work as well as other weighted forecast combinations. As a result, this chapter uses the average of economists' forecasts to measure the market's expectation with regards to macroeconomic news announcements.

Standardized Macroeconomic Surprises

CDS spreads reflect the expected value of macroeconomic indicators and react to the unanticipated component of a news release that represents the distance that separates the released value from its forecast. Following the literature that explores the effects of unexpected macroeconomic news, this chapter adopts the method introduced by Balduzzi, Elton, and Green (2001) and defines the surprise in the nth macroeconomic news announcement at time t as

$$S_{n,t} = A_{n,t} - E_{n,t} \qquad \text{Equation (5.2)}$$

where $A_{n,t}$ is the realized or actual value of the macroeconomic news announcement n at time t; $E_{n,t}$ is the expectation of the market on the macroeconomic news announcement n as provided by Bloomberg.

This chapter removes the difference in measurements units and absolute scales of different macroeconomic news announcements, therefore allowing for more meaningful comparison across different news announcements. A standardized surprise is constructed as

$$SS_{n,t} = \frac{S_{n,t}}{\sigma_n} \qquad \text{Equation (5.3)}$$

where σ_n is the sample standard deviation of the nth macroeconomic news surprise.

Since σ_n is a constant for nth macroeconomic news surprise, the standardization procedure will not affect the statistical significance of the estimated response coefficients or the fit of the regression model. Furthermore, the method of defining the standardized macroeconomic surprise enables this chapter to effectively compare results with those reported by, for example, Huang and Kong (2005) and Barragan (2017) that investigate the effect of macroeconomic news announcement on corporate credit spreads. Summary statistics for the standardized surprises of macroeconomic announcements are reported in Table 5.3.

It is necessary to provide interpretations on standardized macroeconomic surprises. Based on how standardized macroeconomic surprises are constructed, positive standardized macroeconomic surprises of some macroeconomic indicators, including gross domestic product growth, industrial production growth, total nonfarm payroll change, consumer sentiment, Federal Fund rate, advanced retail sales, durable goods new orders, capacity utilization, ISM Manufacturing index, ISM Non-Manufacturing index, and trade balance suggest the actual values of macroeconomic announcement are larger than their expected values. Higher-than-expected values of above macroeconomic indicators indicate that the macroeconomy is better than expected. Therefore, positive standardized surprises of above macroeconomic indicators are good news for the CDS market.

On the other hand, positive standardized surprises of unemployment rate and consumer Price inflation shows that unemployment rate and inflation are higher than expected. Higher-than-expected values of these two macroeconomic indicators indicate that the macroeconomy is worse than expected therefore positive standardized surprises of unemployment rate and consumer price inflation are bad news for the CDS market.

A firm is less likely to default when the economy is expanding but more likely to default when the economy is contracting. As a result, this chapter expects there is a negative relationship between the change of CDX spread and positive standardized surprises of gross domestic product growth, industrial production growth, total nonfarm payroll change, consumer sentiment, Federal Fund rate, advanced retail sales, durable goods new orders, capacity utilization, ISM Manufacturing index, ISM Non-Manufacturing index, and trade balance. However, this chapter expects there is a positive relationship between the change of CDX spread and positive standardized surprises of unemployment rate and Consumer Price inflation.

TABLE 5.2 SUMMARY OF MACROECONOMIC NEWS ANNOUNCEMENTS

Macroeconomic News Announcements	Abbreviation	Unit	Frequency
Gross Domestic Product Growth	GDP	Quarter to Quarter % Change	Monthly
Industrial Production Growth	IP	Month to Month % Change	Monthly
Total Nonfarm Payroll Change	NP	Month-to-month 000's Change	Monthly
Unemployment Rate	UR	% Level	Monthly
Consumer Price Index Growth	CPI	Month to Month % Change	Monthly
Consumer Sentiment	CS	Points Level	Monthly
Federal Fund rate	FR	% Level	8 Times Annually
Advanced Retail Sales Growth	ARS	Month to Month % Change	Monthly
Durable Goods New Orders Growth	DG	Month to Month % Change	Monthly
Capacity Utilization	CU	% Level	Monthly
ISM Manufacturing Index	ISM	Points Level	Monthly
ISM Non-Manufacturing Index	NISM	Points Level	Monthly
Trade Balance	TB	Billions of USD	Monthly

Notes: This table reports descriptive information about macroeconomic announcements that are considered in this chapter.

TABLE 5.3 STATISTICS SUMMARY OF MACROECONOMIC STANDARDIZED SURPRISES

Macro News	No. Obs	Mean	Std. Dev	Min	Max
GDP	94	-0.08	1.00	-2.99	2.27
IP	94	-0.12	1.00	-3.17	2.56
NP	94	-0.02	1.00	-1.96	2.81
UR	94	-0.29	1.00	-3.33	1.84
CPI	94	-0.14	1.00	-2.33	2.85
CS	94	0.09	1.00	-1.86	2.42
FR	63	-0.01	1.00	-6.38	3.72
ARS	94	-0.09	1.00	-3.56	1.96
DG	94	-0.01	1.00	-3.39	5.11
CU	94	-0.06	1.00	-2.91	2.31
ISM	94	0.18	1.00	-2.82	2.19
NISM	94	0.07	1.00	-2.77	2.51
TB	94	-0.09	1.00	-2.69	2.67

Notes: This table presents statistics summary of macroeconomic standardized surprises from March 3, 2009 to December 31, 2016. GDP, IP, NP, UR, CPI, CS, FR, ARS, DG, CU, ISM, NISM, TB are standardised surprises for GDP growth, industrial production growth, total nonfarm payroll change, unemployment rate, consumer price index change, consumer sentiment, Federal Fund rate, advanced retail sales, durable goods new orders, capacity utilization, ISM Manufacturing index, ISM Non-Manufacturing index, and trade balance.

