Essays on contagion analysis in a small open petroleum economy

Scott Mark Romeo Mahadeo

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Abstract

This thesis focuses on how the relationships between the financial markets of the small open energy economy of Trinidad and Tobago and relevant foreign markets evolve, under alternative stable and unstable international market conditions. The research consists of three essays on contagion analysis, where each make original contributions to the empirical approaches for testing contagion. Essay 1 proposes the concept of energy contagion, which is defined as the strengthening of correlations in the energy-finance nexus under crisis periods in the crude oil market. To perform energy contagion analysis, financial contagion tests are augmented. Building on this, Essay 2 puts forward a new rule-based specification to filter structural oil market shocks to obtain discrete calm and extreme oil supply, global demand, and oil-specific demand shocks. These identified oil market conditions are used to construct oil market contagion tests on important oil-finance nexus relationships. In Essay 3, the focus is on testing for contagion from the S&P 500 market to the major stock markets of the Caribbean region. This US financial market index is decomposed into various conditions of stability and stress to determine the scenarios during which the US and the Caribbean equity market relationships might deepen. The central consolidated conclusions of the thesis show: (1) A negative interdependence exists between the international crude oil market and the real effective exchange rate of Trinidad and Tobago, which implies currency appreciations (depreciations) when oil prices fall (rise); (2) The correlations between the Trinidad and Tobago stock market and either the crude oil or US stock markets are, in general, insensitive to the developments in these source markets; and (3) Evidence of contagion from external markets to Trinidad and Tobago is primarily contained to the 2008/2009 Global Financial Crisis.

Keywords: contagion; correlation; crisis; financial markets; oil; Trinidad and Tobago

JEL classification: C58; G01; O54; Q43

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One of the hardest parts of the PhD was being away from family. As they are likely to only read this page of my PhD thesis to see their names, I am happy to do them this honour. To Roger, Suzie, Sarah, Avidesh, and the rest of the Mahadeo, Singh, and Seenath families, your love is the wind beneath my wings.

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Declaration & Dissemination

In my opinion, good research does not happen in a vacuum. Therefore, I declare that this PhD has benefited from the following scholarly activities.

Various parts of my thesis incorporates the technical skills acquired at a Timberlake Consultants Stata School in Time Series with Applications to Energy Markets, held in February 2018 (Cass Business School, City, University of London, London, UK); the Time Series Workshop with EViews and Stata, held in November 2017 (Montpellier Business School, Montpellier, France); and the Lecture Series on Oil Markets and the Macroeconomy Spring course, held in June 2017 (Centre for Applied Macro and commodity Prices (CAMP), BI Norwegian Business School, Oslo, Norway).

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Earlier versions of Chapter 3 have been presented at the 1st International Conference on Energy, Finance, and the Macroeconomy, held in November 2017 (Montpellier Business School, Montpellier, France); at an Economics and Finance Research Group Seminar Series, held in February 2019 (Keele Business School, University of Keele, UK); at the 6th Annual Money, Macro, and Finance (MMF) PhD Conference, held in April 2019 (Department of Economics at City, University of London, London, UK); and at the INFINITI Conference on International Finance, held in June 2019 (Adam Smith Business School, University of Glasgow, Glasgow, UK). I have benefited from the feedback provided by the audience members in attendance at these events. At the INFINTI conference, I have further benefited from the detailed comments arising from the double-blind peer review process and the dedicated feedback from an assigned discussant.

An earlier version of Chapter 4 has been presented at a HUMSS Work in Progress Seminar Series, held in June 2019 (University of Keele, UK). I thank the participants involved for their feedback.

Finally, I confirm that the contents of the thesis have not been previously submitted for a degree in this or any other university. This PhD research has been conceptualised, executed, and written-up by me, and all sources are fully acknowledged and referenced within. The three papers derived from the thesis have been co-authored with my two supervisors, whose contributions have been in the ordinary supervision capacity.

Dedication

For Avidesh.

Just as Joey has Chandler; as Sheldon has Leonard; as Meredith has Cristina; and as Barry has The JTP... You are my person.

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Chapter 1

Introduction

1.1 Scope of the research

The Republic of Trinidad and Tobago is a *small open petroleum* economy located in the Caribbean region (see Figure 1.1), with a population of 1.4 million. It is crucial for policy makers in small open economies to understand how international developments influence the domestic economy (Aastveit et al., 2016). *Smallness* is a feature which conveys a sense of vulnerability (Briguglio, 1995), and this might be the most plausible explanation for this country's *resource curse*-like symptoms[1] (Saad-Filho and Weeks, 2013). *Openness* suggests a heightened exposure to trade relationships, with the United States being the country's most vital trading partner (see Table 1.1), where the majority of this activity is related to the trade in energy commodities (see, for example, Figure 1.4). The *petroleum economy* characteristic implies a potentially low insulation to shocks from the international

[1] The resource curse describes the paradoxical inability of resource-rich countries to experience the economic growth rates achieved by their resource-poor counterparts (see, *inter alia*, Gelb (1988); Auty and Warhurst (1993); Sachs and Warner (1995)).

oil market, as the proceeding section on oil and the Trinidad and Tobago economy alludes to.

Indeed, the future appears to be dismal for undiversified oil and gas exporting economies. This is in part because the case for environmentally sustainable energy sources is driven by both the need for economic insulation against unfavourable fossil fuel costs, as well as the ever-rising global awareness concerning the impact of anthropogenic greenhouse gases on the planet's climate (Ziegler, 2012; Reboredo et al., 2017; Riti et al., 2017, among others). Moreover, commodity exporters are usually strongly affected by fluctuations in global markets (Beckmann et al., 2020). While changes in energy prices generate changes in income for net energy-exporting economies, exactly *how* such changes in income propagate throughout the rest of the economy is much less straightforward (Bjørnland, 2009). Filis (2010) emphasises the need to examine the linkages among the oil market, the real sector, and financial markets in small economies since their economic and financial realities can be vastly different to the experience of their larger counterparts, coupled with the fact that small economies are under-represented in the literature.

Within the aforementioned context, there are various intricate channels through which shocks from external markets, such as the international crude oil market or the US, can be transmitted to a small open petroleum economy like Trinidad and Tobago. Figure 1.2 attempts to simplify the nexus between the external, real, and financial sectors of such an economy. A reasonable assumption presented in this framework is that the external markets in question are strictly exogenous to such a very small country. One transmission mechanism is for external shocks from the international oil or US stock markets to hit the financial market of Trinidad and Tobago via A, which in turn affects the country's real sector via C. For instance, stock markets tend to absorb information about international news relatively quick, inclusive of developments in the crude oil market (Bjørnland, 2009). This becomes even more relevant when oil is important to the macroeconomy (Wang et al., 2013), as is the case in Trinidad and Tobago (see, for example, Figures 1.3, 1.4, and 1.5). Furthermore, developments in the US stock market are also expected to play a significant role for Trinidad and Tobago, as it is the twin-island's most important trading partner (see Table 1.1), and strong trade linkages can amplify the risk of financial contagion from a source to a recipient country (Kali and Reyes, 2010). Additionally, in open macroeconomy models, external shocks affect the equilibrium real exchange rate (Obstfeld and Rogoff, 1995; Edwards and Yeyati, 2005), which in turn affects domestic output as real exchange rates are a determinant of aggregate demand (Melvin, 1985). It is even practical to assume the effects of external shocks on financial markets will circulate between the domestic financial and real sectors for some time, given the strong connection between financial and business cycles (Claessens et al., 2012).

Another possibility is for external shocks to influence the financial markets of a small open economy through the conduit of the macroeconomy (Bjørnland, 2009). This is illustrated by the transmission mechanism B. Furthermore, there can be feedback effects from the financial sector to the macroeconomy via C, which can also perpetuate. The aforementioned smallness, openness, and petroleum economy features are exactly what make Trinidad and Tobago's macroeconomy potentially vulnerable to both oil and US stock market shocks. Subsequent to this, a distressed macroeconomy can then disrupt domestic financial markets. For example, the literature on early warning systems describes the role leading macroeconomic indicators play in predicting episodes of financial instability (Frankel and Saravelos, 2012).

In this thesis, the transmission channel A in Figure 1.2 is the focus. Therefore, the contributions have explicit implications for how external market shocks influence the financial markets of small open economies, with implicit implications for their real sector. Linkages through trade or commodity prices, and global shocks are common propagation mechanisms of financial shocks across countries and markets (Gelos and Sahay, 2001). Contagion describes the condition where connections amplify during crisis scenarios (Forbes and Rigobon, 2002), implying that negative effects can spillover from a source market to a recipient market during such conditions. As both the international crude oil market and the US are important to the macroeconomy of Trinidad and Tobago, contagion analysis is useful to understand how the relationships between relevant foreign markets and the financial markets of this small open commodity exporter change under evolving external market conditions. The overarching aim of this research is to develop appropriate contagion tests for analysing the direct transmission mechanism A.

Throughout the empirical analyses undertaken in this thesis, the sensitivity of the results to the 2008-2009 Global Financial Crisis (GFC) is a recurring robustness check. In a study of nine episodes of turbulence in global financial markets, ranging from 1997 to 2013, Fry-McKibbin et al. (2014) find that the 2008 Great Recession is a true global financial crisis. As this is an unprecedented event appearing in all the samples of the empirical work of this thesis, care is taken to account for the potential role of the GFC in driving the results by examining full samples and samples where the GFC is censored. For a consistent duration of the GFC, the National Bureau of Economic Research (NBER) Business Cycle Dating Committee's time-stamping of this economic crisis is followed. The NBER establishes that the Great Recession in the US occurred from December 2007 to June 2009[2], which captures the fateful collapse of Lehman Brothers and the subprime mortgage crisis. Given the economic importance of the US for Trinidad and Tobago (see

[2]See www.nber.org/cycles/recessions.html.

for example Table 1.1), this dating for the duration of the GFC is adopted.

The main body of the thesis is organised as three self-contained empirical essays. A joint conclusion synthesises the research. The subsequent section gives a concise overview of oil and the Trinidad and Tobago economy, and the rest of the introduction highlight the rationales, research questions, and the significant original contributions for each of the three essays.

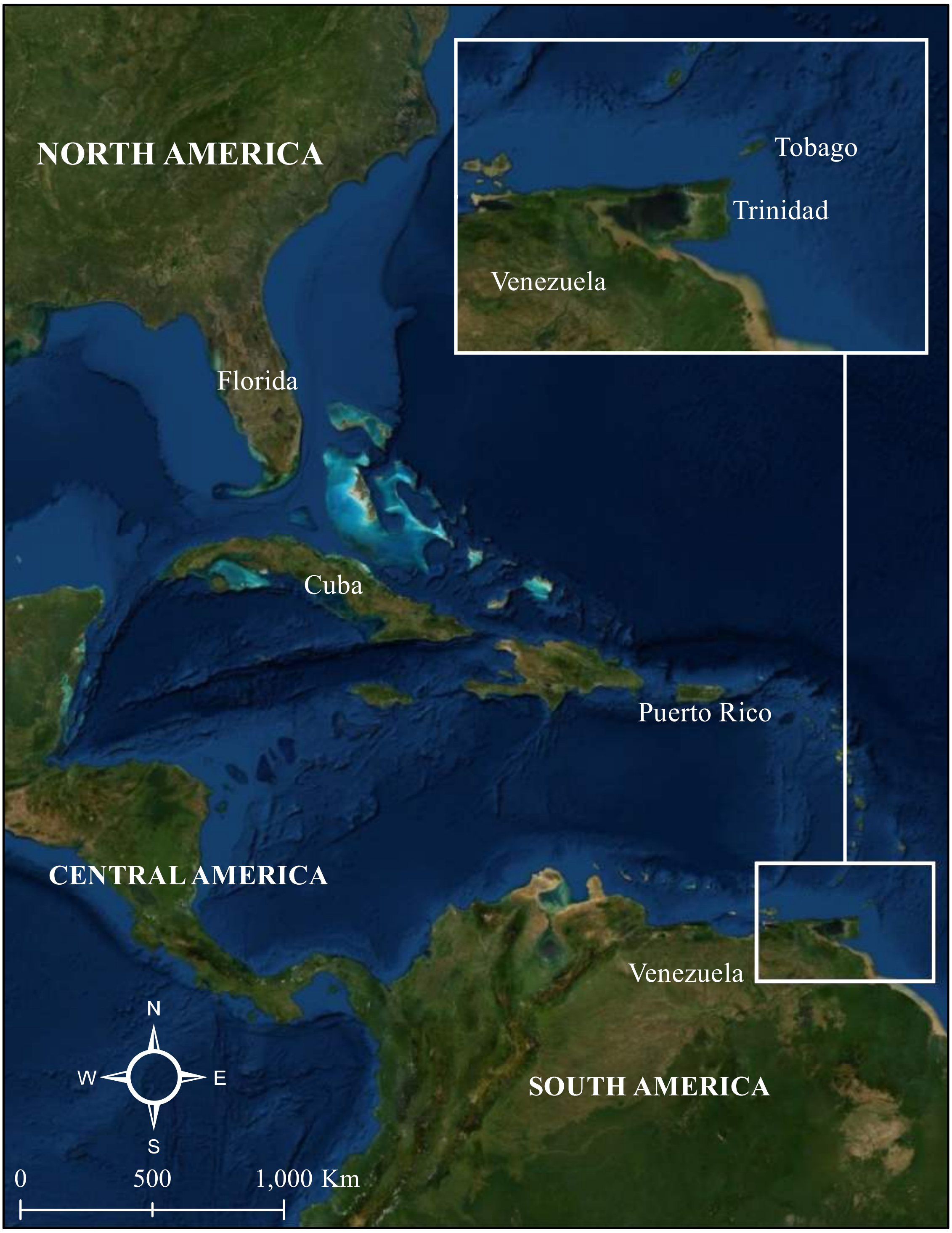

Figure 1.1: Map showing the location of the Republic of Trinidad and Tobago. *Data source*: Created using DigitalGlobe satellite imagery in ArcGIS.

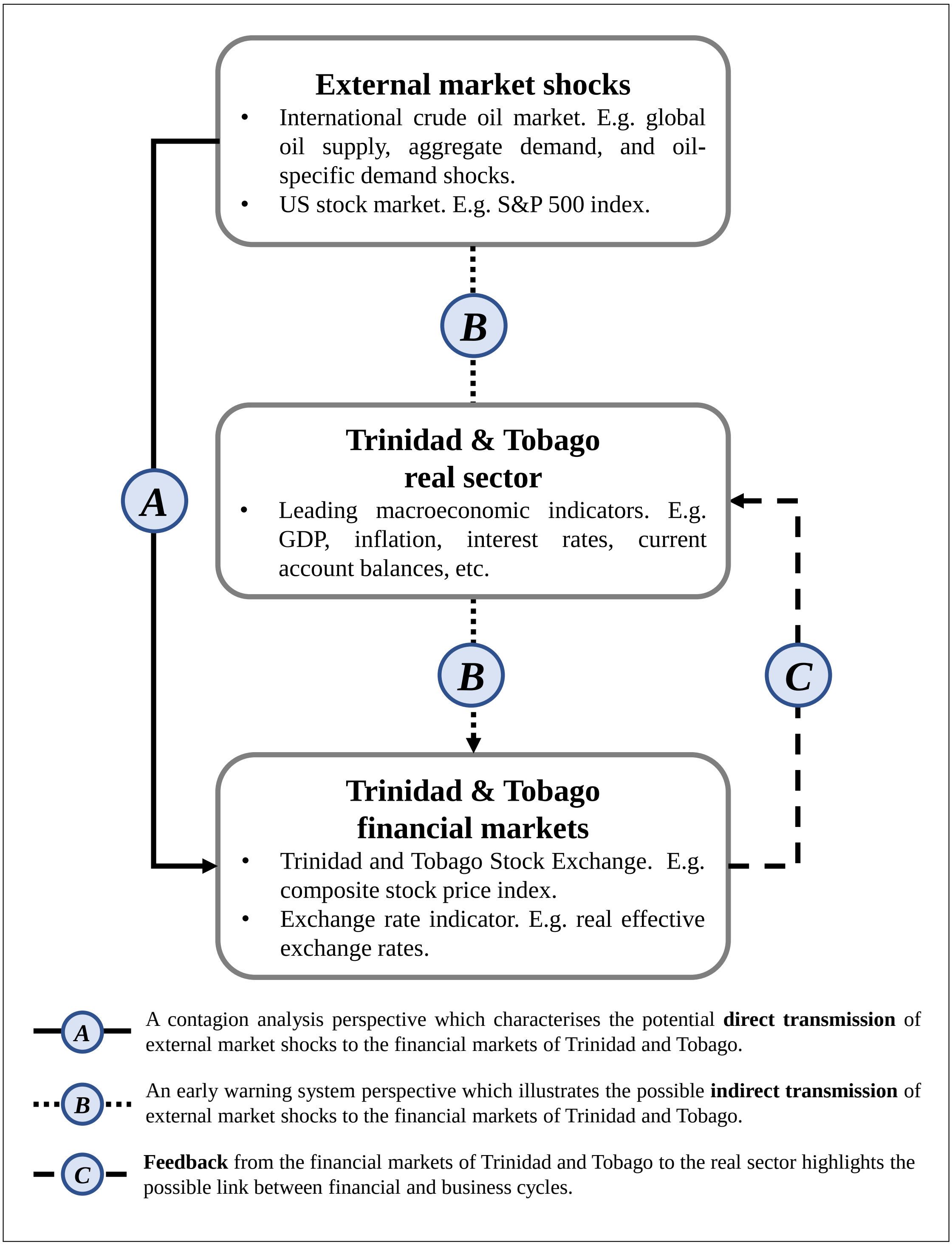

Figure 1.2: Direct and indirect transmission mechanisms of external market shocks to the real and financial sectors of the small open petroleum economy of Trinidad and Tobago. See the text for further explanations of how the transmission mechanisms (A, B, and C) work.

1.2 Oil and the Trinidad and Tobago economy

Oil was discovered in the twin-island in 1857, but production commenced in 1918 with Shell (Gelb, 1988); whereas the first major natural gas reserves were discovered in 1968, off the South East coast of Trinidad, by the Amoco Oil Company (Ram, 2005). Trinidad and Tobago is the sole English-speaking Caribbean small island state to have discovered, extracted, and refined sizeable sub-soil assets. None of Trinidad and Tobago's counterparts have had a comparable pronounced exodus out of the plantation economy inherited from a colonial past (Pollard, 1985). Henry (2007) suggests that the oil fortunes have not been without ramifications, as the country has had to contend with the incredible repercussions[3] of an over-reliance on the energy sector when oil prices collapsed in the 1980s. More recently, Auty (2017) asserts that Trinidad and Tobago's legacy of monetising hydrocarbon assets has fostered a deep rooted energy dependency syndrome, with projected depletion of fossil fuel stocks before 2030.