5.4 METHODOLOGY

The analysis is conducted sequentially, studying the joint effect of nth macroeconomic news announcement on the CDX spread. Specifically, this chapter follows the method of Balduzzi, Elton and Green (2001), Huang and Kong (2005) and Barragan (2017), and regress the daily change of CDX spread during the research period on standardised surprises of all macroeconomic indicators:

$$\Delta CDS_t = \alpha + \sum_{n=1} \beta_n SS_{n,t} + \varepsilon_t \qquad \text{Regression (5.1)}$$

where ΔCDS_t is the logarithm difference of CDX spread from day t-1 to day t; $SS_{n,t}$ is the macroeconomic standardized surprise on the macroeconomic announcement type n; $SS_{n,t}$ equals to the standardized surprises for the nth macroeconomic indicator if t is an announcement day; $SS_{n,t}$ equals to zero if t is not the announcement day for the nth macroeconomic indicator.

Two diagnostic tests, Breusch-Godfrey serial correlation LM test and the ARCH Test, are conducted, to detect the serial autocorrelation and heteroskedasticity in residuals of the Regression (5.1).

5.5 EMPIRICAL RESULTS

This section analyses how standardized surprised of macroeconomic announcement affect CDX spread changes. Regression (5.1) is estimated to explore how macroeconomic announcements jointly affect CDX spreads.

The analysis is to explore the joint effect of standardised surprises in 13 macroeconomic announcements by running Regression (5.1). The investment-grade CDX spread change and the high-yield CDX spread change are used as dependent variables and the estimated results are reported in Table 5.4. Panel A and B report results for the investment-grade CDX spread change and high-yield CDX spread change respectively.

Breusch-Godfrey serial correlation LM test and ARCH test are conducted on Regression (5.1) to detect serial autocorrelations and heteroskedasticity in the residuals and results are reported in Panel A and B of Table 5.5 respectively. The null hypothesis of Breusch-Godfrey serial correlation LM test is that there is no serial correlation up to order twelve. The null hypothesis of the Breusch-Godfrey serial correlation LM test is that there is no serial correlation up to order twelve. P value for F-statistic is smaller than 0.05 for both rows, indicating the rejection of the null hypothesis at 95% confidence level. The null hypothesis of the ARCH test is that there is homoscedasticity in the residuals. P value for F-statistic is smaller than 0.01 for both rows, indicating the rejection of the null hypothesis at 99% confidence level. Results show that there are the serial autocorrelation and heteroskedasticity in residuals of the Regression (5.1). As a result, Newey–West standard errors are used to control for autocorrelations and heteroskedasticity in residuals.

Standardised surprises of the gross domestic product, industrial production, consumer price inflation, consumer sentiment, Federal Fund rate, durable goods new orders, capacity utilization, the ISM Non-Manufacturing index, and the trade balance do not have a significant effect on the CDX spread change.

The total nonfarm payroll announcements have a significant negative effect on investment-grade CDX spread change and high-yield CDX spread change at 99% confidence level. The negative relationship between the standardised surprises in total nonfarm payroll and the CDX spread can be related to Huang and Kong (2007) and Barragan (2017) that find a significantly negative relationship between the corporate bond indices spread change and standardised surprises in total nonfarm payroll. However, this section differs from above two studies in the target variable because this section studies the spread change of CDX while two literature studies the spread change of Bank of America Merrill Lynch US bond indices.

Carnes and Slifer (1991) and Andersen and Bollerslev (1998) refer to the total nonfarm payroll as the 'king' of all announcements because of the documented significant sensitivity of most asset prices to its public release. This section finds the importance of total nonfarm payroll in determining the CDS spread change and makes a contribution to the literature by showing that the release of total nonfarm payroll not only affects prices of traditional assets but also affects the spread of credit derivatives, namely the credit default swap.

A positive standardised surprise in the total nonfarm payroll suggests the firm employs more or dismiss less employees than the market's expectation. As mentioned in Chapter 3 and Chapter 4, total nonfarm payroll contains information about the firm's prospects, indicating whether the firm will expand and shrink in the future. A positive standardised surprise the total nonfarm payroll shows that the firm is going to expand more or shrink less than expected, therefore its default risk is likely to be lower than the market expectation. As a result, a positive standardised surprise in the total nonfarm payroll lowers the CDX spread, reflecting a lower than expected firm's default risk.

Furthermore, as mentioned in Section 5.2.3, Balduzzi, Elton and Green (2001) and Ouadghiri, Mignon, and Boitout (2010) document that the positive standardised surprise in the total nonfarm payroll decreases the Treasury bond price and therefore leads to a higher Treasury yield. The negative effects of the Treasury yield, a measure of risk-free rate, on the CDS spread have been documented in extensive theoretical and empirical studies. Apart from affecting the firm's default probability, the standardised surprise in the total nonfarm payroll may affect the CDX spread through affecting the Treasury bond price.

In addition, the standardised surprise of unemployment rate has an insignificant effect on the investment-grade CDX spread change but has a significantly positive effect on the high-yield CDX spread change. The reason that is mentioned by Chapter 3 and Chapter 4, is that the default rate of high-yield companies is more sensitive to the macroeconomic conditions which at least in part can be explained by a greater reliance of high-yield companies on external funding that changes through the business cycle.