To understand the effects of oil price fluctuations in a petroleum economy, it is the relative size of the resource sector to the rest of the economy which matters as opposed to the absolute size of such an economy in this international commodity market (Bjørnland and Thorsrud, 2016). The share of the petroleum sector to the aggregate economy, in the contemporary period, is illustrated in Figure 1.3. Prior to the booming oil prices of the 2000s, the annual contribution of the petroleum sector to GDP was between 26% and 30%. This ratio grew substantially and peaked at just over 42% in 2006. Since then, oil prices have been turbulent with two distinct plummets: One during the 2008 Global Financial Crisis; and another in the latter part of 2014 into early 2015 (see Figure 2.1,

[3] The severe economic recessions of the 1980s were hallmarked by falling national income per capita, elevated unemployment rates, current account deficits, and worrisome depletions in foreign exchange reserves (Henry, 2007).

Chapter 2). Such events are the likely cause of a reduction in the share of the petroleum sector to total GDP from 40% in 2009 down to 32% by 2016 and a plausible cause of the stagnant level of real GDP since the financial crash, also reflected in Figure 1.3.

Figure 1.4 continues to paint a picture of the macroeconomic landscape of this petroleum economy, showing that the vast majority of Trinidad and Tobago's exports are composed of energy related commodities. Furthermore, Figure 1.5 illustrates how total government expenditure accelerated during the oil price boom of the 2000s due to the increase in government revenues coming from the energy sector. In the 2010s, although the share of government revenues obtained from the energy sector declined substantially, total government expenditure remained high. This is against the background of falling energy exports (see Figure 1.4) caused by falling international energy prices and domestic energy production (CBTT, 2015), as well as a reduction in the ratio of energy output to total output and a stagnant level of real GDP (see Figure 1.3). Tanzi (1982) defines such a scenario as commodity boom induced fiscal disequilibrium, i.e. when permanent government expenditures are based on a temporary increase in government revenues derived from transitory windfalls in commodity prices. Indeed, the fiscal shortfall from falling energy revenues led to a rise in total public sector debt. For instance, in the fiscal year 2014/2015 which included another collapse of global oil prices since the Global Financial Crisis of 2008, public enterprises were financed through increased borrowings by public enterprises to settle liabilities and finance expenditures, and the Central Government budgetary support was provided by the issue of bonds (CBTT, 2015).

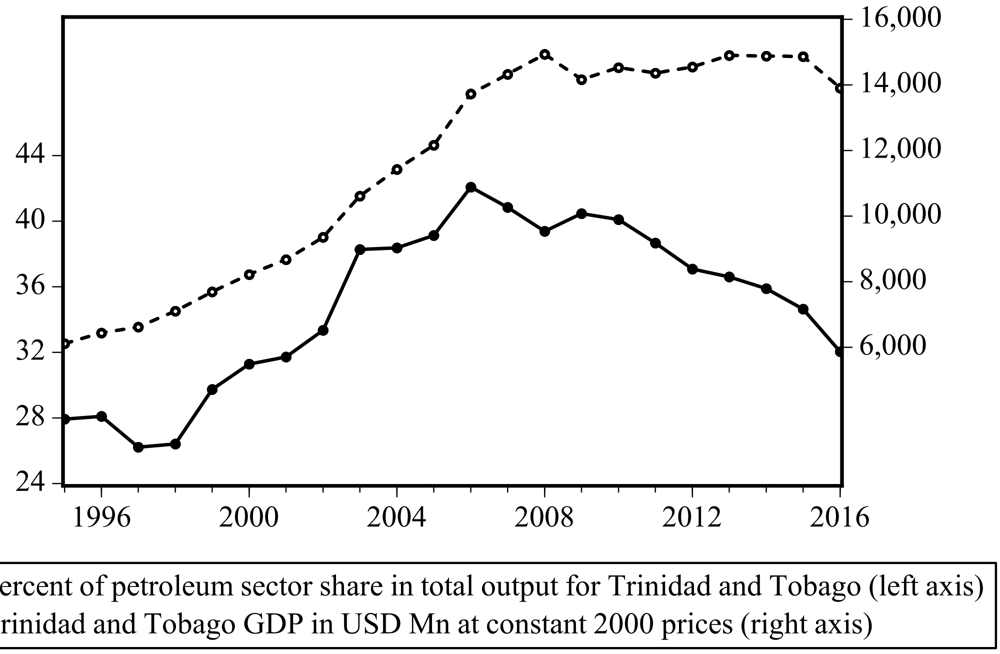

Figure 1.3: Real GDP level and the ratio of the petroleum sector output to total output in Trinidad and Tobago. *Data source*: Calculated using Central Bank of Trinidad and Tobago data, accessed in August 2019.

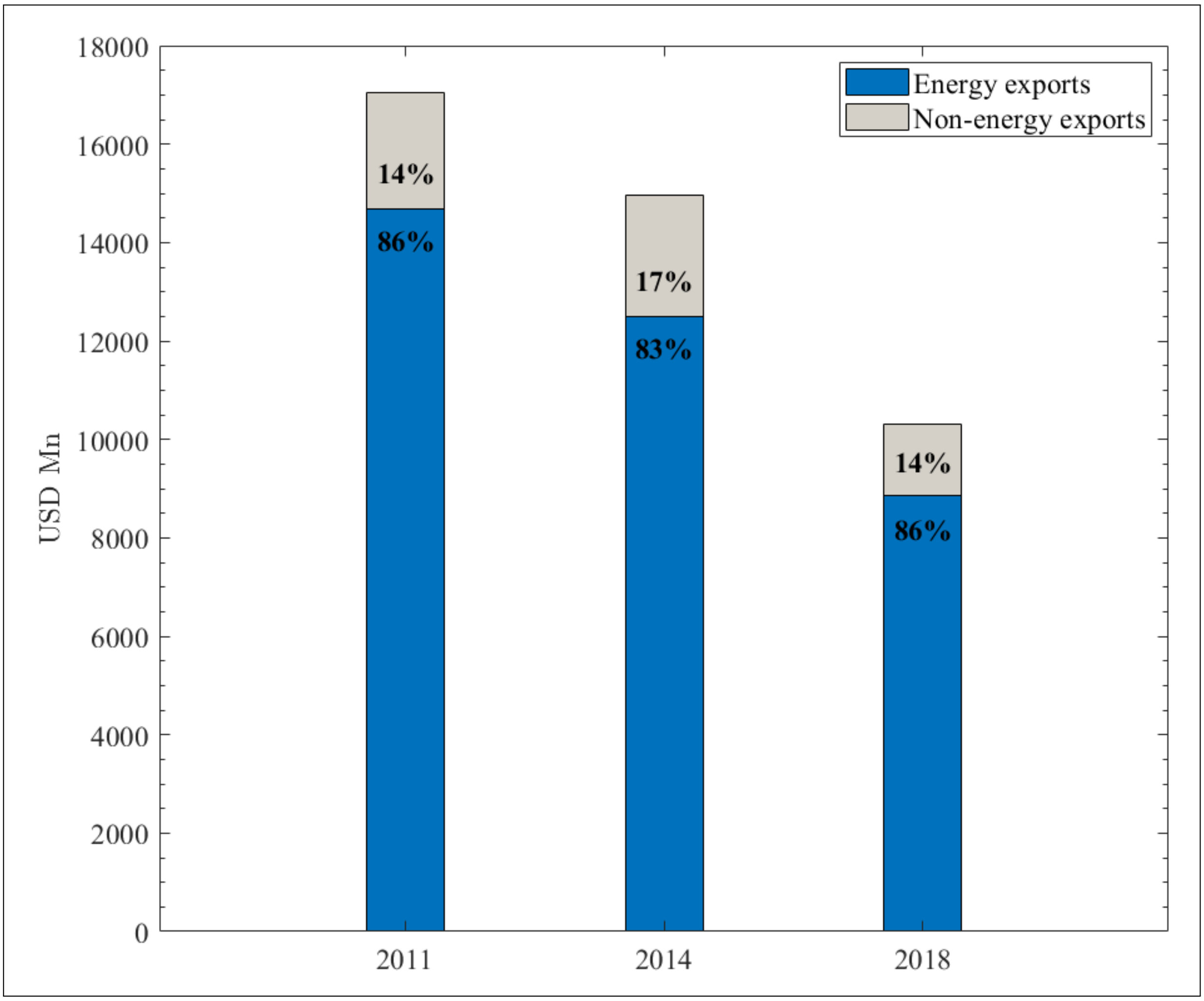

Figure 1.4: Contribution of energy and non-energy exports to total exports in Trinidad and Tobago for selected years. *Data source*: Calculated using Central Bank of Trinidad and Tobago data, accessed in August 2019.

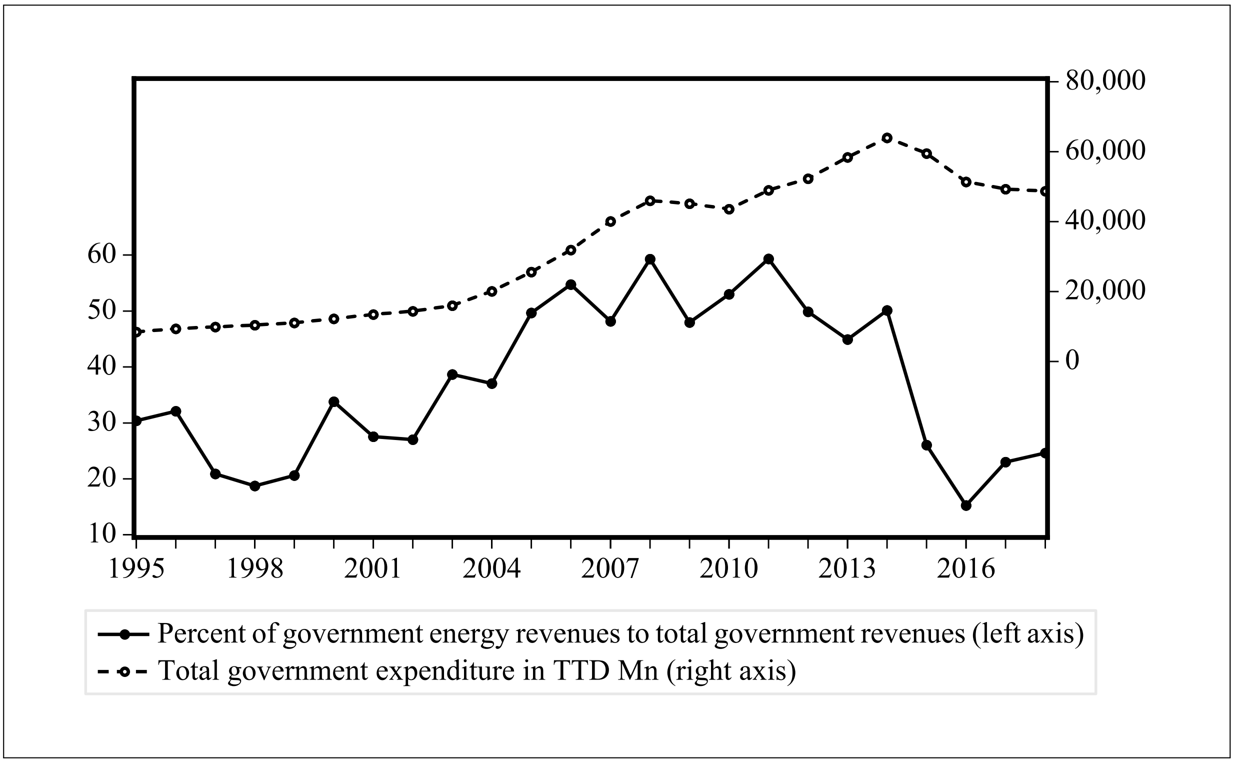

Figure 1.5: Total government expenditure and ratio of government energy revenues to total government revenues in Trinidad and Tobago. *Data source*: Calculated using Central Bank of Trinidad and Tobago data, accessed in August 2019.

1.3 Essay I: Energy contagion analysis - A new perspective with application

1.3.1 Rationale

Oil markets have implications for financial variables such as exchange rates and stock market returns. Considering the former, Ferraro et al. (2015) posit that for a small open economy which exports commodities, the exchange rate is expected to reflect commodity price movements. They find a very short term and contemporaneous relationship between a country's major commodity export prices and the exchange rate. For oil-exporters, the theorised influence of oil price increases on the exchange rate is a currency appreciation through positive wealth effects (Bjørnland, 2004, 2009) and Dutch disease (Corden, 1984, 2012) channels. These theories elaborate on how spending oil income leads to domestic inflation and causes the exchange rate to appreciate, possibly reducing the international competitiveness of such countries as exports (imports) become more expensive (cheaper).

Regarding the oil and stock markets, if these two markets are assumed to be efficient then they should be contemporaneously correlated (Huang et al., 1996). This is plausible given that stock markets rapidly make use of all available information, including developments in the oil market (Bjørnland, 2009). Regarding the nature of the relationship, the expectation is that oil price increases positively stimulate the stock markets of oil-exporters (Filis and Chatziantoniou, 2014), especially in economies where oil constitutes a significant share in GDP (Elwood, 2001; Wang et al., 2013). A reasonable assumption is that oil price decreases will have the reverse effect on the real and financial sectors.

Therefore, financial variables, such as exchange rates and stock market indicators, in small open commodity-exporters are expected to react to developments in the international oil market relatively quick. Contagion analysis can be a useful tool for testing changes in the relationship between oil and financial markets in such countries. However, previous literature which examine contagion in the oil-finance nexus emphasise how the relationship between these markets change in financial crises as opposed to distress in energy markets.

1.3.2 Research question

Do crisis episodes in the international crude oil market deepen the linkages in the energy-finance nexus in Trinidad and Tobago?

1.3.3 Significant original contributions

Chapter 2 makes three original contributions to the energy economics literature. First, the concept of *energy contagion* is introduced, which is defined as a strengthening of energy-finance relationships during crisis periods in energy markets, and is distinguished from financial contagion. Second, using the international crude oil market and the financial markets of Trinidad and Tobago, energy contagion tests are constructed by modifying recently proposed financial contagion tests. Third, the study also addresses a gap in the applied literature as there are no previously published academic studies explicitly investigating the impact of oil returns on the financial variables of this small energy economy. Yet, our approach is straightforward enough to be adapted to any country that intensively trades hard commodities.

1.4 Essay II: Tracing the genesis of contagion in the oil-finance nexus

1.4.1 Rationale

Kilian (2009) specifies a recursively identified vector autoregression (VAR) model to impose restrictions on the contemporaneous matrix of a system of equations containing three variables, which arguably represents the international crude oil market. As such, using variables to proxy global oil production, real global economic activity, and real oil prices, Kilian (2009) disentangles oil supply, global demand, and oil-specific demand shocks. Chapter 3 combines the idea of energy contagion put forward in Chapter 2 with the approach of Filis et al. (2011), who considers how the oil-stock market relationship evolves during different episodes of oil market shocks, which are identified from the structural VAR model proposed in Kilian (2009). The motivation comes from the premise that oil price shocks should be disentangled into supply-side and demand-side components in order to obtain a more comprehensive perspective of the oil-finance relationship, which is likely to respond differently depending on the origin of the shock (see Broadstock and Filis (2014); Degiannakis et al. (2014); and the references therein).

1.4.2 Research question

How are the relationships between the international crude oil market and financial indicators in a small oil-exporter affected during extreme oil supply, global demand, and oil demand shocks?

1.4.3 Significant original contributions

Chapter 3 proposes an original approach to trace the sources of contagion in the oil-finance nexus. This is achieved by applying a new rule-based specification to filter structural oil market shocks into discrete typical and extreme episodes. These periods are used to define the sub-samples for constructing contagion tests. To obtain market correlations for the contagion tests, the oil-stock market dynamic conditional correlations model of Filis et al. (2011) is extended to include a currency market indicator. Within this framework important additional financial relationships, i.e. the oil-exchange rate and exchange rate-stock market correlations, can be considered. The empirical procedures are again illustrated using the international crude oil market and the financial markets of Trinidad and Tobago. This research is useful because oil market contagion analysis has important implications for the financial stability of economies whose prosperity is tied to the international prices of hard commodities.

1.5 Essay III: Contagion testing in embryonic markets under alternative stressful US market scenarios

1.5.1 Rationale

The few studies exploring the economic fundamentals which determine stock market interdependence between countries have produced mixed results: Some suggest that trade intensity is the principal factor, others find bi-lateral trade has no impact, and others are inconclusive (see Paramati et al. (2015) and references therein). With specific reference to financial contagion and trade linkages, the evidence suggests that a financial crisis is amplified if the epicentre country is better integrated into the trade network of the recipient country (Kali and Reyes, 2010). Table 1.1 shows that the US is the uncontested major trading partner for Trinidad and Tobago, Jamaica, and Barbados, both in terms of exports and imports. Hence, based on the trade related exposure of Caribbean economies to the US, it is plausible to hypothesise that stressful events in the US equity market can be transmitted to Caribbean stock markets.

1.5.2 Research question

How do the relationships between the S&P 500 and major Caribbean stock markets evolve under various US equity market scenarios?

Table 1.1: Major trading partners of Trinidad and Tobago (T&T), Jamaica, and Barbados (with each trading partner's share of the total market in italics for various years).