Advanced retail sales announcement is significantly negative for the investment-grade CDX spread change at 90% confidence level and is significantly negative for the high-yield CDX spread change at 95% confidence level. The significantly negative effect of advanced retail services on the CDS spread change shows that announcements of advanced retail services are of importance in determining the CDX spread change. Advanced retail services are important components of the GDP and can capture the different aspects of the aggregate economic output. Positive standardised surprises in advanced retail sales provide signals of a growing U.S. economy in which firms are less likely to default. Negative standardised surprises in advanced retail sales and trade of balance provide signals of a shrinking U.S. economy in which firms are more likely to default. This rationale may help to explain the significantly negative relationship between the CDX spread and the advanced retail sales.

In addition, the significance for advanced retail services may help to explain why GDP announcements, a more comprehensive measure of the economic output, are not significant in determining the CDX spread change. Advanced retail services are released ahead of GDP. The CDS market investors may be obtaining the information about the performance of the aggregate economy from the release advanced retail services and as a result, do not react to the GDP announcements. Another reason for the insignificance of GDP, although it is irrelevant to main topic of this chapter, is that GDP experiences several revisions. These revisions make the CDS market not to react to the announcement of GDP because the investors may believe that the GDP figures released are not accurate and will be revised in the future.

The ISM manufacturing index is found to have a significantly negative effect on investment-grade and high-yield CDX spread changes at 90% confidence level.

Furthermore, the coefficient of independent variables can be interpreted as the percentage change of the CDX spread due to 1 unit of standardised surprise in a macroeconomic announcement. Among all macroeconomic announcements that have significant effects, total nonfarm payroll has the most powerful and profound effect on the CDX spread because the percentage change of CDX spread this is caused by 1 unit of standardised surprise in total nonfarm payroll is the largest. As mentioned in previous paragraphs, the release of total nonfarm payroll can affect the CDX spread change through 2 channels. Furthermore, the employment condition has a direct linkage with the firm's future expansion strategy and the firm's default probability. These reasons may make the total nonfarm payroll the most profound macroeconomic announcement.

Finally, Table 4.7 shows that standardised surprised of macroeconomic indicators can jointly explain 0.66% of total variation in the investment-grade CDX spread change and 0.74% of total variation in the high-yield CDX spread change. The adjusted R squares are small, indicating although standardised surprises in macroeconomic announcements have explanatory power, their power is limited. The small adjusted R square is in line with Huang and Kong (2007) and-Barragan (2017) that find macroeconomic standardised surprise can jointly explain a small percentage of total variation in the credit spread change in Bank of

America Merrill Lynch Corporate bond indices.

In summary, the standardised surprise of total nonfarm payroll, advanced retail sales, and the ISM Manufacturing index have a significantly negative effect. The standardised surprise in the unemployment rate has a significantly positive effect on the high-yield CDX spread change but has insignificant effect on the investment-grade CDX spread change.

TABLE 5.4 THE EFFECT OF MACROECONOMIC STANDARDIZED SURPRISES ON CDX SPREAD CHANGES

	Panel A: CDX IG	Panel B: CDX HY
Constant	-0.0445	-0.0578
	(-0.8234)	(-1.0730)
GDP	0.1787	0.1704
	(0.6521)	(0.7401)
IP	0.0226	-0.1378
	(0.0618)	(-0.3965)
NP	-0.9692***	-0.7998***
	(-3.5057)	(-3.6768)
UR	0.1985	0.4280**
	(0.9570)	(2.3845)
CPI	0.2857	0.2275
	(0.9196)	(0.6751)
CS	-0.1206	-0.0763
	(-0.5237)	(-0.3410)
FR	-0.3954	-0.31898
	(-1.0232)	(-1.0044)
ARS	-0.4126*	-0.5372**
	(-1.9503)	(-2.2660)
DG	-0.0140	-0.1678
	(-0.0606)	(-0.9138)
CU	-0.0530	0.0299
	(-0.1353)	(0.0935)
ISM	-0.5386**	-0.5485***
	(-2.4395)	(-2.6993)
NISM	-0.2458	-0.1636
	(-1.32597)	(-1.00332)
TB	-0.1639	-0.2456
	(-0.6769)	(-1.0666)
Adjusted R Square	0.0066	0.0074
No. Obs	2043	2043

Notes: This table presents estimated results of Regression (5.1) using CDX IG and CDX HY spread changes as dependent variables. CDX IG is the investment-grade CDX spread change; CDX HY is the high-yield CDX spread change; GDP, IP, NP, UR, CPI, CS, FR, ARS, DG, CU, ISM, NISM, TB are standardised surprises in gross domestic product, industrial production, total nonfarm payroll, unemployment rate, consumer price index, consumer sentiment, Federal Fund rate, advanced retail sales, durable goods new orders, capacity utilization, ISM Manufacturing index; ISM Non-Manufacturing index; and trade balance. The sample period is from March 3, 2009 to December 31, 2016. The estimation is carried out by using Newey-West standard errors to control for autocorrelation and heteroskedasticity. T-statistics are given in parenthesis. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

TABLE 5.5 DIAGNOSTIC TEST RESULTS FOR REGRESSION (5.1)

Panel A: Breusch-Godfrey Serial Correlation LM Test for Regression (5.1)

	F-statistic	Prob. F (2,2028)
CDX IG	4.4464**	0.0118
CDX HY	9.3427***	0.0001

Panel B: ARCH Heteroskedasticity Test for Regression (5.1)

	F-statistic	Prob. F (1,2041)
CDX IG	32.7863***	0.0000
CDX HY	23.9818***	0.0000

Notes: Panel A and B of this table shows the results of Breusch-Godfrey serial correlation LM test and the ARCH Heteroskedasticity test on Regression (5.1), with the investment-grade CDX spread change and the high-yield CDX spread change being dependent variables respectively. CDX IG is the investment-grade CDX spread change; CDX HY is the high-yield CDX spread change; GDP, IP, NP, UR, CPI, CS, FR, ARS, DG, CU, ISM, NISM, and TB are standardised surprises of gross domestic product, industrial production, total nonfarm payroll, unemployment rate, consumer price index, consumer sentiment, Federal Fund rate, advanced retail sales, durable goods new orders, capacity utilization, ISM Manufacturing index, ISM Non-Manufacturing index, and trade balance. The sample is from March 3, 2009 to December 31, 2016. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

5.6 CONCLUSION

This chapter is based on previous two chapters and extends the research by analysing how macroeconomic announcements influence the spread of CDS index.

The analysis focuses on daily changes in two CDS indices, investment-grade CDX and high-yield CDX and the research period spans from March 3, 2009 to December 31, 2016. 13 U.S. macroeconomic indicators are included in the chapter and they include the gross domestic product, industrial production, total nonfarm payroll, unemployment rate, consumer price index, consumer sentiment, the Federal Fund target rate, advanced retail sales, durable goods new orders, capacity utilization, ISM Manufacturing index, ISM Non-Manufacturing index, and trade balance. Standardised surprises of macroeconomic news are defined as the ratio of the difference between actual and forecasting release values to its sample standard deviation.

The empirical analysis explores the joint effect of macroeconomic standardized surprises by running multivariate regressions of CDX spread changes on macroeconomic standardized surprises for all macroeconomic variables. The data sample in this analysis includes both announcement and non-announcement days. The regression standard errors are adjusted for serial autocorrelations and heteroskedasticity in residuals.

Macroeconomic standardized surprises in total nonfarm payroll changes, advanced retail sales, and the ISM Manufacturing index have a significant negative effect on CDX spread changes. An unexpected increase in total nonfarm payroll, advanced retail sales, and the ISM Manufacturing index may signal that the economic growth is better than expected, leading to a lower default rate of firms, and hence, lower CDS spreads.

The macroeconomic standardised surprise in the unemployment rate has a significantly negative on the high-yield CDX spread change but does not have significant effect on the investment-grade CDX spread change. This may be because that as discussed in Chapter 3 and Chapter 4, high-yield companies are more sensitive to macroeconomic conditions.

External funding is constrained during recessions, which affects high-yield companies more because their investment and expansion strategies rely more on external funding. As a result, macroeconomic conditions play a more significant effect on the high-yield CDX spread change.

In addition, nonfarm payroll announcements have the most profound effect on the CDX spreads among all significant announcements. This may be because, apart from affecting the CDS directly through updated expectations of default risk of firms, the announcement of total nonfarm payroll also influences the CDX spread indirectly by influencing the Treasury bond yields.

The main contribution of this analysis is that this is the first paper to study how macroeconomic announcements affect the CDX spread. This chapter finds that macroeconomic announcements, including industrial production, total nonfarm payroll, advanced retail sales, ISM Manufacturing index, and trade balance, have significant effect on the CDX spread. Consequently, the analysis provides evidence that macroeconomic announcements affect not only traditional asset markets such as bond and equity markets but also affect derivatives markets, namely the CDS market.

One weakness of this chapter is that it only focuses on the effects of macroeconomic announcements on the CDS index spread change. This weakness gives some inspirations on future research to study the effects of macroeconomic announcements on the single-name CDS spread, with firm heterogeneity being considered.

6. CONCLUSIONS

6.1 SUMMARY OF FINDINGS

This section offers a summary of main findings from the analysis in the three empirical chapters of this thesis. Contributions of the work in this thesis and empirical implications are also outlined. Finally, this chapter identifies some weaknesses of this thesis and suggests potential topics for future research.

The empirical investigation in all three empirical chapters of this PhD thesis focuses on the period from March 2009 to December 2016, with data being collected from Bloomberg and Federal Reserve Economic Data database, to provide an extended analysis on the macroeconomic determinants of the U.S. corporate CDS spread.

The findings from all three chapters provide evidence on the significant effect of macroeconomy on the CDS spread. This result holds for both CDS instruments investigated in the thesis: CDX index and single-name CDS.

First, Chapter 3 investigates how macroeconomic level variables and macroeconomic volatility variables, representing multiple dimensions of the macroeconomy, influence the spread of CDX. The CDX represents a basket of single-name CDS contracts, therefore effects of macroeconomic variables, especially macroeconomic level variables, may average out to some extent, making their effects on the index less pronounced. This reason inspires Chapter 4 to conduct the analysis on macroeconomic determinants of the spread of CDS contracts written on individual firms. Finally, the thesis conducts a separate analysis in Chapter 5, to study how macroeconomy affects the CDX spread from a different perspective by studying how macroeconomic news announcements affect the CDX spread.

Chapter 3 explores how macroeconomic level and volatility affect the CDS index spread in a time series analysis framework. The chapter analyses the spread of two CDS indices in Northern America market, investment-grade CDX and high-yield CDX, as the dependent variables, to separately measure the effect of macroeconomic variables on investment-grade CDX spread and high-yield CDX spread, respectively. The chapter incorporates four macroeconomic indicators, including the industrial production growth, total nonfarm payroll growth, consumer price inflation and 3-month Treasury Bill rate, within the CDS pricing model, to capture multi-dimensional nature of the U.S. macroeconomy. Volatilities of these macroeconomic indicators are constructed using autoregressive moving-average and autoregressive conditional heteroskedasticity (ARMA-GARCH) models. One exception to the volatility measure relates to the 3-month Treasury Bill rate. As the Treasury Bill yields are updated daily, the monthly volatility of the 3-month Treasury Bill rate is measured using the standard deviation of daily data within the month.