Year	Top 3 export markets			Top 3 import markets		
	1	2	3	1	2	3
Trinidad and Tobago						
2015	US	Argentina	Columbia	US	Gabon	China
	41.73%	*6.75%*	*4.07%*	*31.95%*	*12.49%*	*7.10%*
2010	US	Jamaica	Barbados	US	Gabon	Columbia
	48.07%	*6.47%*	*3.40%*	*27.95%*	*12.90%*	*9.47%*
2005	US	Jamaica	France	US	Brazil	Venezuela
	58.58%	*7.46%*	*4.44%*	*29.16%*	*13.55%*	*6.03%*
2000	US	Jamaica	Barbados	US	Venezuela	Columbia
	46.59%	*7.82%*	*4.82%*	*35.38%*	*18.40%*	*7.94%*
1995	US	Jamaica	Barbados	US	UK	Germany
	42.91%	*8.43%*	*3.46%*	*50.59%*	*7.23%*	*5.89%*
Jamaica						
2015	US	Canada	Netherlands	US	T&T	China
	36.99%	*14.45%*	*8.74%*	*37.51%*	*9.50%*	*8.19%*
2010	US	Canada	UK	US	Venezuela	T&T
	49.65%	*12.31%*	*6.32%*	*35.89%*	*14.02%*	*13.80%*
2005	US	Canada	UK	US	T&T	Venezuela
	25.56%	*19.40%*	*10.72%*	*41.55%*	*15.03%*	*5.39%*
2000	US	UK	Netherlands	US	T&T	Japan
	39.16%	*11.45%*	*11.10%*	*45.46%*	*10.01%*	*6.00%*
Barbados						
2015	US	T&T	Guyana	US	T&T	China
	32.62%	*8.25%*	*5.32%*	*39.23%*	*15.79%*	*5.65%*
2010	US	UK	T&T	US	T&T	UK
	24.92%	*16.78%*	*8.44%*	*43.95%*	*7.18%*	*5.37%*
2005	US	T&T	UK	US	T&T	Japan
	13.42%	*10.82%*	*8.79%*	*35.91%*	*21.16%*	*7.64%*
2000	US	T&T	UK	US	T&T	UK
	15.80%	*13.22%*	*13.17%*	*41.55%*	*16.45%*	*8.08%*

Data source: Compiled using World Integrated Trade Solution (WITS), World Bank data, retrieved in September 2019.

1.5.3 Significant original contributions

Chapter 4 employs a financial practitioner's approach and well-established econometric strategies to filter the S&P 500 market into discrete sub-samples of stable and stressful periods, which are used to construct financial contagion tests across various co-moment transmission channels. In particular, the various ways in which this source market is decomposed includes low and high volatility regimes with a financial practitioner's rule on the VIX to gauge investor fear; bull and bear market phases using a rule-based algorithm suggested in Pagan and Sossounov (2003); and normal periods with asset bubbles and crisis identified in Phillips and Shi (2020). These alternative conditions are used to determine the samples for recently developed correlation, co-volatility, and co-skewness contagion tests. The S&P 500 is used as the source market of financial stress and the major emerging stock markets of the Caribbean are used as the recipient markets. As the latter markets are immensely dependent on trade with the US, it is worthwhile investigating whether close real sector ties might translate into a heightened vulnerability to financial market developments in the US. The approach proposed in this chapter is important because examining alternative stressful market conditions can help policy makers and investors understand the type of US financial environment during which shocks will be able to proliferate and propagate in recipient markets that are particularly exposed to developments in this source market.

1.6 Summary

With reference to direct transmission channel, A, shown in Figure 1.2, this thesis uses contagion analysis to critically examine how the relationship between external markets and key financial indicators in Trinidad and Tobago change during stable and unstable conditions in pertinent foreign markets. In Chapter 2, energy contagion testing in the oil-exchange rate relationship provides a novel way of considering the direct transmission of adverse effects in times of crisis in the international oil market to the exchange rates in a small open energy economy. On the other hand, contagion testing in the oil-stock market relationship gives an explicit sense of how sensitive financial markets are to oil market conditions, which can be used as a high frequency data proxy to the oil-macroeconomy relationship. Then, Chapter 3 builds on Chapter 2 by looking at how these direct transmission channels between the international crude oil market and financial indicators in Trinidad and Tobago are affected under changes in the main drivers of the oil market, i.e. oil supply, global aggregate demand, and oil-specific demand shocks. Finally, Chapter 4 investigates whether stressful shock conditions transmitted from the US stock market influences the contemporaneous relationships between the US stock market and the emerging stock markets of small open Caribbean economies.

Chapter 2

Energy contagion analysis - A new perspective with application

Abstract

We put forward the novel concept of energy contagion, i.e. a deepening of energy-finance linkages under crisis conditions in energy markets. Further, we show how to construct tests for energy contagion through correlation, co-skewness, and co-volatility channels. The samples of our contagion measures are defined in terms of calm and crisis periods in the international crude oil market. In particular, we compare how these various co-moments in the energy-finance nexus change during: (1) Oil booms and slumps using semi-parametric rule-based algorithms; (2) Tranquil and turbulent oil price volatility episodes using a non-hierarchical k-means clustering algorithm. Energy contagion analysis is essential to financial stability analysis in economies where prosperity is linked to the prices of hard commodities. Our applications are performed on the oil-exchange rate and oil-stock market relationships of the small petroleum economy of Trinidad and Tobago. The main results show a negative oil-real effective exchange rate dependency; a weak oil-stock returns association; and the existence of several energy contagion channels in both financial relationships, which are sensitive to the contemporary global financial crash.

Keywords: contagion; correlation; exchange rate; oil; stock market; Trinidad and Tobago
JEL classification: C58; Q49

2.1 Introduction

Recently, contagion analysis has been gaining traction in the energy-finance nexus, especially in areas considering the spillover effects from oil prices to exchange rates (Reboredo et al., 2014; Baruník and Kocenda, 2019) and stock markets (Wen et al., 2012; Ding et al., 2017). Yet, this literature places the emphasis on comparing energy-financial markets relationships in and out of financial crisis time periods. While *financial* contagion tests tends to be based on a set financial crisis timespan[1], we propose constructing *energy* contagion tests by comparing financial correlations during relatively calm and chaotic energy market conditions. We define energy contagion as a deepening of energy-finance linkages under crisis periods in energy markets. In particular, we consider crude oil market contagion because the connections between oil and other financial assets have recently deepened (Serletis and Xu, 2018), likely due to the leftover spillover effects from the recent Global Financial Crisis (GFC) (Wen et al., 2012). There is also a growing concern about the increasing financialisation of oil (Zhang and Broadstock, 2018), which is a consequence of the increasing participation and speculation of hedge funds in the oil market (see, *inter alia*, Boldanov et al. (2016)).

Further, we make a contribution to empirical methods in energy economics by modifying the calm and crisis sample conditions of recently proposed contagion measures to test for energy, rather than financial, contagion. For this purpose, we take two approaches to identify discrete good and bad episodes in the international crude oil market. One is based on detecting oil booms and slumps proxied by bull and bear states, respectively, using semi-parametric rule-based algorithms. There are relatively few applications on detecting bull/bear phases in crude oil markets (see, for example,

[1] For example, the National Bureau of Economic Research defines the timespan of contemporary Global Financial Crisis from December 2007 to June 2009. See www.nber.org/cycles, accessed in August 2018.

Chang et al. (2010), Ntantamis and Zhou (2015), and Gil-Alana et al. (2016)). Yet, such an approach resonates well with the empirical oil studies which advocate that positive and negative oil price movements have asymmetric effects on the rest of the economy[2]. Our second approach employs a non-hierarchical k-means clustering algorithm to categorise realised crude oil market volatility measures into discrete groups of relative tranquillity and turbulence. The importance of the oil price volatility channel is also well established (see, for example, Lee et al. (1995); Elder and Serletis (2011); Baumeister and Peersman (2013)). Indeed, hard commodities are the most volatile class of financial assets due to the high inventory costs and risk of shortages, which tend to prolong, compared to the quicker market adjustments that occur for bonds, equities, and currencies (Downey, 2009).

We can then compare the oil-finance relationships under the calm and crisis oil market conditions identified. Correlation, co-skewness, and co-volatility contagion tests are used to construct energy contagion hypothesis testing across important co-moment transmission channels between crude oil and financial markets. For instance, co-skewness contagion can be observed for any pair of markets in two possible ways: Either, the mean behaviour of one market affecting the volatility of another; or, the volatility of one market affecting the mean behaviour of another (Fry et al., 2010). These two asymmetric dependence channels have the potential to identify additional linkages between markets with implications in the energy-finance nexus. Looking at how oil price volatility affects the performance of average financial returns, little research has been conducted in this area despite the repercussions that commodity price volatility has for asset prices through production costs and investment decisions (Diaz et al., 2016).

[2]The seminal works on testing the effects of non-linear oil price censoring specifications on the economy include Mork (1989) and Hamilton (1996, 2003).

Likewise, a clear understanding of the relationship between the crude oil prices and asset volatility is essential for formulating economic, energy, and financial policy in order to mitigate associated risks (Bastianin et al., 2016). Considering the co-volatility channel, which identifies contagion between the second moments of two markets (Fry-McKibbin et al., 2014), such a perspective is relevant as twenty-first century commodity prices are hallmarked with exceptional volatility and commodity-equity market linkages have deepened in the GFC aftermath (Creti et al., 2013). Relatively little research has been conducted on the linkages between oil and stock market volatilities (Boldanov et al., 2016), and oil market and exchange rate volatilities.

Energy contagion analysis is potentially important for small extractive resource economies, which have real and financial sectors that are heavily exposed to shocks from international hard commodity markets. Indeed, the propagation of oil prices are more consequential for small open economies than larger ones (Abeysinghe, 2001) and, on average, small resource-endowed countries have a history of underperformance compared to their larger resource-rich equivalents (Auty, 2017). Our study focuses on the links between the international crude oil market and the financial markets of the small open petroleum economy of Trinidad and Tobago, to evaluate whether we are able to diagnose energy contagion in such an environment. Testing a new concept is often done on relatively extreme cases. From this perspective, Trinidad and Tobago is an appropriate case as hydrocarbon assets have been extracted for over a century on the twin-island (Gelb, 1988). However, this country's legacy of monetising its sub-soil assets fosters a deep rooted energy dependency syndrome, with projected depletion before 2030 (Auty, 2017). In the twenty-first century, due in part to the pronounced fluctuations in international energy prices, the petroleum sector contribution to total output has been a roller-coaster: 32% in 2001, 42% in 2006, 39% in 2011, and 32% in 2016[3]. The latest current account data convey an energy export to total export ratio of 78%; while revised estimates show that 21% of government revenue in the fiscal year 2016/2017 derives from the energy sector, down from 48% in the fiscal year 2013/2014[4].

We are the first to explicitly evaluate the spillover effects international oil prices have on the financial markets of Trinidad and Tobago. Yet, our approach to energy contagion testing can be similarly applied for systemic risk analysis in any country whose fate is tied to the international prices of a hard commodity. Our empirical applications address two inter-related research questions: Do crisis episodes in the international crude oil market deepen the linkages in the energy-finance nexus in Trinidad and Tobago? If so, can higher co-moment channels provide further insights in such contagion scenarios? We find that the co-skewness and co-volatility dependence tests are able to detect additional channels of energy contagion not identified by the adjusted linear correlation test. However, our robustness analysis shows that such evidence is GFC-driven and we even observe *reverse* contagion in the oil-exchange rate relationship. Energy contagion in Trinidad and Tobago is subdued, likely due to country-specific characteristics: A dirty floating exchange rate and an embryonic stock market.

The rest of the chapter is organised as follows. In Section 2.2 we examine the literature on the oil-exchange rate and oil-stock market relationships, and review studies on contagion testing followed by previous applications of contagion testing in the oil-financial market nexus. Then, in Section 2.3, we explain our empirical procedures by specifying the contagion tests used and how they are augmented to test for energy contagion. In Section 2.4, we describe our data and procedures for adjusting our return

[3]These statistics are based on our own calculations using Central Bank of Trinidad and Tobago data. Available at www.central-bank.org.tt and retrieved in November 2019.

[4]These statistics are based on our own calculations using data in CBTT (2018).

series. Subsequently, we present the results in Section 2.5, provide policy implications in Section 2.6, and conclude in Section 2.7.

2.2 The energy-finance nexus: Relationships and contagion analysis

2.2.1 Oil price-exchange rate relationship

The effect of oil prices on the exchange rate typically depends on the net energy-exporting status of a country (Reboredo et al., 2014; Turhan et al., 2014; Basher et al., 2016; Tiwari et al., 2019). Furthermore, the crude oil-exchange rate relationship is typically more pronounced in oil-exporting countries than in their oil-importing counterparts (Reboredo, 2012; Yang et al., 2017). *Petrocurrencies* tend to appreciate when oil prices are rising and depreciate when they decline (Bjørnland, 2004). This occurs due to the positive (negative) wealth effects channel in oil-exporting countries: Higher (lower) oil income generated from oil price booms (slumps) stimulate (inhibit) economic activity, putting upward (downward) pressures on domestic prices, causing the exchange rate to appreciate (depreciate) (Bjørnland, 2009). Corden (1984, 2012) provides a related explanation for exchange rate appreciations in oil-exporting economies with the *Dutch disease*[5] theory; where commodity boom-induced revenues stimulate import expenditure, and increase wages and prices on the domestic market. This is called the *spending effect* and, akin to the wealth effect, it causes domestic inflation and currency appreciation which reduces the export competitiveness of non-booming commodities. Korhonen and Juurikkala (2009)

[5]The name "Dutch" disease was coined in the 1970s to describe the noteworthy demise of several manufacturing industries in the net energy-exporting Netherlands, coinciding with the oil price boom of 1973/4.

use data from 1975 to 2005 in pooled mean group and mean group estimators, and find supporting evidence of appreciating exchange rates in response to higher oil prices in OPEC territories.

As the US dollar is a vehicle currency and the energy sector in Trinidad and Tobago has traditionally been the main source of foreign currency for authorised dealers, the Central Bank of Trinidad and Tobago supports the local foreign exchange market with the sale of foreign reserves to authorised dealers. Such interventions maintains exchange rate stability when there is a shortfall in the inflows of foreign exchange or when the demand for foreign exchange is robust (CBTT FSR, 2019; CBTT MPR, 2019). Because a dirty float has been the de facto exchange rate regime in Trinidad and Tobago since April 1993, with a stabilisation arrangement which anchors the Trinidad and Tobago dollar to the US dollar (Samuel and Viseth, 2018), the oil-exchange rate relationship in the US is important to consider. The US economy is peculiar as it is a large net oil-importer albeit major oil-producer. Furthermore, in global markets, crude oil is commonly invoiced and traded in US dollars (Reboredo, 2012; Hou et al., 2016). The long run and forecasting results of Lizardo and Mollick (2010) suggests a depreciation of the US dollar against the currencies of net oil-exporters when oil prices increase. If this currency depreciates (appreciates) then crude oil becomes cheaper (more expensive) for non-US consumers, which increases (decreases) their demand for crude oil, placing upward (downward) pressures on the price in this hard commodity market (Reboredo et al., 2014). Additionally, Ghosh (2011) and Lizardo and Mollick (2010) find the currencies of selected net oil-importers depreciate against the US dollar when oil prices increase.

However, the aforementioned dichotomous perspective on how oil prices affect oil-exporters and importers is not a consensus. In the case of the small open petroleum-exporting economy of Norway, mixed results are observed. Using a structural

VAR model, Bjørnland (2004) finds that the real exchange rate depreciates in the first six months following an oil price shock and becomes insignificant thereafter, due to the slow response of the domestic price level relative to the immediate reaction of foreign prices. Also, Bjørnland (2009) uses a recursive VAR model with data on oil prices and the real, monetary, and financial sectors and finds a minimal appreciation of the real exchange rate, concluding that this unresponsiveness of the exchange rate to oil price shocks appear to be why Norway benefits from oil price increases. In light of the Norwegian peculiarity, we seek to understand the oil-exchange rate relationship in the small open petroleum economy of Trinidad and Tobago to unearth whether this is a case of conformity or also an anomaly.

2.2.2 Oil price-stock market relationship

Economists, investors, and policy makers are increasingly focusing on the correlation between oil and stock markets (Wen et al., 2012). Capital markets facilitate economic growth through the efficient allocation of financial resources to the real sector and allow for greater risk sharing (Laeven, 2014). Composite stock market indicators can also be used as a barometer for macroeconomic performance, making it possible to proxy the impact of oil prices on the economy with the oil-stock market relationship (Ding et al., 2017). This is a reasonable point of view given that oil is a fundamental factor of production which affects the costing, cash flow, and expected returns on investments of firms, which are all determinants of stock returns (Jiménez-Rodríguez, 2015; Diaz et al., 2016). Assuming both crude oil and stock markets are efficient, then these assets should be, on average, contemporaneously correlated (Huang et al., 1996). Indeed, stock markets quickly make use of all information available to them inclusive of the developments in oil prices (Bjørnland, 2009), especially in countries where the importance of oil to the macroeconomy is high (Wang et al., 2013).

The empirical literature shows that the nature of the oil-stock market relationship is context specific, since this association is sensitive to the type of industry (Gogineni, 2010) and country in question. Focusing on the latter, the results of Jones and Kaul (1996), Sadorsky (1999), and Papapetrou (2001) show that oil price shocks adversely affect the stock markets of selected developed countries. On the other hand, Aloui et al. (2013) employs a time-varying copula approach and infers that advanced-emerging and emerging Central and Eastern European countries exhibit a positive dependence between these two variables. Moreover, using structural VAR analysis, Wang et al. (2013) finds that the magnitude, duration, and direction of the stock market response to oil price shocks depend on the oil-exporting or oil-importing status of a country.

For oil-exporting economies, Bjørnland (2009) and Mohanty et al. (2011) show that rising oil prices typically have a stimulating effect on stock returns. However, Basher et al. (2018) find that while oil market shocks affect most oil-exporting countries, the sign and magnitude of oil market shocks are country specific. Interestingly, Basher et al. (2018) also observes that oil market shocks are not significant determinants of stock returns in Mexico and attributes this artefact to the possibility that this oil-exporting country has no large publicly traded petroleum companies. Therefore, it is important to consider whether the findings of Basher et al. (2018) on Mexico can be generalised for Trinidad and Tobago, as the first energy security was only listed on the Trinidad and Tobago Stock Exchange (TTSE) in October 2015 (TTSE, 2016). Within this context, we investigate how the stock market of this small emerging energy economy performs under good and bad crude oil market conditions.

2.2.3 Contagion analysis approaches

Although there is no consensus on what contagion means (Forbes and Rigobon, 2000), it is commonly defined as the deepening of cross-market co-movement after a shock occurs in one market (Forbes and Rigobon, 2002). The key idea is that more intimate connections between markets under adverse conditions imply market vulnerabilities, as negative shocks are able to propagate and proliferate more relative to weakly associated markets in times of turmoil (Kritzman et al., 2011). This phenomenon is measured by the excess correlation of returns net of the expected correlation related to economic fundamentals (Bekaert and Harvey, 2003; Pericoli and Sbracia, 2003), and so it is typical to adjust returns to accommodate for market fundamentals in contagion analysis (see, *inter alia*, Forbes and Rigobon (2002), Fry et al. (2010), and Fry-McKibbin et al. (2014)). Contagion has a tendency to appear and vanish quickly, relative to interdependence and cointegrating relationship which are inclined to endure (Reboredo et al., 2014).

In addition, we define *reverse* contagion as strong associations under calm periods which become significantly weaker, in absolute value, during crisis events. Such a situation might arise in the correlation between a source and recipient market if there is some insulation in the latter to buffer a shock from the former. The breakdown in the transmission of a shock which gives rise to reverse contagion can be either intentional or more innate. A strengthened commitment to a currency peg when devaluation policies pursued by neighbours appear to reveal weaknesses, such as how China and Hong Kong defended their fixed exchange rate regimes during the Asian financial crisis in the region, is a possible example of an intentional departure from linkages with other currency markets (Drazen, 2000). Holy grail safe haven assets which are positively correlated with the main assets of a portfolio in non-crisis periods and, because of a flight-to-quality, become negatively or weakly correlated in crisis times (Flavin et al., 2014); as well as country-specific factors during a crisis that may actually reduce correlation in asset price movements (Pericoli and Sbracia, 2003), are potential examples of innate cushions which breakdown the transmission of a shock in a crisis.

Correlation is the most widespread way of measuring the dependence structure between a pair of random variables (Reboredo, 2012). A straightforward way to test for contagion is to compare financial correlations in calm and crisis periods. If the magnitude of the relationship is notable and similar in both samples this is interdependence not contagion, as contagion is observed if market correlations deepen under crisis periods (Forbes and Rigobon, 2002). While comparing linear (Pearson product-moment) correlation coefficients in calm and crisis periods is a typical way of testing for contagion, this approach is biased in the presence of heteroskedasticity which is a common feature of financial variables in a crisis and leads to a false positive detection of contagion (Boyer et al., 1999; Loretan and English, 2000; Forbes and Rigobon, 2002; Inci et al., 2011).

Therefore, it is not surprising that the empirical literature is ripe with solutions on how to overcome this issue. Some studies have used various non-parametric measures of correlation to study contagion (see, for example, Reboredo (2012); Li and Zhu (2014)). Other studies have sought to introduce corrections for the possible bias in the linear correlation coefficients for the increase in volatility which occurs in times of crisis (see, for example, Forbes and Rigobon (2002); Fry et al. (2010); Fry-McKibbin et al. (2014); Fry-McKibbin and Hsiao (2018); Fry-McKibbin et al. (2019)). Another branch of papers have employed dynamic conditional correlation generalised autoregressive conditional heteroskedastic (DCC-GARCH) models, which estimate time varying correlation coefficients using standardized residuals and thus accounts for heteroskedasticity directly, to test for contagion (see, for example, Chiang et al. (2007); Syllignakis and Kouretas (2011); Hemche et al. (2016)). Yet another strand of literature have focused on the dependence structure between markets with the analysis of copula functions, which couple multivariate distribution functions to their one-dimensional marginal distribution functions, to study contagion (see, for example, Rodriguez (2007); Aloui et al. (2011); Reboredo (2012); Wen et al. (2012)).

2.2.4 Financial contagion testing in the oil-finance nexus

Turning to the oil-finance relationship, the applied work on contagion analysis in this literature focuses on how the relationship between commodity markets and financial assets might change during and in the aftermath of a financial crisis event, such as the GFC, when compared to pre-crisis era linkages. Regarding the oil-exchange rate relationship, Reboredo (2012), Reboredo and Rivera-Castro (2013), and Reboredo et al. (2014) all use different methodologies, on the same dataset[6], to examine the crude oil price-US dollar exchange rate dependency with respect to seven important currencies[7] around the world and an aggregate exchange rate indicator, during pre-GFC and GFC periods. All three studies find consistent results. In particular, Reboredo (2012) employs standard correlation measures and a copula approach and observes that albeit the oil-exchange rate dependence is generally weak, these relationships deepen under crisis. In a similar spirit, Reboredo and Rivera-Castro (2013) use a wavelet multi-resolution decomposition approach and find no association in the pre-crisis sample but negative dependence in the crisis sample, suggestive of contagion effects in the latter period. Finally, Reboredo

[6]Each consecutive study extends the GFC sample by a few months.

[7]The currencies included in these three studies are the Australian dollar, Canadian dollar, EU's euro, Japanese yen, Mexican peso, Norwegian krone, and UK's pound sterling.

et al. (2014) apply detrended cross-correlation analysis, and find a weak negative oil price-exchange rate association which increases in the wake of the GFC, once again providing evidence for contagion.

Concerning contagion analysis in the crude oil-stock market connection, Guo et al. (2011) model the non-linear relationship between oil, stock, credit, and real estate markets in a four-dimensional Markov switching VAR for the US economy from October 2003 to March 2009. In the riskier of the two regimes they identify, which contains the GFC period, oil prices shocks drive stock market variability and the oil market is more responsive to stock market movements than the credit or real estate markets. In another study, Wen et al. (2012) use time-varying copulas to test for contagion between oil prices, and the US and Chinese stock markets. Additionally, they specify the dependence structures as an autoregressive model developed by Chiang et al. (2007), with a dummy variable to denote periods in and out of the GFC. In essence, the results of Wen et al. (2012) show a rise in the oil-stock market dependence structure during the GFC, indicative of contagion. However, they find this contagion effect is much stronger in the US compared to China.

Kayalar et al. (2017) also considers the dependence structure between crude oil prices and both exchange rate and stock markets. Their analysis is applied to selected developed and emerging oil-exporting and importing countries. They use copula measures, as well as ARIMA and GARCH models, and find that both currency and equity markets exhibit stronger oil price dependency since the GFC. Kayalar et al. (2017) also note that both the currency and stock markets of oil-exporters have a higher oil price dependency compared to oil-importers.

Contagion analysis also features in studies on commodity market interactions. For instance, Zhang and Broadstock (2018) estimate the dynamic connectedness between global commodity markets using a spillover index computed from the forecast error variance decomposition of a VAR system put forward in Diebold and Yilmaz (2009, 2014). Generally, Zhang and Broadstock (2018) observe that the co-dependence among commodity returns dramatically increases in the GFC aftermath and this continues to endure to the present. Focusing on their results as it relates to crude oil, Zhang and Broadstock (2018) find that even though this is the most volatile commodity class with one of the lowest average returns, oil prices show no strong integration with other commodities. On the other hand, Algieri and Leccadito (2017) use a delta conditional value-at-risk approach based on quantile regression and find that a distress occurring in the crude oil market has the largest negative consequences for the rest of the US economy when compared to food, metals, and other energy commodities. Yet, as no control is provided for the GFC, it is not possible to deduce if the inferences of Algieri and Leccadito (2017) are GFC driven.

2.2.5 Energy contagion analysis in the oil-finance nexus

While the previous studies on testing for contagion in the relationships between oil and financial markets have primarily focused on defining the pre-crisis and crisis periods of contagion tests based on a financial crash, this chapter instead contributes to the field by constructing tests based on the calm and crisis periods in energy markets. Hence, we make a distinction between constructing tests based on financial crises scenarios as financial contagion analysis and contagion testing based on energy crises as energy contagion analysis.

In the preceding sub-sections we saw that a variety of approaches have previously been used to test for contagion in the energy-finance literature. For the main empirical work of this chapter, we apply recent tests from the financial contagion literature for energy contagion analysis. These include correlation, co-skewness, and co-volatility contagion channels. A benefit of using these contagion tests is that each co-moment captures a different feature of the joint asset returns relationship between the international crude oil market and the financial markets of a country exposed to disturbances from this source market.

For the correlation channel we incorporate the Forbes and Rigobon (2002) linear dependence measure corrected for heteroskedasticity in crisis periods, suggested in Fry et al. (2010). This allows us to more accurately compare how the relationship between the international crude oil and the financial variables of a small oil-exporter change during calm and crisis periods in the crude oil market.

We employ the co-skewness contagion tests introduced in Fry et al. (2010). These contagion channels provide two important perspectives about how the asymmetric dependence structure between the oil market and the financial markets of a recipient country change during energy crises. One channel allows us to understand if oil returns affect financial volatility in a country potentially vulnerable to oil market disturbances, which is a fundamental energy-finance relationship (see, for example, Bastianin et al. (2016)). The other channel informs whether oil volatility affects financial returns, which is another important energy-finance connection (see, for example, Diaz et al. (2016)).

The co-volatility test we adopt is introduced in Fry-McKibbin et al. (2014). This contagion channel gives an insight into an extremal dependence structure between energy and financial markets. In particular, co-volatility allows us to understand whether crude oil market volatility affects the financial market volatility of a recipient country. This is yet another pertinent energy-finance issue as it is volatility connectivity, rather than returns, which are related to the flow of information between markets (Vo, 2011).

Within the flexible constructs of these contagion tests, we can modify the calm periods and crisis conditions in energy markets to determine how oil-finance relationships might change between these time periods. Two types of energy market conditions we are concerned with in this chapter are comparing oil-finance relationships in an environment where oil prices are increasing to when oil prices are decreasing; as well as comparing such relationships when oil volatility is low to when it is high. Examining the latter, volatility in financial market can have wide reaching repercussion on the economy as a whole (Poon and Granger, 2003). It is not surprising, therefore, that the importance of oil volatility in economics and finance is widely studied (see, for example, Lee et al. (1995); Elder and Serletis (2011); Baumeister and Peersman (2013)), especially in financial markets (see, for example, Bouri (2015); Ewing and Malik (2016)).

Considering the former, since the work of Mork (1989) who decomposes oil price changes into increases and decreases to investigate the possibility of an asymmetric impact on the economy, understanding how rising and falling oil prices might influence the real and financial sectors of an economy has been a long standing empirical issue in the applied oil economics and oil finance literature. An *a priori* expectation is that oil-importers suffer under rising oil prices and thrive under falling oil prices, and that the converse is anticipated for oil-exporters. One of the ways we contribute to the literature in this chapter is to permit the calm and crisis conditions to reflect periods where oil prices are increasing to when they are decreasing, and examine whether the relationships between the crude oil market and an appropriate recipient market changes.

While we are the first to test for contagion based on rising and falling oil prices using bull and bear oil market phases, respectively, this type of approach has already had a number of applications in the applied oil literature (see, for example, Chen (2010); Chang et al. (2010); Ntantamis and Zhou (2015); Gil-Alana et al. (2016)). Harding and Pagan (2003) state that the desirable properties for dating business cycles are algorithms which are simple, robust, as transparent as possible, and replicable. They find that for dating cycles, Markov-switching models are unattractive when compared to non-parametric methods and that the former depends on the validity of the underlying statistical model. Hanna (2018) explains that two commonly used rule-based approaches for identifying bull and bear phases in asset prices are the Pagan and Sossounov (2003) and Lunde and Timmermann (2004) algorithms. Using these two rule-based methods, Kole and Dijk (2017) find that these approaches are preferred for in-sample identification of market phases, whereas Markov-switching models are preferred for forecasting. They explain that this is because in-sample only the mean return of the market index matters, which is precisely what the rule-based methods capture. As we do not use our procedures for out-of-sample analysis, we proceed with the rule-based algorithm as the more appropriate approach for our study. We employ both the Pagan and Sossounov (2003) and Lunde and Timmermann (2004) procedures to identify bull and bear market phases in the crude oil market, and use these booming and slumping oil price phases to form the calm and crisis samples, respectively, for our contagion tests.

Altogether, the energy contagion analysis procedure we propose contributes to the field of energy finance by consolidating recent financial contagion methods with important relationships between the international crude oil market and the financial markets of a recipient country. The purpose of such work is to provide a comprehensive view of how linkages might change under calm and crisis energy market scenarios.

2.3 Methodology

2.3.1 Contagion analysis methods

We first describe some standard parametric and non-parametric correlation measures to get a preliminary feel for the relationship between oil and the financial markets of Trinidad and Tobago when the international crude oil market is in calm versus crisis months. These include Pearson's ρ, Spearman's ρ, and Kendall's τ. Then, we outline the contagion tests which we will augment for our energy contagion analysis. These consists of correlation, co-skewness, and co-volatility contagion tests. For all correlation analysis and contagion tests employed in this chapter, the returns we work with are *adjusted* returns, in the sense that the returns are net of market fundamentals. We explain the motivation and procedure for filtering the returns in a subsequent section which describes our data.

2.3.1.1 Correlation comparisons using Pearson's ρ, Spearman's ρ, and Kendall's τ

Pearson correlation is popular in financial contagion analysis for comparing dependence structures in calm and crisis periods (Inci et al., 2011; Li and Zhu, 2014). The bivariate linear correlation is measured using the simple Pearson product-moment correlation coefficient (Pearson's ρ) for the returns between oil and a financial market of Trinidad and Tobago. This is computed as the covariance of the pair of returns divided by the product of their standard deviations suggested in Eq. (2.1):

$$Pearson's\ \rho = \frac{\sum_{t=1}^{T}(a_{i,t} - \overline{a_i})(a_{j,t} - \overline{a_j})}{\sqrt{\sum_{t=1}^{T}(a_{i,t} - \overline{a_i})^2}\sqrt{\sum_{t=1}^{T}(a_{j,t} - \overline{a_j})^2}} \tag{2.1}$$

where $-1 \leq \rho \leq 1$, and 0 implies no linear correlation but increases as absolute values of ρ move away from 0 with +/- indicating positive/negative associations between the returns of a source market (denoted a_i) and a recipient market (denoted a_j). The Pearson correlation coefficient is computed for overall, calm, and crisis crude oil market conditions for insights into how market dependence changes under these different samples. However, as a measure of contagion, Pearson's ρ has several shortcomings: It is ill-suited for non-linear dependence; the coefficient can vary based on monotonic transformations[8]; and it is symmetric and cannot distinguish between associations during market ups and downs, or between large and small movements, and assumes homoskedasticity (see Reboredo (2012) and references therein). Consequentially, we follow Reboredo (2012) and use the Spearman and Kendall rank correlation coefficients, respectively shown in Eqs. (2.2) and (2.3), as alternative measures of correlation to be used in conjunction with Pearson's ρ. These are also computed to obtain the energy-finance correlations during calm and crisis oil market samples.

$$Spearman's\ \rho = \frac{\frac{1}{T}\sum_{t=1}^{T}\Bigg((Ra_{i,t}-\overline{Ra_i})(Ra_{j,t}-\overline{Ra_j})\Bigg)}{\sqrt{\Bigg(\frac{1}{T}\sum_{t=1}^{T}(Ra_{i,t}-\overline{Ra_i})^2\Bigg)\Bigg(\frac{1}{T}\sum_{t=1}^{T}(Ra_{j,t}-\overline{Ra_j})^2\Bigg)}} \tag{2.2}$$

where Spearman's ρ is a modified Pearson's ρ, such that $Ra_{i,t}$ ($Ra_{j,t}$) and $\overline{Ra_i}$ ($\overline{Ra_j}$) are the rank and average rank of a_i (a_j), respectively.

$$Kendall's\ \tau = \frac{n_c - n_d}{\frac{1}{2}n(n-1)} \tag{2.3}$$

where the numerator is known as Kendall's score which is the difference between the

[8]For example, the linear correlation coefficient for returns and log returns are likely to be different for a pair of continuous random variables. However, by construction, correlation is invariant to whether or not the returns are standardised as the coefficient is normalised by the standard deviations in the denominator.

concordant(n_c) and discordant (n_d) pairs, and the denominator is the total number of pair combinations to guarantee the coefficient is bounded between -1 and 1 for an interpretation similar to other correlation measures.

Both Spearman's ρ and Kendall's τ are measures of ordinal association, which are determined based on the degree of similarity between the rankings of two returns. By using rankings instead of observation values, these rank correlation coefficients are more robust to outliers than Pearson's ρ (Abdullah, 1990), since the latter is computed from the sample means of the market returns. Such non-parametric dependence measures are particularly attractive in the analysis of financial markets prone to conditions of extreme values.

2.3.1.2 Adjusted linear correlation contagion test

Given that Pearson's correlation coefficient spuriously increases with market volatility, Forbes and Rigobon (2002) propose a correction for this heteroskedasticity bias. Eq. (2.4) shows a two-sided test statistic variant of the Forbes and Rigobon (2002) contagion test as suggested in Fry et al. (2010) and Fry-McKibbin et al. (2014), which is a significance test for a change in the adjusted crisis period correlation (i.e., $\hat{\rho}_{y|x_i}$) compared to the calm period correlation (i.e., $\hat{\rho}_x$) from the source market i to the recipient market j. For our purposes, i denotes international crude oil returns and j indicates the returns of a financial market indicator (i.e., exchange rate or stock market returns) for a small oil-exporter (i.e., Trinidad and Tobago).

$$CR_{\overline{FR}}(i \rightarrow j) = \left(\frac{\hat{\rho}_{y|x_i} - \hat{\rho}_x}{\sqrt{Var(\hat{\rho}_{y|x_i} - \hat{\rho}_x)}} \right)^2 \tag{2.4}$$

where, under the null hypothesis of "no contagion", the test statistic is asymptomatically distributed as $CR_{\overline{FR}}(i \to j) \xrightarrow{d} \chi_1^2$, and where the adjusted sample correlation coefficient, which permits for an increase in volatility in the crude oil market, is given in Eq. (2.5):

$$\hat{\rho}_{y|x_i} = \frac{\hat{\rho}_y}{\sqrt{1 + ((\sigma_{y,i}^2 - \sigma_{x,i}^2)/\sigma_{x,i}^2)(1 - \hat{\rho}_y^2)}} \tag{2.5}$$

where $\sigma_{x,i}^2$ and $\sigma_{y,i}^2$ are the return variances in the international oil market (i) in calm and crisis oil market periods, correspondingly; and where $\hat{\rho}_x$ in Eqs. (2.4) and $\hat{\rho}_y$ in Eq. (2.5) are the oil-financial market Pearson correlation in the calm and crisis oil market samples, respectively. Additionally, the variance in the denominator of Eq. (2.4) is the standard error of the numerator and is decomposed in Eq. (2.6):

$$Var\left(\widehat{\rho}_{y|x_i} - \widehat{\rho}_x\right) = Var\left(\widehat{\rho}_{y|x_i}\right) + Var\left(\widehat{\rho}_x\right) - 2Cov\left(\widehat{\rho}_{y|x_i}, \widehat{\rho}_x\right) \tag{2.6}$$

where the second term is a sampling variance of the correlation coefficient. An approximation for large samples, and moderate or small correlations has been derived in Hotelling (1953, p. 212) as $Var\left(\widehat{\rho}_x\right) = \frac{1}{T_x}\left(1 - \rho_x^2\right)^2$. As the relevant population value ρ_x is unknown in practice, it is replaced in the calculation by the corresponding sample value[9].