Chapter 3 first finds that macroeconomic level variables and macroeconomic volatility variables both have significant effects on the CDX spread. In particular, the total nonfarm payroll growth, an employment indicator that has not been previously examined in the CDS pricing literature, has a significantly negative effect on the CDX spread. The total nonfarm payroll reflects companies' hiring decisions that signal their expansion or growth prospects that, in turn, are linked to their future risk of default. This finding highlights the importance of employment conditions in determining the CDX spread and suggests that total nonfarm payroll growth or alternative employment indicators may be of relevance to future studies on pricing the CDX spread.

Chapter 3 also finds that the volatility of industrial production growth has a significantly positive effect on the CDX spread. This finding is consistent with the theoretical model by Tang and Yan (2006) and empirical findings by Baum and Wan (2010) and Tang and Yan (2010). Furthermore, Chapter 3 finds that the volatility of 3-month Treasury rate has a significantly positive effect on the high-yield CDX spread but an insignificant effect on the investment-grade CDX spread. This may be because high-yield companies are known to heavily rely on short-term external funding. As the cost of such funding tends to change with the short-term risk-free interest rate, high-yield CDX spread is more sensitive to the volatility of the short-term rate that may be informative of its future changes.

Furthermore, Chapter 3 shows that macroeconomic variables can explain around 65% of total variation in the high-yield CDX spread and around 43% of the total variation in the investment-grade CDX spread. This finding suggests that credit quality play a role when macroeconomy affect the CDX spread. The potential explanation for a greater explanatory power of macroeconomic variables for the high-yield CDX spread is that the investment decisions of high-yield companies relies more on external funding that is exposed to business cycle variations, therefore default probabilities of high-yield companies change more with the business cycle relative to the investment-grade companies.

Chapter 3 further evaluates the relative importance of macroeconomic level variables and macroeconomic volatility variables in determining the CDX spread by comparing the marginal contributions of the two variable groups to the explained variation in the CDX spread. The findings show that both macroeconomic variable groups are of importance in explaining the total variation in the CDX spread, with macroeconomic level variables and macroeconomic volatility variables contributing approximately 75% and 25% to the explained variation in the CDX spread, respectively. This finding may help to improve the explanatory power of future CDS pricing studies as some current literature such as Lesplingart, Majois, and Petitjean (2012) do not control for macroeconomic conditions or volatility and Ericsson, Jacobs and Oviedo (2009) consider macroeconomic level but omits macroeconomic volatility variables when pricing the CDS spread. In addition, the results show that macroeconomic level group of variables makes a notably greater marginal contribution than macroeconomic volatility variables to explaining the CDX spread. One potential reason for the lower marginal contribution made jointly by macroeconomic volatility variables is that macroeconomic volatility variables can affect the CDX spread indirectly via affecting macroeconomic level variables. As a result, the marginal contribution measure may not reflect the whole effect of macroeconomic volatility variables.

Chapter 3 also contributes to the literature by studying the sensitivity of the CDX spreads with different credit qualities to macroeconomic variables. To the best of my knowledge, this is the first sensitivity analysis study that accounts for the substantial difference in the absolute values of the investment-grade and high-yield CDX spread. Results show that the high-yield CDX spread is more sensitive to macroeconomic variables than the investment-grade CDX spread. In particular, the high-yield CDX spread is 1.5 to 2 times more sensitive to the total nonfarm payroll growth, the volatility of industrial production growth and the volatility of 3-month Treasury Bill rate than the investment-grade CDX spread. The higher sensitivity of the high-yield CDS spread to macroeconomic variables might because investment and financing strategies of high-yield companies heavily rely on the external funding that changes significantly with macroeconomy.

The analysis in the next empirical Chapter 4 builds on the analysis in Chapter 3 and further extends the research by studying the effects of macroeconomic growth and volatility on the CDS spread at the firm level in a panel data analysis framework.

Chapter 4 uses single-name CDS contracts that are written on 197 companies. The whole data sample contains 18105 monthly CDS spreads quotes, with 13116 quotes for 154 firms falling into investment grade sub-sample and 4989 quotes for 75 firms falling into the high yield sub-sample. Apart from macroeconomic condition and volatility variables that are used in Chapter 3, several firm-specific variables, leverage, cash flow, and cash flow volatility, are introduced in Chapter 4 as firm-specific variables.

Chapter 4 finds that leverage, industrial production growth, total nonfarm payroll growth, the volatility of industrial production growth, and the volatility of 3-month Treasury Bill rate play a significant role in determining the single-name CDS spread.

Chapter 4 also conducts separate analysis on the investment-grade and high-yield sub-sample. Results show that effects of firm-specific and macroeconomic variables differ across CDS of different credit qualities. Operating cash flow volatility has a significantly positive effect on the investment-grade CDS spread but has no effect on the high-yield CDS spread. One explanation for this is that the investment of high-rated companies typically relies on internal funding and, therefore, it is more sensitive to the firm cash flow, with a more volatile cash flow indicating a higher uncertainty about future investment projects for investment-grade firms.

Similarly, the volatility of total nonfarm payroll growth has a significantly positive effect on the investment-grade CDS spread but has no effect on the high-yield CDS spread. A potential explanation for this finding is that more volatile employment conditions, associated with a higher uncertainty about the company's growth prospects, may be also indicative of greater uncertainty about the firm's operating cash flow that, in turn, as indicated in the previous paragraph, has greater implications for investment-grade companies than high-yield companies.