It is also worth mentioning that the accuracy of the adjusted linear correlation test can be affected by omitted variables, as well as the degree of endogeneity between the markets. We address both of these issues in the data section.

[9]For a further decomposition and computation of the other terms see the Appendix in (Fry et al., 2010, p. 435-436).

2.3.1.3 Co-skewness contagion tests

Fry et al. (2010) take contagion analysis a step further and put forward two higher order co-moment contagion tests to ascertain whether there are statistically significant differences in calm and crisis market correlations based on changes in co-skewness, i.e. a shared higher-order (third) moment for a pair of continuous random variables. Co-skewness contagion can occur in one of two ways: Either, the mean behaviour of one market affecting the volatility of another as given by Eq. (2.7); or, the volatility of one market affecting the mean behaviour of another as illustrated in Eq. (2.8). Fry et al. (2010) show that this asymmetric dependence perspective is able to reveal additional channels of contagion, beyond the approach described by Forbes and Rigobon (2002). Further applications of these tests are covered in Fry-McKibbin et al. (2014) and Fry-McKibbin and Hsiao (2018). Eq. (2.7) conveys the test statistic corresponding to the null hypothesis of no contagion spillover from average oil returns to the volatility of a financial asset market in Trinidad and Tobago:

$$CS_1(i \to j; r_i^1, r_j^2) = \left(\frac{\hat{\psi}_y(r_i^1, r_j^2) - \hat{\psi}_x(r_i^1, r_j^2)}{\sqrt{(4\hat{\rho}_{y|x_i}^2 + 2)/T_y + (4\hat{\rho}_x^2 + 2)/T_x}} \right)^2 \tag{2.7}$$

whereas, the test statistic denoted in Eq. (2.8) is associated with the null hypothesis of no contagion spillover from oil market volatility to an average financial market returns in Trinidad and Tobago:

$$CS_2(i \to j; r_i^2, r_j^1) = \left(\frac{\hat{\psi}_y(r_i^2, r_j^1) - \hat{\psi}_x(r_i^2, r_j^1)}{\sqrt{(4\hat{\rho}_{y|x_i}^2 + 2)/T_y + (4\hat{\rho}_x^2 + 2)/T_x}} \right)^2 \tag{2.8}$$

where r_i^1 and r_i^2 are the mean and standard deviation of returns in the crude oil market, correspondingly, and r_j^1 and r_j^2 are the same for a given financial asset market in Trinidad and Tobago which can potentially be affected. Furthermore, T_x and T_y are defined as the calm and crisis oil market sample sizes, respectively, and $\hat{\rho}_x$ in Eq.s (2.7) and (2.8) is the conditional correlation estimate between crude oil and a given financial market in calm oil market conditions. Furthermore, $\hat{\rho}_{y|x_i}$ is a sample correlation coefficient which corrects the heteroskedasticity bias in the oil market crisis period conditional on the volatility in the calm oil market period, as described earlier in Eq.(2.5). Additionally, Eqs. (2.9) and (2.10) show the respective forms the standardisation parameters $\hat{\psi}_x(r_i^m, r_j^n)$ and $\hat{\psi}_y(r_i^m, r_j^n)$ take:

$$\hat{\psi}_x(r_i^m, r_j^n) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left(\frac{x_{i,t} - \hat{\mu}_{xi}}{\hat{\sigma}_{xi}} \right)^m \left(\frac{x_{j,t} - \hat{\mu}_{xj}}{\hat{\sigma}_{xj}} \right)^n \tag{2.9}$$

$$\hat{\psi}_y(r_i^m, r_j^n) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left(\frac{y_{i,t} - \hat{\mu}_{yi}}{\hat{\sigma}_{yi}} \right)^m \left(\frac{y_{j,t} - \hat{\mu}_{yj}}{\hat{\sigma}_{yj}} \right)^n \tag{2.10}$$

where x reflects the calm and y is the crisis oil market behaviours; $\hat{\mu}$ and $\hat{\sigma}$ are the mean and standard deviation, respectively, for a given market (i.e., i or j) under a given sample (i.e., x or y); and r^m (r^n) is the average returns for market i (j) in the test version CS_1 (CS_2) and squared returns in the test version CS_2 (CS_1). The test statistics in Eqs. (2.7) and (2.8), when their associated null hypotheses are true, are asymptotically distributed as $CS(i \to j) \xrightarrow{d} \chi_1^2$.

2.3.1.4 Co-volatility contagion test

Fry-McKibbin et al. (2014) and Fry-McKibbin and Hsiao (2018) introduce an extremal dependence test based on changes in co-volatility. The test statistic for the transmission from market i (i.e., the crude oil market) volatility to market j (i.e., the exchange rate or stock market in Trinidad and Tobago) volatility is given in Eq. (2.11).

$$CV(i \to j; r_i^2, r_j^2) = \left(\frac{\hat{\xi}_y(r_i^2, r_j^2) - \hat{\xi}_x(r_i^2, r_j^2)}{\sqrt{(4\hat{\rho}_{y|x_i}^4 + 16\hat{\rho}_{y|x_i}^2 + 4)/T_y + (4\hat{\rho}_x^4 + 16\hat{\rho}_x^2 + 4)/T_x}} \right)^2 \tag{2.11}$$

Once again, $\hat{\rho}_{y|x_i}$ enters into the computation to adjust for the heteroskedasticity bias in the oil market crisis period, and the standardisation parameters $\hat{\xi}_x(r_i^2, r_j^2)$ and $\hat{\xi}_y(r_i^2, r_j^2)$ take the form shown in Eqs. (2.12) and (2.13), respectively.

$$\hat{\xi}_x(r_i^2, r_j^2) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left(\frac{x_{i,t} - \hat{\mu}_{xi}}{\hat{\sigma}_{xi}} \right)^2 \left(\frac{x_{j,t} - \hat{\mu}_{xj}}{\hat{\sigma}_{xj}} \right)^2 - (1 + 2\hat{\rho}_x^2) \tag{2.12}$$

$$\hat{\xi}_y(r_i^2, r_j^2) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left(\frac{y_{i,t} - \hat{\mu}_{yi}}{\hat{\sigma}_{yi}} \right)^2 \left(\frac{y_{j,t} - \hat{\mu}_{yj}}{\hat{\sigma}_{yj}} \right)^2 - (1 + 2\hat{\rho}_{y|x_i}^2) \tag{2.13}$$

and where all other notations are defined according to the previous contagion tests and under the null of "no contagion", the co-volatility test is also asymptotically distributed as $CV(i \to j) \xrightarrow{d} \chi_1^2$.

2.3.2 Identifying calm and crisis energy market conditions

Another original contribution of our paper is based on the identification strategy for the calm and crisis samples of the aforementioned contagion tests. We use booming/slumping and tranquil/turbulent volatility scenarios to proxy calm/crisis energy periods across our sample.

2.3.2.1 Bull/bear proxy for booming/slumping oil market phases

As surrogates for oil booms (calm) and slumps (crisis) periods, we employ rule-based algorithms to identify bull and bear crude oil market phases, respectively, following the approaches of Pagan and Sossounov (2003) and Lunde and Timmermann (2004). The phases in these two methods are determined by maxima and minima in crude oil prices, but vary in which of these extrema result in a state switch (see Kole and Dijk (2017) for a more thorough comparison).

Pagan and Sossounov (2003) approach

In this approach, bull and bear phases are identified based on the programmed determination of turning points outlined in Pagan and Sossounov (2003). This procedure applies rules such that a peak (trough) is based on whether the oil price in month t is above (below) other months within the interval $t - \tau_{window}$ and $t + \tau_{window}$. As the maxima and minima that triggers the shifts between bull and bear phases, extrema values towards the end of the interval are prevented from distorting the identification of markets states, with a further rule τ_{censor}. We follow Pagan and Sossounov (2003) and set $\tau_{window} = 8$ months and $\tau_{censor} = 6$ months. Gil-Alana et al. (2016) also adopts this calibration to identify bear and bull phases in the crude oil market. This yields a dummy variable with oil crisis (bear) and calm (bull) sample periods for our energy contagion test.

Lunde and Timmermann (2004) approach

Here, a shift in a market phase is determined by two threshold scalars: λ_1 and λ_2, where λ_1 (λ_2) activates a switch from a bear (bull) to a bull (bear) market. We follow a feasible combination suggested in Lunde and Timmermann (2004) and employed in Kole and Dijk (2017), and set $\lambda_1 = 0.20$, which indicates a minimum increase of 20% in the market index since the last trough will activate a switch from a bearish regime to a bullish regime, and $\lambda_2 = 0.15$, which provides a rule that a minimum decrease of 15% since the last peak is needed to activate a switch from a bull phase to a bear phase. For previous empirical work done on commodity markets, Ntantamis and Zhou (2015) use alternative λ_1 and λ_2 combinations marginally higher and lower than the standard thresholds we employ here and find no substantial difference in their results. Again, we acquire a dummy variable with discrete bear and bull phases for testing energy contagion.

2.3.2.2 Tranquil and turbulent oil market volatility scenarios

To determine tranquil (calm) and turbulent (crisis) crude oil market volatility samples, we first estimate two simple oil price volatility measures: A range estimator and realised monthly volatility[10]. Then, we apply a non-hierarchical k-means clustering algorithm to sort oil market volatility into two discrete groups of relatively lower (tranquil) and higher (turbulent) volatility periods. The clustering is based on Euclidean distance as the measure of similarity/dissimilarity in order to maximise between cluster variance and minimise within cluster variance of the two groupings.

Oil price range estimator

We augment the range estimator suggested in Brooks (2008, p. 386) which is the range component of the high-low volatility method proposed in Parkinson (1980)[11], to compute

[10]For these estimators, we work with daily data averaged over a month but we also find that our results are consistent with the use of annualised monthly data based on a daily frequency.

[11]We also estimate the high-low volatility method in Parkinson (1980). This involves simply multiplying a scaling factor to the squared range estimator, which is $\frac{1}{4\ln 2}$ (i.e., ≈ 0.361) for daily data. While these two variants of the estimator have a Spearman correlation of 0.99, the inclusion of the scaling factor over-emphasises extreme volatility episodes, resulting in a reduction of high volatility periods in our full sample to just 13 months identified with the clustering algorithm. Given the strong relationship between the measures, suggesting that the two variants capture the same information content about oil market volatility, we proceed without the scaling factor which is more suitable for our intended analysis.

the monthly average oil price range using daily maximum and minimum spot values, as Eq. (2.14) shows:

$$range_t^{OP} = \frac{1}{n}\sum_{\tau=1}^{n}\left(\ln\left(\frac{OP_{t,\tau}^{max}}{OP_{t,\tau}^{min}}\right)\right) \tag{2.14}$$

where $\ln(OP_{t,\tau}^{max}/OP_{t,\tau}^{min})$ is the log of the ratio of the highest to lowest observed oil prices for day τ, and this range is averaged over a given month t with n as the amount of days crude oil was traded in that month. Next, using cluster analysis, we acquire a binary outcome of tranquil and turbulent sub-samples, as shown in Eq. (2.15), for the energy contagion tests.

$$Dummy_t^{range} = \begin{cases} 1, & \text{if } [range_t^{OP} - c_1]^2 < [range_t^{OP} - c_0]^2 \\ 0, & \text{otherwise} \end{cases} \tag{2.15}$$

where c_0 and c_1 are the centroids (i.e., the mean values) of tranquil and turbulent clusters, respectively, of the oil price range estimator.

Realised monthly oil price volatility

To analyse oil volatility, Mohaddes and Pesaran (2013) use an annualised variation of realised volatility commonly employed for calculating daily realised volatilities of financial returns. Their computation differs from the realised standard deviation estimator in the finance literature, which is typically just the square root of the sum of squared returns. The Mohaddes and Pesaran (2013) measure instead resembles the more generic standard deviation formula often used in finance and statistics (see, also, Poon and Granger (2003, 480)) to standardise how dispersed each observation is from a lower frequency data average. As such, the authors obtain annual volatility using monthly changes in oil prices. However, Mohaddes and Pesaran (2013) explain that this measure can involve the use of higher frequency data to obtain more accurate volatility measures. Here, we adopt a modified version of their formula, in Eq. (2.16). Since every month has a different amount of trading days, which will obviously impact the volatility summed in each month, we use daily volatility averaged over the month to circumvent this issue.

$$rmv_t^{OP} = \sqrt{\frac{1}{n}\sum_{\tau=1}^{n}(\Delta \ln OP_{t,\tau} - \overline{\Delta \ln OP_t})^2} \tag{2.16}$$

where rmv_t^{OP} is the realised monthly average volatility of seasonally adjusted real daily oil returns; n is the amount of days crude oil was traded in a given month; $\Delta \ln OP_{t,\tau}$ is monthly oil returns for day τ in month t; and $\overline{\Delta \ln OP_t} = \frac{1}{n}\sum_{t=1}^{n} \Delta \ln OP_{t,\tau}$, denoting the average daily oil returns during the month. Subsequently, we cluster oil market volatility into the binary outcome of tranquil and turbulent samples, as suggested by Eq. (2.17).

$$Dummy_t^{rmv} = \begin{cases} 1, & \text{if } [rmv_t^{OP} - c_1]^2 < [rmv_t^{OP} - c_0]^2 \\ 0, & \text{otherwise} \end{cases} \tag{2.17}$$

where c_0 and c_1 are the centroids of tranquil and turbulent clusters, respectively, of rmv_t^{OP}.

2.4 Data

Our data is monthly and spans January 1994 to August 2017 on oil prices, US interest rates, as well as exchange rates, interest rates, and stock returns for Trinidad and Tobago. Table 2.1 provides the data definitions and sources.

Table 2.1: Data definitions and sources

Series	Definition	Source
Real Oil Prices (OP)	European Brent crude oil spot prices expressed in constant 2010 USD, using the consumer price index on all items for the United States.	Calculated using Federal Reserve Economic Data (FRED)
Interest Rates (IR)	Trinidad and Tobago's commercial banking median basic prime lending rate.	The Central Bank of Trinidad and Tobago (CBTT)
Real Composite Stock Price Index (CSPI)	A market-value weighted index collectively measuring the price movement of the ordinary shares for companies listed on the First Tier market of the Trinidad and Tobago Stock Exchange, delimited in a base year of 1983, adjusted for inflation using the retail price index on all items with a base year of 2010.	Calculated using data from the Central Bank of Trinidad and Tobago (CBTT)
Real Effective Exchange Rates (REER)	Trinidad and Tobago's Nominal Effective Exchange Rate (NEER) adjusted for inflation using the local 2010 retail price index, where the NEER is a measure of the value of a currency against a weighted average of several foreign currencies.	International Monetary Fund (IMF) International Financial Statistics
Shadow Short Rates (SSR)	SSR is the shortest maturity rate from the estimated shadow yield curve in the United States. This policy interest rate can take on negative values to reflect unconventional monetary policy during the contemporary quantitative easing era in the United States (see Krippner (2016)).	Leo Krippner, Research programme, Reserve Bank of New Zealand.

Note: All data were retrieved between March and May 2018.

We use international crude oil prices as our energy market performance indicator. This is because oil remains the primary source of global energy consumption, i.e. 32.9%, with no challenging substitutes threatening more than 5% of this share before 2020 (WEC, 2016). Also, although Trinidad and Tobago is an oil and gas economy, natural gas prices are often indexed to crude oil prices implying that most of the information contained in gas prices are already captured by oil prices (Zhang and Broadstock, 2018). The two most important global oil price benchmarks are the reference prices associated with the Brent and West Texas Intermediate (WTI) crude blends. Despite the fact that world crude oil prices trend together due to arbitrage (Reboredo, 2011), the WTI benchmark has departed from this co-movement between 2011 and 2014, trading at a discounted price. This is due to the US shale boom causing excess supply of light sweet crude in the central US market (Kilian, 2016). Due to these developments, Brent oil has further fortified its prominence as global benchmark, as the WTI price increasingly reflects US-specific dynamics (Manescu and Van Robays, 2016). Yet, even for the US economy, Gormus and Atinc (2016) show that the Brent oil prices contain more information in predicting macroeconomic variables than the WTI prices and they argue the value of using the former instead of the latter for US-based studies. Moreover, Trinidad and Tobago produces water-borne crude which is pegged to the Brent crude oil price benchmark, trading at either a premium or a discount to this international reference price. Within this context, we follow Baumeister and Kilian (2016a) and use Brent crude oil prices. Regarding the real price level per barrel of crude oil, an upward trend is noted from 2003 until mid 2008 in Figure 2.1, denoting the oil price boom of the 2000s. However, this commodity enters an era of uncertainty as real prices fell by 68% between July 2008 and December 2008, and by 57% from June 2014 to January 2015.

We use the Real Effective Exchange Rate (REER) of Trinidad and Tobago as our exchange rate indicator. The REER index has a straightforward interpretation: An increase implies exports have become relatively more expensive and imports cheaper, which indicates a reduction in the country's trade competitiveness. Figure 2.1 shows that from the start of the sample until the GFC, the REER exhibits a relatively gradual upward trend when compared to the more steep growth experienced in the post-GFC period. It is interesting to note that the appreciation in the REER index coincides with the aforementioned international oil price plummets. CBTT (2009, 2015) explains that these appreciations in the Trinidad and Tobago REER are indirectly tied, via the managed float, to the strengthening US dollar relative to other major currencies.