In contrast, industrial production growth and the nonfarm payroll growth have a significant effect on the high-yield CDS spread but not on the investment-grade CDS spread. This result can be linked to high-yield companies relying more on external funding, with both the cost and availability of such funding changing dramatically with the business cycle.

Furthermore, the relative importance analysis of the firm-specific and macroeconomic variable groups shows that firm-specific variables account for more than 90% of explained variation in the CDS spread. Macroeconomic variables make only a moderate marginal contribution to the explained variation in the CDS spread. This might because macroeconomic variables, especially macroeconomic level variables, are known to affect the firm-specific variables, especially those reflecting the firm's financing decisions such as leverage. Therefore, the explanatory power of the macroeconomic variables may be not fully reflected by the marginal contribution measure. The relative importance analysis further shows that among the two groups of macroeconomic variables, macroeconomic volatility variables are more important. This is potentially because the effect of the macroeconomic levels is absorbed to some extent by the firm-level variables.

Finally, the sensitivity analysis shows that high-yield CDS spreads are more sensitive to leverage, the volatility of industrial production growth, and the volatility of 3-month Treasury rate. The volatility of industrial production growth and the volatility of 3-month Treasury rate can affect high-yield CDS spreads more via the external funding channel.

The final empirical chapter, Chapter 5 further extends the analysis in the previous chapters by adopting a different angle, focusing on the effect of macroeconomic news announcements on the CDS index spread. This chapter analyse this research topic using daily investment-grade CDX spread change and high-yield CDX spread change data spanning from March 3, 2009 to December 31, 2016 in a time series analysis framework. Following the literature, the analysis adopts CDX spread changes, measured as the logarithm differences between daily CDX spread, as the target variable. The analysis examines the effect of announcements for 13 macroeconomic indicators, including gross domestic product, industrial production, total nonfarm payroll, consumer price index, Federal Fund rate, advanced retail sales, durable goods new orders, capacity utilization, ISM Manufacturing index, ISM Non-Manufacturing index, and trade balance, within a multivariate regression frameworks.

Multivariate analysis results further show that the surprise components in total nonfarm payroll, advanced retail sales, and the ISM Manufacturing Index significantly decrease the CDX spread change. The standardised surprise in the unemployment rate has a significantly negative on the high-yield CDX spread change but does not have significant effect on the investment-grade CDX spread change. A potential explanation for this finding is that the investment of high-yield companies relies more on external funding that changes dramatically with the macroeconomy, making high-yield companies' CDS more sensitive to changes in macroeconomic indicators.

In addition, among all macroeconomic announcements, total nonfarm payroll has the most profound effect on the CDX spread change because the percentage change of CDX spread caused by 1 unit of standardised surprise total nonfarm payroll is the largest. This maybe because total nonfarm payroll can affect the CDX spread directly by updating CDS traders' expectations of default risk of firms, and also indirectly by influencing the Treasury bond yields.

6.2 CONTRIBUTIONS TO THE LITERATURE

The findings of the analysis in the three empirical chapters make the following main contributions to the literature.

This thesis contributes to the literature by exploring joint effects of various dimensions of the macroeconomy on the CDS spread of two different CDS instruments, namely CDX index spread and single-name CDS. A relatively small number of papers that include Baum and Wan (2010) study empirically the effects of macroeconomy on corporate credit spreads or CDS spreads. In contrast to the study here, they consider only a limited set of macroeconomic variables that tend to capture only one or two aspects of the economy, typically the risk-free rate and economic output. This thesis a more comprehensive set of macroeconomic variables, including industrial production, total nonfarm payroll, consumer price index, and 3-month Treasury rate for United States, to explore how real economic activity, inflation, employment and interest rates determine the CDS index spread and the single-name CDS spread.

In addition, previous CDS literature either omits macroeconomic volatility from consideration altogether or like in Tang and Yan (2010) and Baum and Wan (2010) only considers the volatility of macroeconomic output as captured either by the GDP growth volatility or industrial production volatility. The analysis in this thesis expands this literature by studying the effect of uncertainty in several key macroeconomic indicators, reflecting real economic activity, inflation, employment and interest rates.

Furthermore, the relative importance analysis further evaluates the relative contribution of various variable groups and shows that both macroeconomic level variables and macroeconomic volatility variables matter for explaining the variation in the CDX index spread. For the single-name CDS spread, all three groups of variables: firm-specific variables, macroeconomic fundamentals and macroeconomic volatility are of importance in explaining the spread variation.

Another contribution is that this thesis conducts a sensitivity analysis of the investment-grade and high-yield CDX/CDS spreads to various macroeconomic variables that explicitly accounts for a considerable difference in the absolute value of high-yield and investment grade spreads. In this respect, this thesis extends the work of Baum and Wan (2010) that examines the CDS spreads of different credit quality to the economic output growth volatility measures only. In this thesis, the sensitivity of CDX/CDS spread to a broader set of macroeconomic level variables and macroeconomic volatility variables is compared.

Finally, this thesis contributes to the literature on the effects of macroeconomic announcements on financial market series by studying the link between the macroeconomic announcements and the CDS market. The previous literature focuses on equity, Treasury bond and corporate bond markets, overlooking the corporate CDS market. This thesis is the first to show that macroeconomic announcements, such as total nonfarm payroll and advanced retail sales, not only play a role in affecting the stock market, corporate bond market, and Treasury bond market, but also affect the corporate CDS market. In addition, the chapter examines the effect of macroeconomic news announcements separately on CDX of high and low credit quality, providing evidence of some differences in how CDX of high and low credit quality responds to certain macroeconomic announcements.