We use the Composite Stock Price Index (CSPI) compiled by the TTSE as the stock market performance indicator. The TTSE is just about 4 decades old and currently consists of First Tier, Second Tier, and Mutual Funds markets. We focus on the First Tier Market[12], the most important group based on market capitalisation, which lists 31

[12]The Second Tier and Mutual Funds markets of the TTSE lists only 1 and 5 securities, respectively.

securities classified under: Banking, conglomerates, energy, property, manufacturing, trading, non-banking finance, and non-sector (TTSE, 2017). The CSPI is a market-value weighted index collectively measuring the price movement of the ordinary shares for companies listed on the First Tier Market. Figure 2.1 depicts a bullish trend in the real CSPI stretching from the latter half of 2003 to early months of 2005 that is interrupted by two corrections for overheating stock prices from the previous year. The first correction in March 2005 is due to the introduction of automated trading, and the second in May 2005 happens when registered pension plan equities sell down (TTSE, 2006). Furthermore, the subsequent wave of optimistic stock market behaviour in the first half of 2008 is supplanted by the GFC and remains relatively stagnant for the rest of the sample.

Real oil prices, the REER index, and real CSPI are expressed as returns, i.e. the first difference in the natural logarithm for each series, times 100. Subsequently, to remove lead-lag effects and serial correlation from the return series, we work with residuals (ε_t) from Eqs. (2.18), (2.19), and (2.20), respectively, as our adjusted returns. The exogeneity of international oil prices for a small economy like Trinidad and Tobago drives our choice of specification for these regressions. Adjusted oil returns is acquired from the single equation model specified in Eq. (2.18):

$$\Delta \ln OP_t = \alpha_0 + \alpha_1 \Delta \ln OP_{t-1} + \alpha_2 SSR_{t-1} + \varepsilon_t \tag{2.18}$$

where $\Delta \ln OP_t$ are real Brent crude oil returns, α_0 is a constant, $\Delta \ln OP_{t-1}$ is an autoregressive term, and SSR_{t-1} are the US interest rates. An optimal lag order of 1 month is determined by Akaike, Hannan-Quinn, and Schwarz information criteria and there is no residual autocorrelation based on the Portmanteau autocorrelation test at the conventional levels of significance. The estimated coefficients and the results of the serial correlation test are both provided in Table 2.6 of the chapter appendix.

As neither exchange rates nor stock returns from Trinidad and Tobago can affect international crude oil returns, we use the residuals from Eqs. (2.19) and (2.20) from a VARX(1) system to obtain these adjusted financial returns:

$$\Delta \ln REER_t = \alpha_{10} + \alpha_{11}\Delta \ln REER_{t-1} + \alpha_{12}\Delta \ln CSPI_{t-1} + \alpha_{13}IR_{t-1} + \alpha_{14}\Delta \ln OP_{t-1} + \alpha_{15}SSR_{t-1} + \varepsilon_{1t} \quad (2.19)$$

$$\Delta \ln CSPI_t = \alpha_{20} + \alpha_{21}\Delta \ln CSPI_{t-1} + \alpha_{22}\Delta \ln REER_{t-1} + \alpha_{23}IR_{t-1} + \alpha_{24}\Delta \ln OP_{t-1} + \alpha_{25}SSR_{t-1} + \varepsilon_{2t} \quad (2.20)$$

where $\Delta \ln REER_t$ is the growth rate of the REER, $\Delta \ln CSPI_t$ is real composite stock returns, IR_{t-1} denotes domestic interest rate for Trinidad and Tobago, along with exogenous variables for oil returns ($\Delta \ln OP_{t-1}$) and US interest rates (SSR_{t-1}). An appropriate lag length of 1 month is selected using Akaike, Hannan-Quinn, and Schwarz information criteria and the computed multivariate Box-Pierce/Ljung-Box Q-statistics for residual serial correlation shows there is no statistically significant residual autocorrelation. Again, the estimated coefficients and the results of the serial correlation test are both provided in Table 2.6 of the chapter appendix.

Following Forbes and Rigobon (2002), interest rates are included in Eqs. (2.18), (2.19), and (2.20) to account for macroeconomic and monetary performance. This is because the correlation between asset returns might occur due to the omission of economic fundamentals and not because of contagion. We use US short term interest rates as a foreign economic activity measure for the following reasons. Crude oil is primarily invoiced in US dollars (Kayalar et al., 2017) and fluctuations in this currency may affect the behaviour of crude oil prices (Zhang et al., 2008). Furthermore, Kilian and Zhou (2018) find that exogenous fluctuations in US real interest rates have quantitatively important effects on oil prices (see also Hou et al. (2016)). These perspectives motivate accounting for the real sector and policy environment of the US in the oil returns model. Also, the USA is Trinidad and Tobago's major trading partner, in terms of both exports and imports, providing a rationale to include US interest rates in our models for adjusting the exchange rate and stock returns as well. To these ends, we use US Shadow Short Rates (SSRs)[13] as a foreign interest rate measure relevant to this small island economy. US SSRs adjusts the conventional policy rate to accommodate for unconventional monetary authority actions, like quantitative easing, by permitting the rate to take on values below the zero lower bound.

We use the commercial banking median basic prime lending rate to proxy real, policy, and financial activity in Trinidad and Tobago. This interest rate is available for our entire sample and is highly positively correlated with other important monetary policy rates[14] and also conveys financial sector-specific information. Additionally, we allow exchange rate and stock returns to enter each other's regression functions endogenously to account for potential lead-lag interactions. For instance, the flow-oriented model characterises the influence exchange rates can have on the stock market, while the portfolio balance approach establishes that stock prices affect exchange rates (see Chkili and Nguyen (2014) and references therein).

Figure 2.1 shows plots of the main time series variables used in our study: The monthly unadjusted levels and adjusted returns for the three series, along with foreign (US) and domestic (Trinidad and Tobago) interest rates. The GFC period, i.e. from December 2007 to June 2009, is clearly marked on the graphs. It can be seen that the

[13] See Table 2.1 for further details.

[14] For example, the median prime lending rate and the 3 month treasury bill average discount rate has a Pearson's ρ of 0.93 between 1995m1-2017m8, and median prime lending rate and the Central Bank's repo and discount rates from 2002m5-2017m8 have a Pearson's ρ of 0.91.

three adjusted returns (and their levels) have all been impacted by the GFC, as these assets all exhibit breaks coinciding with that time period. Hence, our sensitivity analysis involves comparing samples with and without this period to evaluate if the energy contagion results are robust to the GFC.

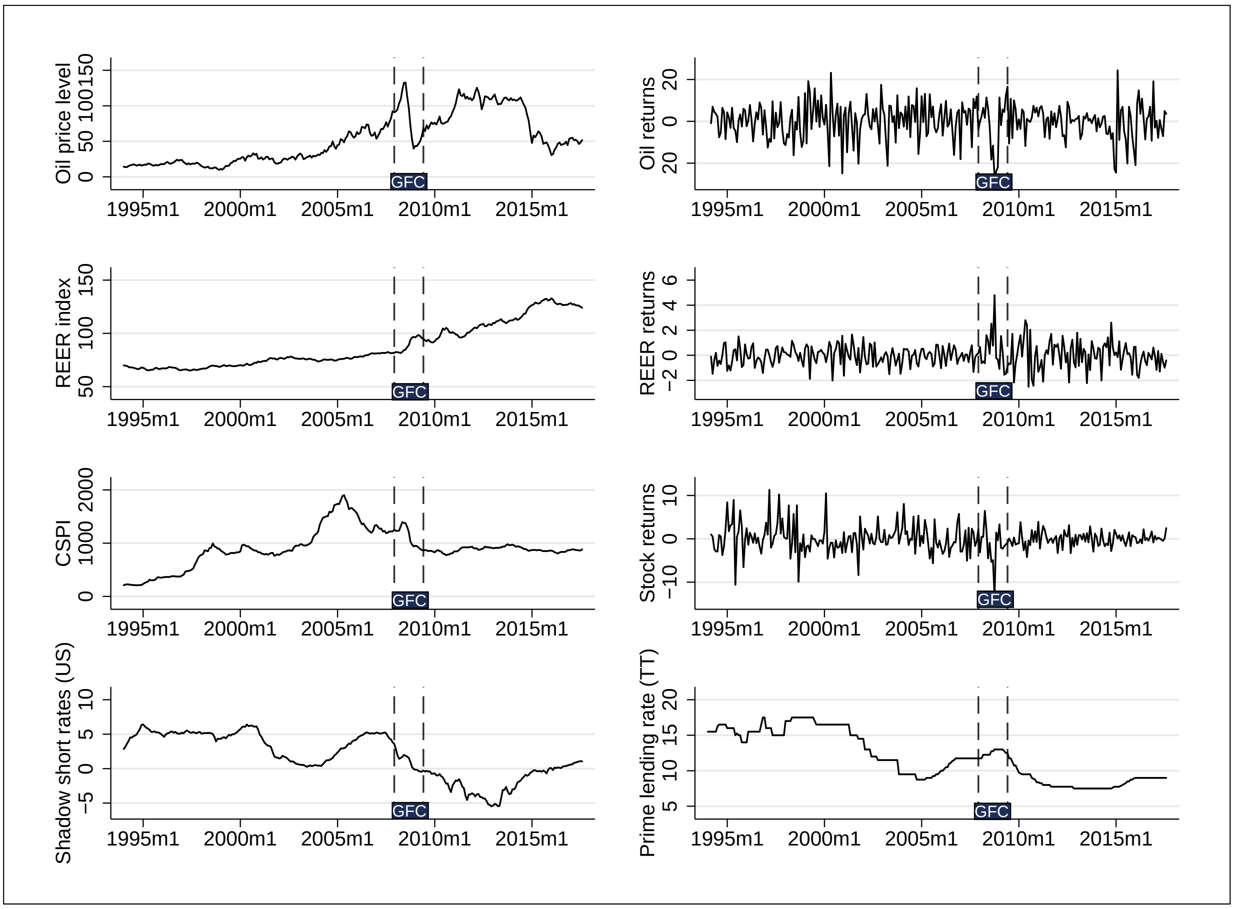

Figure 2.1: Monthly unadjusted levels and adjusted returns (in %) of real Brent crude oil prices, Trinidad and Tobagos's REER, and real stock market (CSPI) indices; as well as foreign (US shadow short rates) and domestic (Trinidad and Tobago) interest rates. The GFC refers to the Global Financial Crisis period. See the text for further explanations.

2.5 Results

2.5.1 Comparing the identification strategies for calm and crisis crude oil market periods

Graphs (A) and (B) in Figure 2.2 show the bear market phases of Brent crude oil prices identified by the two semi-parametric rule-based algorithms. The two approaches yield similar results with only marginal differences. Noticeably, many of the bearish trends which dominate the international crude oil market, coincide with periods of global turmoil: The Asian financial crisis (1997), the dot-com crash and the 9/11 terrorist attacks (2001), and the GFC (2008). Bearish phases are noted in the post-GFC era, the most striking of which was the sharp oil price collapse between June 2014 and January 2015. This decline is attributed, in part, to a negative oil demand shock from a slowdown in the world economy, as well as positive oil supply shocks coming from the US shale boom and other oil producers such as Canada and Russia (Baumeister and Kilian, 2016b,a).

Also depicted in Figure 2.2 are the two volatility estimates[15] of Brent crude oil prices over our sample period. The realised monthly volatility (D) is a much more volatile measure than the range estimator (C), where the standard deviations of former and latter are 5.03 and 1.09, respectively. This diagram also illustrates the turbulent (crisis) and tranquil (calm) classifications based on the cluster analysis of the two volatility measures. The clustering algorithm is applied to each series for the full sample and the sample where the GFC is censored. As such, the higher red triangles (additional blue lower squares) in each graph indicate the threshold values between the turbulent and tranquil scenarios of the full (censored) sample, which corresponds to values $\geq$ 3.40 ($\geq$ 2.93) for oil volatility based on the range estimator in (C) and $\geq$ 10.15 ($\geq$ 9.50) for

[15] Scaled up by 100 for ease of interpretation.

the realised monthly oil volatility in (D). These thresholds are calculated as the sum of the minimum value of the turbulent group and the maximum value of the tranquil group, divided by two.

It is useful to understand how the calm and crisis periods identified by the four aforementioned strategies, i.e. the two semi-parametric rule-based algorithms and the two volatility measures, are related. Nested in Table 2.2 are the contingency tabulations for any two identification strategies, represented as a 3 x 3 matrix. Together, these 12 matrices allow for comparisons between all four techniques in both the full and GFC-censored samples. A simple measure of similarity (dissimilarity) between two identification approaches is computed by summing the two leading (off) diagonal elements and diving by the grand total of that 3 x 3 contingency table. For example, we note a 97.16% similarity (i.e. ((168+106)/282)x100) between the Pagan and Sossounov (2003) (P&S) and Lunde and Timmermann (2004) (L&T) rule-based algorithms in the full sample. In fact, because the similarity between these two techniques is so high throughout Table 2.2, to avoid repetition in the results section we only report the findings using the Pagan and Sossounov (2003) method, since this is the more widely deployed method in the applied literature.

Concerning the two volatility measures, the similarity between them in the full and GFC-censored samples are 80.14% and 69.96%, respectively. Therefore, we report on both methods in the results as they appear to capture different perspectives. Furthermore, the similarity between the P&S and the crude oil range estimator is 63.12% in full sample and 56.65% in the GFC-censored sample, whereas the similarity between P&S and the realised monthly average crude oil volatility was 60.28% in the full sample and 60.08% in the GFC-censored sample. This suggests that bear (bull) market phases are not clear indicators of turbulent (tranquil) volatility scenarios, providing only partial evidence for leverage effects[16] in the international crude oil market based on the Brent benchmark.

Table 2.2: Combined contingency table for measuring the similarity between the calm and crisis months in the crude oil market across the four identification strategies, for both the full and GFC-censored samples. All values for calm, crisis, and total periods in the tabulations are in months. The following abbreviations apply- P&S (2003) for the groupings obtained from the Pagan and Sossounov (2003) procedure; L&T for Lunde and Timmermann (2004); range est. for range estimator; and realised vol. for realised volatility.

Sample			L&T			Range est.			Realised vol.		
			Calm	Crisis	Total	Calm	Crisis	Total	Calm	Crisis	Total
		Calm	168	4	172	148	24	172	143	29	172
	P&S	Crisis	4	106	110	80	30	110	83	27	110
		Total	172	110	282	228	54	282	226	56	282
		Calm				148	24	172	144	28	172
Full	L&T	Crisis				80	30	110	82	28	110
		Total				228	54	282	226	56	282
		Calm							199	29	228
	Range est.	Crisis							27	27	54
		Total							226	56	282
		Calm	155	4	159	112	47	159	131	28	159
	P&S	Crisis	4	100	104	67	37	104	77	27	104
		Total	159	104	263	179	84	263	208	55	263
		Calm				112	47	159	132	27	159
GFC-censored	L&T	Crisis				67	37	104	76	28	104
		Total				179	84	263	208	55	263
		Calm							154	25	179
	Range est.	Crisis							54	30	84
		Total							208	55	263

[16]Leverage effects imply that falling (rising) asset prices propagate higher (lower) volatility.

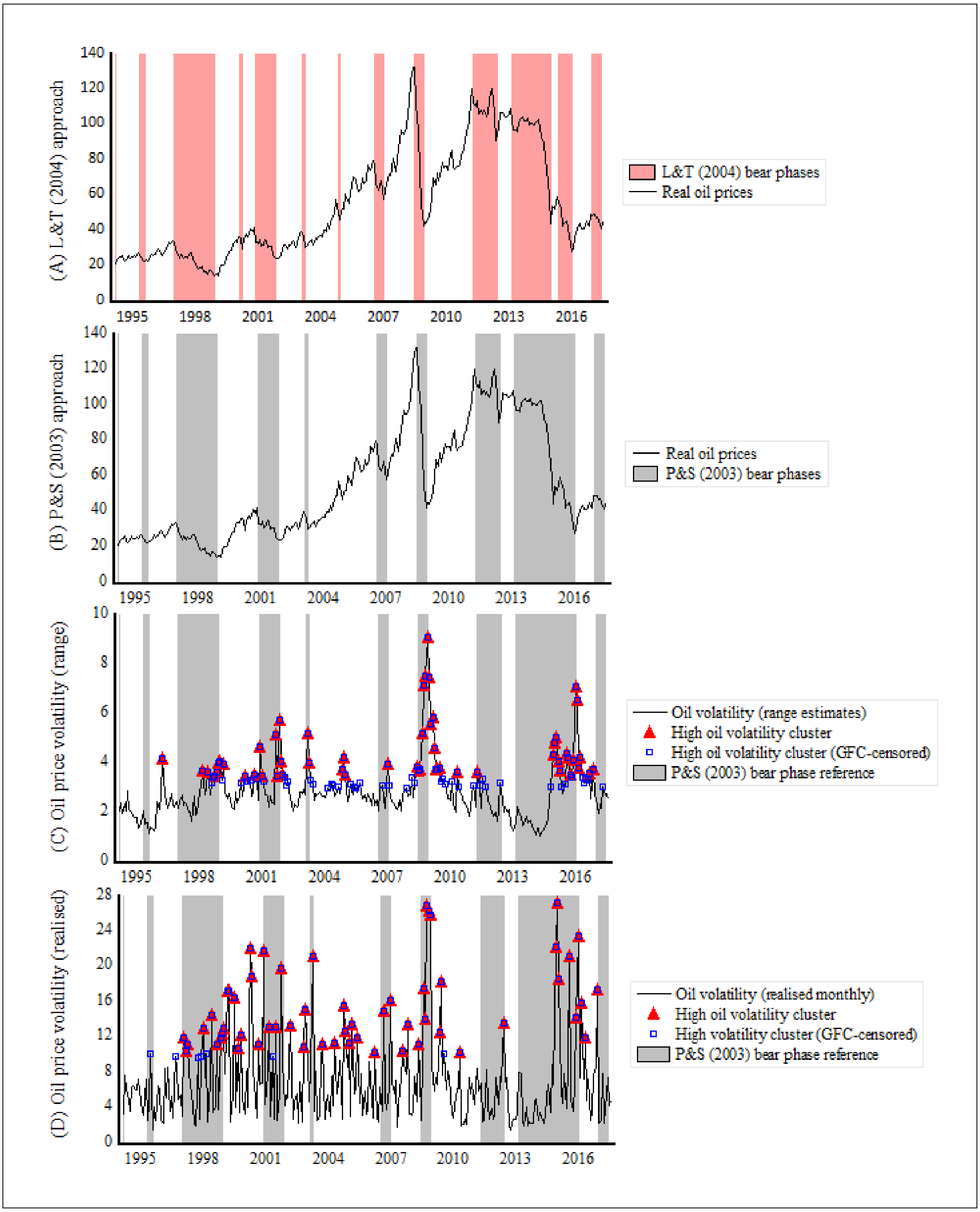

Figure 2.2: Oil market crisis identification using bear phases and high volatility clustering. *Caption continues on the next page.*

Graph (A) shows real Brent crude oil prices under bear phases identified by the Lunde and Timmermann (2004) (L&T 2004) rule-based algorithm; Graph (B) shows real Brent crude oil prices under bear phases identified by the Pagan and Sossounov (2003) (P&S 2003) rule-based algorithm; Graph (C) shows the high oil volatility months in Brent crude oil market identified by the clustering algorithm on the oil price range estimator; and Graph (D) shows the high oil volatility months in the crude oil market identified with the realised monthly oil volatility measure. In the oil price volatility measures (C) and (D), the red triangles display the high volatility months in the full sample, whereas the blue squares illustrate the high volatility months which permit the identification of additional months when the extreme values associated with the Global Financial Crisis (GFC) months are censored from distorting the clustering algorithm as a fundamental robustness check for the correlation analysis and energy contagion tests. As the bear market phases identified by the Pagan and Sossounov (2003) approach are our main bull/bear identification strategy, these bearish states are superimposed into the two volatility measure graphs (C) and (D) for ease of visual comparisons.