6.3 CONTRIBUTIONS TO POLICY DEBATES

Apart from contributing to the literature, the empirical findings in this thesis have some implications for economic policy makers and financial markets regulators. In particular, the findings in this thesis show that macroeconomic variables can explain approximately 40% to 65% of the total variation in the CDX spread. The strong explanatory power of macroeconomy is of importance to economic policy makers who should be aware of how changes of macroeconomic conditions affect CDS markets when developing economic policies. This finding will also improve the ability of financial market regulators to better understand the key risk-factors affecting the CDS markets.

Furthermore, Chapter 3 and Chapter 4 identify a novel important determinant, highlighting the significant effect of total nonfarm payroll and its volatility for the CDS markets, highlighting the importance of accounting for employment conditions when pricing CDS. This finding may be of interest to credit rating agencies. As the CDS reflect the market pricing of firms' default risk, credit rating agencies may benefit from paying a closer attention to the country' employment conditions when determining the company's credit rating.

6.4 SUGGESTIONS FOR FURTHER RESEARCH

This study has the following weaknesses. The first weakness of this PhD thesis is that this thesis only examines data from March 2009 to December 2016, with more recent data not being included. Including more recent data can update pricing dynamics of the CDS contract. Furthermore, including more recent variables can extend the sample period, which make the ARMA-GARCH model to produce more representative and reliable conditional variance.

Furthermore, as mentioned in Chapter 5, the daily end-of-day data may not fully capture the reaction of the CDS market to macroeconomic announcements. The CDX spread may contain additional new information, not related to the macroeconomic announcement of interest, at the end of announcement day. Therefore, a follow up study that uses higher frequency data may provide additional useful insights.

This thesis establishes a link between the macroeconomy and credit derivatives pricing and provides diverse directions for the future research.

This thesis studies the macroeconomic determinants of corporate CDS spread in U.S. market and finds that macroeconomic factors play a significant role in determining the CDS spread. This finding inspires the future research to focus on other regional markets, such as Eurozone market and emerging markets.

Furthermore, Chapter 4 does not report of any significant effect of the firm's cash flow measure on the single-name CDS spread. One potential reason, as mentioned in Chapter 4, is that the operating cash flow over total asset does not sufficiently capture cash flow level of the firm. This explanation inspires future research to study how cash flow affect the CDS spread, with the application of alternative cash flow measures.

In addition, several studies have documented cross-border effects of U.S. macroeconomic announcements on other regional stock markets. These studies give some ideas about the future research on cross-border effects of U.S. macroeconomic announcements on other regional CDS markets.

In relation to the analysis of how macroeconomic announcements affect the index-level CDS spread, future research can be based on Chapter 5 to study how macroeconomic announcements affect the firm-level CDS spread with an event study framework.

Furthermore, as mentioned in this chapter, one potential reason for the low explanatory power of macroeconomic announcements is that the end-of-day CDX spread cannot fully capture the reaction of the CDS market to macroeconomic announcements. High-frequency data, such as tick-by-tick CDX spread, might be better option to capture the reaction of the CDX spread. Due to the restriction on accessing the high-frequency data, this chapter can only conduct the analysis on daily basis. The shortcoming of this chapter inspires the future research to study this topic using high-frequency data.

APPENDIX A

Appendix A provides further detail on the interpolation methods utilised in Chapter 3 to derive monthly values for real gross domestic product (GDP) using the Chow-Lin method.

The original Chow and Lin (1971) paper outlined a method for disaggregating time series using time series models. Without loss of generality, assume that, given annual values of a time series, y^A, the objective is to construct, by interpolation, a quarterly series, y^Q. Chow-Lin's proposal is based on the assumption that it is possible to write the series to be constructed as a linear stochastic relationship of some observed quarterly series, x^Q:

$$y^Q = \beta x^Q + \varepsilon \qquad \text{Equation (A.1)}$$

Denoting K as the n x 4n aggregation matrix that converts quarterly series to annual values by pre-multiplication, then the annual series y^A can be represented as:

$$y^A = K\beta x^Q + K\varepsilon \qquad \text{Equation (A.2)}$$

where Kx^Q represents the annual equivalent value of x^Q; and $K\varepsilon$ is a vector of random disturbances.

The original Chow and Lin (1971) paper does not consider the issue of non-stationarity of regression which commonly arises among macroeconomic time series variables. However, subsequent analysis by, for example, Pinheiro and Coimbra (1992), Aadland (2000), and Fonzo (2003) do, with the latter suggesting that the Chow-Lin method can be applied to the logarithmic difference of non-stationary variables by running the following equation:

$$\Delta GDP_t = \alpha + \beta \Delta ARS_t + \varepsilon_t \qquad \text{Equation (A.3)}$$

where ΔGDP_t is the logarithmic difference of the GDP level in Quarter t; ΔARS_t is the logarithmic difference of the advanced retail sales in Quarter t.

Potentially compounding the problem of non-stationarity is the possibility that the non-stationary time series to be interpolated and interpolating series are co-integrated. In this case, Santos Silva and Cardoso (2001) offer a simple methodology for interpolation.

To test whether our two series, GDP and advanced retail sales are non-stationary and co-integrated, we first apply the augmented Dickey-Fuller test to the quarterly series prior to conducting the Johansen co-integration test. These results are reported in Table A.1 and A.2 respectively.

The null hypothesis for the augmented Dickey-Fuller test is that there is a unit root in the series. P values for quarterly GDP and quarterly advanced retail sales level are larger than 0.1, which suggests a non-rejection of the null hypothesis at 90% confidence level. P values for quarterly logarithmic differences of GDP and advanced retail sales are smaller than 0.01, which suggests a rejection of the null hypothesis at 99% confidence level.