2.5.2 Performance of financial returns by energy market conditions

Table 2.3 presents summary statistics for the adjusted returns by energy market conditions, i.e. bullish or bearish and tranquil or turbulent scenarios. In addition, our empirical applications are performed on both the full and a GFC-censored sample to see whether the results are sensitive to the contemporary financial crash. Interestingly, we observe that the REER appreciates (depreciates) under bearish (bullish) and turbulent (tranquil) oil market conditions, suggesting that Trinidad and Tobago is more uncompetitive (competitive) in periods of crisis (calm) in the crude oil market. Moreover, in the full sample exchange rates are more volatile under bearish and turbulent oil market conditions, whereas these results are inconclusive in the GFC-censored sample, implicitly implying that the rise in volatility is associated with the GFC period.

Additionally, mixed results are received concerning Trinidad and Tobago's stock market. When the crude oil market is slumping (booming), as conveyed by bearish (bullish) oil market conditions, stock returns are positive (negative). Yet, under turbulent (tranquil) oil price volatility, stock returns are falling (rising). Generally, higher stock market volatility is noted under crisis periods (both bearish and turbulent) in the oil market, compared to calm periods.

Table 2.3: Descriptive statistics of adjusted monthly returns (%) by sample (full and GFC-censored) and energy conditions (bull vs. bear phases and tranquil vs. turbulent volatility). The abbreviations are obs. for observations, SD for standard deviation, Min. for minimum, and Max. for maximum. The descriptive statistics for the adjusted returns are based on the residuals of the regressions specified in Eqs. (2.18), (2.19), and (2.20).

			Real oil returns				REER returns				Real stock returns			
Sample	Energy conditions	Obs.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Bull & Bear oil market scenarios														
Pagan and Sossounov (2003) algorithm														
Full	Bullish	172	2.86	7.15	-21.41	23.22	-0.13	0.93	-2.50	2.80	-0.02	2.64	-6.51	10.51
	Bearish	110	-4.48	8.96	-26.54	24.39	0.20	0.95	-2.22	4.79	0.03	3.46	-13.29	11.29
GFC-censored	Bullish	159	2.64	7.20	-21.41	23.22	-0.13	0.92	-2.50	2.80	-0.02	2.62	-6.51	10.51
	Bearish	104	-3.73	8.40	-24.89	24.39	0.14	0.83	-2.22	2.61	0.26	3.22	-10.59	11.29
Volatility scenarios														
Crude oil price range estimator														
Full	Tranquil	228	1.08	6.88	-21.41	23.22	-0.03	0.89	-2.50	2.61	0.16	2.88	-10.59	11.29
	Turbulent	54	-4.56	13.00	-26.54	24.39	0.14	1.17	-1.79	4.79	-0.70	3.31	-13.29	7.70
GFC-censored	Tranquil	179	1.01	6.45	-16.03	19.08	-0.06	0.87	-2.50	2.61	0.25	2.90	-10.59	11.29
	Turbulent	84	-1.77	11.07	-24.89	24.39	0.05	0.95	-2.17	2.80	-0.25	2.78	-9.88	7.72
Realised monthly oil price volatility														
Full	Tranquil	226	0.57	5.32	-10.60	11.36	-0.06	0.91	-2.50	2.61	0.16	2.76	-10.59	10.51
	Turbulent	56	-2.32	16.15	-26.54	24.39	0.23	1.08	-1.88	4.79	-0.63	3.69	-13.29	11.29
GFC-censored	Tranquil	208	0.43	5.14	-10.60	10.74	-0.05	0.92	-2.50	2.61	0.14	2.74	-10.59	10.51
	Turbulent	55	-1.05	15.18	-24.89	24.39	0.08	0.76	-1.88	2.80	-0.08	3.33	-9.88	11.29

2.5.3 Energy contagion evidence

2.5.3.1 Correlation analysis

Table 2.4 shows the calm and crisis correlation coefficients using the Pearson, Spearman, and Kendall[17] measures, for both the full and GFC-censored samples under the various calm/crisis classification methods. In the far right column, the adjusted linear correlation coefficient (i.e., $\hat{\rho}_{y|x_i}$) gives the Pearson correlation between oil and financial returns in the crisis period, corrected to accommodate for spurious increases in crisis period volatility. A relatively modest negative interdependence is observed in the crude oil-exchange rate relationship in the two samples, across all identification strategies. This implies an inverse oil-exchange rate relationship, i.e. the REER appreciates (depreciates) when oil prices decrease (increase). However, in the full sample, the financial relationship between crude oil and stock markets are negative in calm periods and positive in crisis periods; but these connections are not robust to the GFC-censored sample, which suggests the GFC period has distorting effects on the country's equities.

The correlation measures provide no compelling support for the transmission of energy contagion in the returns channel between oil and financial markets in the traditional sense of a notable deepening of cross-market linkages under crisis conditions. However, the sizeable reduction in the strength of the adjusted linear correlation coefficient in the oil-exchange rate dependence under the oil price volatility calm/crisis classifications, for both the full and GFC-censored samples, presents a case for *reverse* energy contagion. Furthermore, the two non-parametric correlation measures paint a similar picture for the range estimator in the GFC-censored sample. Thus, turbulent volatility conditions in

[17] Generally, in absolute value, Kendall's τ tends to be smaller than the other two correlation measures (see also Conover (1999)).

crude oil markets appears to weaken the inverse oil-exchange rate association.

Table 2.4: Correlation coefficients from parametric and non-parametric measures for the overall sample, and during calm and crisis months in the oil-exchange rate and oil-stock market relationships, across the different calm/crisis identification methods, for both the full and GFC-censored samples. All correlation coefficients lie between 0 and 1, where 0 implies no correlation but increases as absolute values move away from 0 with +/- indicating positive/negative associations between crude oil and the returns of a given financial market. The following abbreviations apply- P&S (2003) for Pagan and Sossounov (2003); range est. for range estimator; and realised vol. for realised volatility.

Sample	Calm/crisis classification method	Correlation measure									
		Pearson's ρ			$\hat{\rho}_{y\|x_i}$	Spearman's ρ			Kendall's τ		
		Overall	Calm	Crisis	Crisis	Overall	Calm	Crisis	Overall	Calm	Crisis
Oil-exchange rate relationship											
Full	P&S (2003)	-0.30	-0.23	-0.30	-0.24	-0.30	-0.25	-0.23	-0.20	-0.17	-0.15
	Range est.	-0.30	-0.27	-0.37	-0.20	-0.30	-0.31	-0.29	-0.20	-0.20	-0.19
	Realised vol.	-0.30	-0.31	-0.35	-0.12	-0.30	-0.32	-0.34	-0.20	-0.22	-0.22
GFC censored	P&S (2003)	-0.26	-0.23	-0.21	-0.18	-0.28	-0.24	-0.21	-0.18	-0.16	-0.14
	Range est.	-0.26	-0.30	-0.21	-0.12	-0.28	-0.34	-0.19	-0.18	-0.22	-0.13
	Realised vol.	-0.26	-0.31	-0.30	-0.10	-0.28	-0.32	-0.30	-0.18	-0.22	-0.19
Oil-stock market relationship											
Full	P&S (2003)	0.03	-0.06	0.12	0.10	-0.03	-0.07	0.09	-0.02	-0.04	0.06
	Range est.	0.03	-0.04	0.08	0.04	-0.03	-0.03	-0.04	-0.02	-0.02	-0.03
	Realised vol.	0.03	-0.01	0.04	0.01	-0.03	-0.01	-0.01	-0.02	-0.01	0.01
GFC censored	P&S (2003)	-0.04	-0.06	0.01	0.01	-0.06	-0.07	0.04	-0.04	-0.05	0.02
	Range est.	-0.04	0.00	-0.13	-0.08	-0.06	-0.02	-0.12	-0.04	-0.01	-0.09
	Realised vol.	-0.04	0.01	-0.12	-0.04	-0.06	0.01	-0.09	-0.04	0.01	-0.05

2.5.3.2 Contagion testing

Table 2.5 provides the adjusted linear correlation test statistic, $CR_{\overline{FR}}$; the two variants of the co-skewness test where, under crisis, CS_1 shows whether the correlation between average crude oil returns and financial asset volatility increases and CS_2 conveys that the correlation between crude oil volatility and the average returns of a financial asset increases; and the co-volatility test statistic, CV. These are shown for each pair of energy-finance relationships, in both the full and GFC-censored samples, under each calm/crisis classification method. Focusing on the adjusted linear correlation test statistic, there are three statistically significant results illustrated in Table 2.5, all of which are associated with the oil-exchange rate relationship. However, in each of these cases, we observe *reverse* contagion since the correlation in the crisis period weakens substantially below the correlation in the calm period once the heteroskedasticity bias is adjusted, as given by the $\hat{\rho}_{y|x_i}$ correlation coefficients in Table 2.4.

Consistent with Fry et al. (2010), there is evidence to suggest that the co-skewness correlation tests are able to reveal additional higher moment contagion channels in cases where the adjusted linear correlation approach suggests none. Co-skewness contagion occurred with weak significance using the bear/bull rule-based algorithm and moderate significance with the realised monthly crude oil volatility in the oil-exchange rate relationship, in the full sample. In either case, the results imply that mean crude oil market returns affect currency volatility in energy crisis periods. Turning to the oil-stock market relationship, in the full sample, the co-skewness contagion test conveys links between average oil returns and stock market volatility across all identification strategies, as well as oil market volatility and average stock returns under the bear/bull classification.

Considering the co-volatility channel, under the Pagan and Sossounov (2003) energy conditions in the full sample, there are contagion effects from oil market volatility to both exchange rate and equity volatilities. We also observe weak evidence of this contagion channel under the range estimator in the oil-exchange rate relationship, also in the full sample.

In totality, we only find evidence of energy contagion associated with the full sample. Once the GFC period has been censored, we by and large fail to reject the null hypothesis of no contagion. As such, this implicitly implies that the contagion effects noted in the full returns sample are likely a result of GFC spillovers. Thus, we observe minimal support for energy contagion in financial markets of this small island energy economy.

Table 2.5: Test statistics for the adjusted linear correlation ($CR_{\overline{FR}}$), co-skewness (CS_1 and CS_2), and co-volatility (CV) energy contagion tests, in the oil-exchange rate and oil-stock market relationships, across the different calm/crisis identification methods, for both the full and GFC-censored samples.

Sample	Identification method	Oil-exchange rate relationship				Oil-stock market relationship			
		$CR_{\overline{FR}}$	CS_1	CS_2	CV	$CR_{\overline{FR}}$	CS_1	CS_2	CV
Full	P&S (2003)	0.010	3.549*	0.028	8.499***	2.215	3.974**	4.055**	8.620***
	Range est.	0.450	2.498	0.018	3.404*	0.783	12.439***	0.261	2.335
	Realised vol.	6.291**	4.605**	0.395	1.919	0.130	3.413*	0.389	0.328
GFC-censored	P&S (2003)	0.164	2.118	0.959	1.797	0.376	0.111	1.384	0.238
	Range est.	3.668*	0.317	0.031	0.159	0.579	0.546	1.418	0.649
	Realised vol.	7.186***	0.187	0.422	0.004	0.380	0.694	0.132	0.078

Notes: $***$, $**$, and $*$ denote the conventional 1% (strong), 5% (moderate), and 10% (weak) levels of statistical significance, respectively, which corresponds to χ^2_1 critical values of 6.635, 3.841, and 2.706 for the $CR_{\overline{FR}}$, CS_1, CS_2, and CV contagion tests. Additionally, all abbreviations used in the identification method column, are the same as described in Table 2.4.

2.6 Policy implications

At first glance, oil price changes are considered to be a leading indicator of exchange rate fluctuations, because rising prices in this commodity market transfers the wealth from oil-importers to oil-exporters (Turhan et al., 2014; Kumar, 2019). However, the increased uncompetitiveness of Trinidad and Tobago, as indicated by the appreciation (depreciation) of the REER when crude oil markets are in crisis (calm) periods, along with negative correlation between exchange rate and oil returns across all energy market conditions, are surprising artefacts for a small open energy intensive economy. Indeed, the positive wealth transfer effect from higher oil prices and Dutch disease conjecture suggests the opposite, i.e. oil booms are associated with exchange rate appreciations. In fact, our results for Trinidad and Tobago are more consistent with oil-importing countries[18] and we attribute this to the de facto exchange rate regime, which anchors the Trinidad and Tobago dollar to the US dollar. A natural concern is whether such an exchange rate policy is appropriate for this small petroleum economy. From the standpoint of our analysis, the current currency stabilisation arrangement appears sufficient for the following reasons. Firstly, given that both the theoretical and empirical literature generally find a negative link between oil prices and the US dollar exchange rate (Akram, 2009; Wu et al., 2012; Reboredo et al., 2014), for some oil-exporting emerging economies with currencies tied to the US dollar, part of the gains (losses) arising from oil price increases (decreases) are absorbed by the depreciation (appreciation) of the US dollar and such a currency peg provides the potential to taper the influence of oil price volatility on the purchasing power (Reboredo, 2012).

Furthermore, if the existence of a positive association between oil prices and the REER is indeed a requisite for the Dutch disease (Mironov and Petronevich, 2015), then our finding of an inverse oil-exchange rate relationship implies that the managed float buffers Trinidad and Tobago from this infection. Although our contagion analyses are based on returns and do not take into account the long run behaviour of these variables, we argue that this short run outlook is appropriate for Dutch disease diagnostics. The Dutch disease is an acute, not chronic, problem with no inhibiting long run macroeconomic growth consequences for resource-rich economies (Kojo, 2015). In the presence of a boom, any potential exchange rate appreciation will occur in the short run, but this is merely a transitory equilibrium, which dissipates as the time horizon expands (van der Ploeg, 2011).

[18] For example, see Lizardo and Mollick (2010) for Japan and Ghosh (2011) for India.

As such, the Dutch disease is relevant to countries that have experienced unanticipated exogenous shocks of foreign income derived from a natural resource discovery that is not expected to endure, and is less applicable to countries where a natural resource is the apex commodity and has been for a relatively long time (Mohaddes and Pesaran, 2013).

Additionally, in small island states characterised by high export concentration and a limited range of internationally competitive tradeable goods, it may be tempting to argue for the devaluation of the currency to promote export-led growth. However, the mechanical outlook that depreciations are perceived to improve the international competitiveness of a country, by making exports relatively cheaper and imports more expensive, while appreciations do the opposite, is dogmatic as it does not take into account the import content of exports (Abeysinghe and Yeok, 1998) and may be impractical for the small open economy whose size does not permit them to reasonably displace imports (Worrell et al., 2018). For example, provisional data for 2017 which shows that 37.50% of the total value of imports in Trinidad and Tobago consisted of energy commodities (CBTT, 2018), which were likely destined to be refined for exportation. The Central Bank of Trinidad and Tobago intervenes in the local foreign exchange market in an effort to maintain the currency peg to the US dollar. This policy action is done through the sale of foreign currency to authorised dealers and is supportive of the type of economic activity in this country. For instance, the consumption and manufacturing activities in Trinidad and Tobago are largely based on imports, which require a stable exchange rate (CBTT MPR, 2019).

Turning to the oil-stock market linkages, given that stock price volatility can be used as an indicator for the uncertainty faced by the firms quoted on that market (Lee et al., 2011), then our finding of higher standard deviations in stock returns under energy crisis conditions suggest rising investment uncertainty in such times. However, from the correlation and contagion analyses, the weak relationship between the crude oil market and equities in Trinidad and Tobago is consistent with the findings of Basher et al. (2018) regarding the inconsequential role played by oil prices in the Mexican stock market, which is also an oil-exporter with no substantial energy commodities traded on the stock exchange. Yet, this current dependence structure is likely to change if more energy related securities are traded on the stock market of such countries. For Trinidad and Tobago, while the relatively new[19] and only energy security listed on the TTSE consists of about 2.06% of the market capitalisation for the First Tier Market (TTSE, 2017), an additional public offering of approximately USD 125.40 million was put forward in 2017 bringing the market capitalisation contribution of this security to around 2.50% (TTSE, 2018). Therefore, it will be interesting to see how the oil-stock market relationship evolves in this environment if further public offerings are made for the sole energy listing, or more energy firms pursue equity financing and commence trading on the TTSE.

The stock market is an important projection of the economic development of a country or region (Liu et al., 2020). In order for the TTSE to benefit from oil price increases as other oil-exporters have, and to build up resilience when such prices collapse, financial inclusion and development will need to be aggressively pursued on the policy agenda. At the moment, the regional environment in which the TTSE operates poses unique challenges which can potentially inhibit spillover benefits from the energy and real sectors to financial markets. In the Caribbean region, even the more advanced stock markets like the TTSE are still embryonic in comparison to those of advanced economies; these stock exchanges are too illiquid to be an appealing option for some investors; the local

[19]The initial public offering of the only energy security traded on the TTSE occurred in the last quarter of 2015 (TTSE, 2016).

business community in Trinidad and Tobago has a culture which favours commercial bank credit over equity financing; there is a reluctance to dilute family ownership and publicly disclose company information; the general public has a risk averse culture; and financial illiteracy concerning investment options is pervasive (see Cozier and Watson (2018) and references therein). To complement the ongoing national financial literacy initiatives in Trinidad and Tobago, we endorse the policy prescriptions of Cozier and Watson (2018), which includes: The divestment of state enterprises, especially energy sector holdings, onto the TTSE; fiscal incentives, like tax moratoriums for companies that are quoted on the TTSE and tax relief for individuals who invest in these; and forging further strategic alliances with more developed financial markets to increase investment options.