In relation to the Johansen co-integration test we explore the presence of a common stochastic trend under alternative assumptions regarding the deterministic trend. The null hypothesis is that there is no co-integration and in all cases the p-value is larger than 0.1, which suggests acceptance of the null hypothesis and no co-integration between the two series.

In the absence of co-integration, monthly interpolated values for real GDP can be obtained from estimation results for Equation (A.3). These estimates are reported in Table A.3 below. In addition, Table A.3 is accompanied by Figure 8 that plots the quarterly GDP growth and quarterly advanced retail sales growth.

TABLE A.1 UNIT ROOT TEST ON QUARTERLY LEVEL OF GDP AND ADVANCED RETAIL SALES AND QUATERLY LOG-DIFFERENCES OF GDP AND ADVANCED RETAIL

	t statistics	P value
Log-levels		
GDP	0.96	0.99
ARS	-0.12	0.94
Log-differences		
GDP	-6.33***	0.00
ADS	-6.35***	0.00

Notes: The table shows the unit root test on GDP and ARS. GDP is the quarterly GDP; ARS is the quarterly advanced retail sales. The sample is from 2009Q1 to 2016 Q4. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

TABLE A.2 JOHANSEN CO-INTEGRATION TEST

Panel A Linear Deterministic Trend		Panel B Quadratic Deterministic Trend	
Trace Statistic	P value	Trace Statistic	P value
3.86	0.76	1.67	0.20

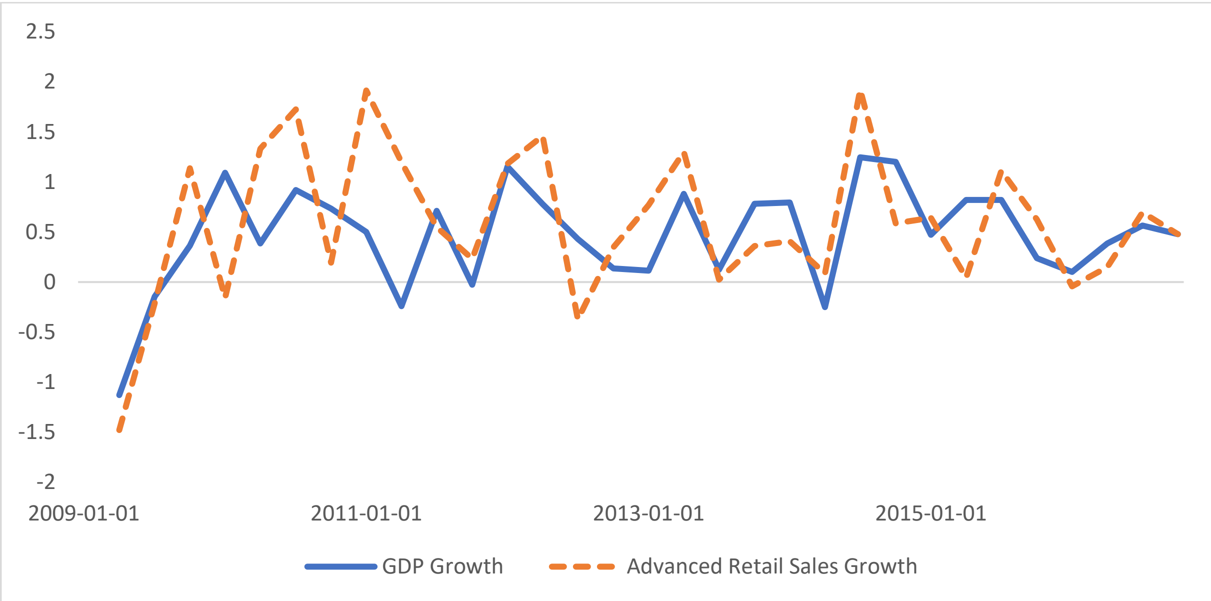
Notes: The table shows the Johansen co-integration test on GDP and ARS. GDP is quarterly value of real GDP; ARS is the quarterly value of advanced retail sales. The sample is from 2009Q1 to 2016 Q4. *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

TABLE A.3 REGRESSION RESULTS FOR CHOW-LIN INTERPOLATION METHOD FOR OBTAINING MONTHLY REAL GDP GROWTH USING ADVANCED RETAIL SALES

	Quarterly GDP Growth
Constant	0.2461**
	(2.5209)
ARS	0.3766***
	(3.5490)
R square	0.2957
Number of observations	32

Notes: The dependent variable is the quarterly growth of real gross domestic product. The explanatory variable is the quarterly growth of Advanced Retail Sales (ARS). Both series are expressed in log-difference form. Advanced retail sales data are available monthly and data in quarter t represents the quarterly-sum of the corresponding monthly data in quarter t. The sample period is from quarter 1, 2009, to quarter 4, 2016. The regression is carried out by using ordinary least square with t-statistics given in parentheses: *, ** and *** denote statistical significance, respectively, at 10%, 5% and 1% level.

FIGURE 8 QUATERLY GROWTH OF THE REAL GDP AND ADVANCED RETAIL SALES



Note: This figure shows quarterly growth of Real GDP and Advanced Retail Sales. The sample is from 2009 Q1 to 2016Q4.

APPENDIX B

Table B.1 shows the number of firms with missing daily quotes CDS spread. The sample is from March 3, 2009 to December 30, 2016.

TABLE B.1

No. of Missing Daily Quotes	0	1 to 40	41 to 80	81 to 120	121 to 160	161 to 200	>= 201	Total No. of Daily Quotes	Total No. of Firms
No. of Firms	155	14	11	4	8	3	2	2045	197

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