2.7 Conclusion

We make three original contributions to the current energy-finance literature. First, we put forward the novel concept of energy contagion, i.e. a strengthening of energy-finance relationships during crisis periods in energy markets. Energy contagion analysis is pertinent for academic research, policy formulation, and investment decisions centred on how developments in the international crude oil market affect the macroeconomic and financial environment of commodity exporters and importers.

Second, we introduce tests for energy contagion using crude oil as the source market. To detect energy contagion across various co-moment transmission channels, we define the calm and crisis sub-samples of correlation, co-skewness, and co-volatility contagion tests based on energy, instead of financial, market conditions. Two types of calm/crisis identification methods are used to determine calm and crisis scenarios in the crude oil market: Semi-parametric rule-based algorithms for detecting bull and bear oil price phases, which proxies booms and slumps in oil prices; and a non-hierarchical k-means clustering algorithm to sort volatility measures into discrete episodes of tranquil and turbulent volatility.

Third, we address a gap in the literature by applying our analysis to the small open petroleum-exporting economy of Trinidad and Tobago. Not only is this country an appropriate study site for our analysis but it is one where published studies on the energy-finance nexus are, to the best of our knowledge, virtually non-existent. We test the aforementioned co-moment transmission channels for energy contagion in the crude oil-exchange rate and crude oil-stock market relationships to better understand the ramifications of oil market crises on financial stability in the setting of this small and heavily petroleum-dependent economy.

Our results for Trinidad and Tobago show an inverse correlation between oil and real effective exchange rate returns. Although the literature suggests the opposite result for an oil-exporting country, we attribute this empirical peculiarity to the domestic currency peg to the US dollar. We also find weak correlation between oil and stock returns. This insensitivity is likely due to the embryonic local equity market. While we observe the transmission of energy contagion through multiple co-moment channels, these occur only during the contemporary Global Financial Crisis. Altogether, the results provide unique insights into the relationship between international oil prices and key financial variables in this small petroleum economy.

Chapter 2 Appendix

Output from regression Eqs. (2.18), (2.19), and (2.20) for adjusting returns

Table 2.6 shows the output from the regression models used to adjust the returns for market fundamentals. The single equation regression for adjusting the real Brent crude oil returns implied by Eq. (2.18) is in the top part of the table. Also, the VARX(1) model for adjusting the exchange rate and stock returns of Trinidad and Tobago implied by Eqs. (2.19) and (2.20) is provided in the bottom part of the table. The extreme right column provide the Box-Pierce/Ljung-Box Q-statistics associated with the residual Portmanteau Autocorrelation Tests (PAT), which are evaluated against an approximate χ^2 distribution. These results show that there are no residual autocorrelation in the regression models specified. For each of the regression equation estimates, it can be seen that only the lag dependent variables are highly statistically significant.

Table 2.6: Output from regression models for adjusting monthly returns. Each row corresponds to the regression functions implied by Eqs. (2.18), (2.19), and (2.20), for Brent crude oil returns and the returns of Trinidad and Tobago's REER and stock market, respectively. Regression coefficients are presented beneath each term. $***$, $**$, and $*$ associated with coefficients stand for the 1% (strong), 5% (moderate), and 10% (weak) conventional levels of statistical significance, respectively, evaluated against the Student's t-distribution. The extreme right column provide the Box-Pierce/Ljung-Box Q-statistics associated with the residual Portmanteau Autocorrelation Tests (PAT) up to two lags, which are evaluated against an approximate χ^2 distribution. The samples (after adjustments, i.e. first difference transformation and the lag operator) ranges from 1994M03 to 2017M08.

Dependent variable	Regression coefficients						PAT
Single equation regression estimates for oil returns							
$\Delta \ln OP_t$	α_0	$\alpha_1 \Delta \ln OP_{t-1}$	$\alpha_2 SSR_{t-1}$				0.026
	0.003	0.174***	0.001				
VARX(1) model estimates for REER and stock returns							
$\Delta \ln REER_t$	α_0	$\alpha_{10} \Delta \ln REER_{t-1}$	$\alpha_{12} CSPI_{t-1}$	$\alpha_{13} \Delta \ln IR_{t-1}$	$\alpha_{14} \Delta \ln OP_{t-1}$	$\alpha_{15} SSR_{t-1}$	3.635
	0.327	0.319***	-0.009	-0.015	-0.563	0.001	
$\Delta \ln CSPI_t$	α_0	$\alpha_{21} \Delta \ln CSPI_{t-1}$	$\alpha_{22} REER_{t-1}$	$\alpha_{23} \Delta \ln IR_{t-1}$	$\alpha_{24} \Delta \ln OP_{t-1}$	$\alpha_{25} SSR_{t-1}$	–
	-0.801	0.470***	0.106	0.091	2.964	-0.028	

Chapter 3

Tracing the genesis of contagion in the oil-finance nexus

Abstract

A new procedure to trace the sources of contagion in the oil-finance nexus is proposed. We do this by consolidating veteran rules derived from the empirical oil literature to filter oil supply, global demand, and oil-specific demand shocks into discrete typical and extreme conditions. We show how these identified conditions can then be used to determine the stable and extreme sub-samples to compare market relationships for contagion analysis. Our original approach is useful for systemic risk assessment in countries vulnerable to oil market shocks. We illustrate the procedure using the dynamic relationships between the international crude oil market and the financial markets of a small oil-exporter.

Keywords: contagion; correlation; exchange rate; oil; stock market

JEL classification: C32; O54; Q43

3.1 Introduction

Closely linked markets are more vulnerable as negative shocks are able to propagate and proliferate more relative to weakly associated markets (Kritzman et al., 2011). Meaningful market linkages can be either intermittent or consistent. Contagion characterises a marked increase in cross-market linkages after a shock to one country, whereas interdependence refers to a maintained co-movement under pre- and post-shock conditions (Forbes and Rigobon, 2002). The concept of *energy* contagion, which is pertinent to countries whose financial and macroeconomic fate are tied to hard commodity prices, was put forward in Chapter 2. To reiterate, energy contagion refers to the deepening of energy-finance linkages under crisis periods in energy markets. In this chapter, we provide a novel approach for tracing the potential sources of oil market shocks for contagion testing, as there is convincing empirical evidence suggesting that different types of oil market shocks have different consequences for financial markets (see for example, Kilian and Park (2009); Filis et al. (2011); Broadstock and Filis (2014); Güntner (2014); Kang et al. (2015b); Basher et al. (2018)). Our original procedure makes the following important contributions to the oil-finance literature.

First, we propose a new rule-based specification to classify oil market shocks into discrete typical and extreme shock episodes. The motivation for our censoring measure comes from combining two concepts in the empirical oil literature. One is that only the most profound oil price movements over the preceding year are consequential to the economy (Hamilton, 1996). Another is that only oil price deviations outside a normal band are considered pertinent (Akram, 2004). We then apply these rules to structural oil supply, global demand, and oil-specific demand innovations estimated from a Kilian (2009) type of international oil market structural vector autoregression (SVAR). Second, we show these typical and extreme conditions can be used to design oil market contagion tests to trace the genesis of contagion. Such tests compare how correlations in the oil-finance nexus might change during periods of typical and extreme oil supply, global demand, and oil-specific demand shocks.

In a seminal paper, Filis et al. (2011) use a dynamic conditional correlation (DCC) model and examine how the oil-stock market correlations for oil-exporting and importing countries change during momentous episodes in the crude oil market collated from Kilian (2009) and Hamilton (2009a,b). Moreover, Broadstock and Filis (2014) are the first to explicitly estimate the time-varying relationship between the various structural oil market shocks suggested in Kilian (2009) and stock market returns. The economic significance of the oil-stock market relationship is well-established in the energy-finance literature. For instance, the oil-stock market association explains the impact oil price changes have on investment and is a high frequency data proxy for the oil-macroeconomy connection. Although there is no consensus on whether the relationship between oil price shocks and aggregate stock returns are positive or negative (Chen et al., 2014), a reasonable assumption held is that oil price shocks create uncertainty for firms which is reflected in higher stock market volatility (Degiannakis et al., 2018b). In particular, many studies find that oil price increases due to oil demand shocks are positive news for markets, while oil price increases due to oil supply shocks hurt the real and financial sectors (Cheema and Scrimgeour, 2019). In the case of oil-exporting economies, the empirical evidence suggests that the sign and magnitude of responses to oil market shocks are country-specific (Basher et al., 2018).

We build on the work of Filis et al. (2011) and estimate a DCC model to acquire the time varying oil-stock market relationship, and augment the model to include the oil-exchange rate and the exchange rate-stock market relationships. The importance of the oil-exchange rate relationship is also well-known. In particular, the oil-exchange rate linkage has implications for the international competitiveness of an oil-exporter via the wealth effects (see, *inter alia*, Bjørnland (2009); Basher et al. (2016)) and Dutch disease (see, *inter alia*, Corden (1984, 2012)) channels. Both such channels detail the mechanisms by which oil price increases lead to exchange rate appreciations for oil-exporters, making their exports (imports) more expensive (cheaper). Our modification to the model put forward in Filis et al. (2011) is important because little is still known about the dynamic relationship between oil prices, exchange rates, and emerging market stock prices (Basher et al., 2012). It is crucial to understand the dependence between several variables interacting simultaneously, since essential omissions provide incomplete information (Aloui and Aïssa, 2016).

Another contribution of our work is that we are the first to explicitly consider how the exchange rate-stock market relationship evolves under alternative global crude oil market conditions. The trade flow-oriented model characterises the influence exchange rates can have on the stock market, while the portfolio balance approach establishes that stock prices affect exchange rates (see Chkili and Nguyen (2014) and references therein), and the correlation between these two variables can be either positive or negative (Tang and Yao, 2018). Lin (2012) finds that exchange rate and stock price relationship increases during crisis episodes in comparison with tranquil periods, which is consistent with contagion between financial asset classes.

We also extend the idea to qualitatively tie correlations to oil market episodes in the literature, suggested in Filis et al. (2011), by using our discrete typical and extreme oil market conditions to test for oil market contagion. Additionally, our new procedure is complemented by comparing whether financial relationships change under booming and slumping oil price phases, as testing the economic effects of crude oil price increases and decreases is a long-standing practice in the applied literature (see for example, Mork (1989) and Hamilton (1996, 2003)). For this purpose, Chapter 2 is followed and we decompose crude oil prices into bull and bear states using a semi-parametric rule-based algorithm.

The relative influence of oil market shocks are based on the degree of importance of oil to national economy (Wang et al., 2013). Our new procedure is illustrated using the dynamic relationships between the international crude oil market and financial variables in Trinidad and Tobago. The main advantage of focusing on Trinidad and Tobago is that this is a small petroleum intensive economy, which makes it an appropriate study site to examine how the connections between oil and financial markets change in light of developments in the international oil market. Over the period of 1995 to 2016 the petroleum sector in Trinidad and Tobago contributed, on average, to 36% of GDP[1]. Empirical evidence suggests that small open economies are more vulnerable to oil price changes compared to larger ones (Abeysinghe, 2001), and small resource-rich economies have a documented legacy of underachievement relative to both their larger counterparts and small resource-poor countries (see Auty (2017) and references therein).

The rest of this chapter is organised as follows: Section 3.2 details the methodology and data we utilise; an application of our procedure to the international crude oil market and the financial markets of a small petroleum economy is presented in Section 3.3; and we conclude in Section 3.4.

[1]Calculated using data obtained from the Central Bank of Trinidad and Tobago available at https://www.central-bank.org.tt/statistics/data-centre/output-gdp-2000 and retrieved in October 2019.

3.2 Methods and data

Our empirical procedures can be outlined in three parts. In the first part, we estimate global oil market shocks with a recursive SVAR model and, using rule-based specifications, we classify these shocks into relatively typical and extreme episodes. We also decompose crude oil prices into bull and bear market phases. For the second part, we estimate a DCC model to acquire the dynamic financial correlations. In the third part, we compare the equality of means for the dynamic correlations under these typical/extreme and bull/bear oil market conditions. The period under investigation is January 1996 to August 2017[2], and the description, sources, and transformations of the data required at each step are elaborated therein. All data are monthly, primarily because the approach for identifying the structural oil market shocks is based on delay restrictions which are only economically plausible at this frequency (see Kilian (2009)).

There are a number of reasons why the contemporaneous nature of the time-varying correlations are appropriate for our analysis. First, contagion tends to appear and vanish quickly unlike interdependence and cointegrating relationships which are maintained over a much longer horizon (Reboredo et al., 2014). Second, stock prices absorb all available information relatively instantaneously including developments in international oil markets (Bjørnland, 2009), particularly in oil dependent economies (Wang et al., 2013). Third, crude oil is mainly indexed in US dollars (Kayalar et al., 2017), implying that this commodity is likely to be affected by movements in this currency (Zhang et al., 2008). At the same time, currency markets are one of the most liquid class of financial assets and the Trinidad and Tobago dollar is anchored to the US

[2]A switch to a dirty floating exchange rate from a fixed exchange rate regime in Trinidad and Tobago occurred in April 1993. On this grounds we start our analysis in January 1996, to allow for some time for the economy to get accustomed to the new exchange rate regime.

dollar. As such, the oil-exchange rate relationship is expected to promptly adjust to reflect the changes in this common factor.

3.2.1 Identifying discrete oil market conditions

Below, we detail the two rule-based approaches used to identify discrete oil market conditions.

3.2.1.1 Discrete typical and extreme oil market shock conditions from a global oil market SVAR model

We derive oil supply, global demand, and oil-specific demand shocks from an international oil market SVAR model postulated in Kilian (2009). This step requires monthly data from January 1994 to August 2017 on the growth rate in global oil production, which we proxy with the percent change in world petroleum production[3]; a Kilian (2019) correction of the global index of real economic activity introduced in Kilian (2009)[4]; and the log of real oil prices calculated from the European Brent crude oil spot prices deflated using the US CPI[5]. Eq. (3.1) gives the Kilian (2009) SVAR representation.

$$A_0 z_t = \alpha + \sum_{i=1}^{24} A_i z_{t-i} + \varepsilon_t \tag{3.1}$$

[3]The data are available from the US Energy Information Administration at www.eia.gov/international/data/world and accessed in September 2018.

[4]It is important to note that Hamilton (2018) points out a data transformation error in the index of nominal freight rates underlying the Kilian (2009) global real economic activity measure, where the log operator is performed twice. Kilian (2019) acknowledges this coding error and corrects the global business cycle index. We use this updated data, which are available at https://sites.google.com/site/lkilian2019/research/data-sets and accessed in September 2018.

[5]These data are available from the Federal Reserve Economic Data (FRED) at fred.stlouisfed.org/, accessed in May 2018. Like Broadstock and Filis (2014), we use the Brent benchmark instead of the West Texas Intermediate (WTI) to represent the global price of oil. The latter has been traded at a discounted price since 2011 due to the the US shale boom (Kilian, 2016).

where ε_t is a vector of serially and mutually uncorrelated structural errors; and A_0^{-1} is recursively identified so that the reduced-form errors e_t are linear combinations of the structural errors of the form $e_t = A_0^{-1}\varepsilon_t$, as described in Eq. (3.2). Consistent with the empirical literature, we use a lag length of 24 months to remove residual autocorrelation and account for the possibility of delays in adjusting to shocks in the international oil market (see Kilian and Park (2009), as well as Kang et al. (2015a) and references therein).

$$e_t \equiv \begin{pmatrix} e_t^{\Delta global\ oil\ production} \\ e_t^{global\ real\ activity} \\ e_t^{real\ oil\ price} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{oil-specific\ demand\ shock} \end{pmatrix} \tag{3.2}$$

The identification strategy of the SVAR assumes a vertical short-run oil supply curve. This indicates that demand innovations in the oil market are contemporaneously restricted from affecting oil supply, as implied by the zeros imposed in the a_{12} and a_{13} positions of the A_0^{-1} matrix in Eq. (3.2). Kilian (2009) argues that such a specification is reasonable as the cost associated with adjusting oil production disincentivises oil-producers to adjust to high frequency demand shocks. Further, aggregate demand shocks are innovations to global real activity unexplained by oil supply shocks. Another zero restriction is imposed in the position of a_{23} to delay real oil prices from affecting the aggregate demand within the same month. Lastly, oil-specific demand shocks are the unexplained innovations to the real price of oil after oil supply and aggregate demand shocks have been accounted for.

Subsequently, to classify each of the structural oil market shocks into typical and extreme disturbances, we propose a new discrete rule-based specification which consolidates two veteran measures for identifying extreme oil prices: Outlier oil prices outside a normal range and net oil price increases over the preceding year. Regarding the former measure, the idea that oil prices are important if found to be atypically high or low stems from the work of Akram (2004), who constructs extrema bands based on a normal range of oil prices with lower and upper bounds of USD 14 to USD 20, respectively, where values within the band are forced to zero and values outside the band are retained. Akram (2004) and Bjørnland (2009) use this oil price band to investigate the asymmetric effects extreme oil price changes have on the Norwegian exchange rate and stock market, respectively. However, this range is an artefact of oil price behaviour during the 1990s and much has changed since this period with unprecedented oil booms and busts characterising the 21st century energy markets. Therefore, we augment this approach by using the standard deviation value of the three structural oil market shocks to determine the maximum and minimum values of the band.

On the other hand, the net oil price increases measure is proposed by Hamilton (1996) as an extension of the positive and negative oil price transformation suggested in Mork (1989), in an effort to preserve the empirical importance of oil prices in the US macroeconomy. The net oil price increases measure compares the current growth rate in the price of oil with the rate over the preceding year and censors the current observation if it does not exceed the values observed over that period. It is straightforward to extend this approach beyond oil prices to consider net increases from all oil market shocks. We also invert this approach to also allow for net oil market shock decreases, which are also expected to have influential implications if, for instance, a small energy-exporting economy is being considered as is the case here.

We combine these rules to filter the oil market shocks into discrete typical and extreme oil market conditions defined in Eq. (3.3).

$$shock_{i,t}^{dummy} = \begin{cases} 1, & \text{if } |\varepsilon_{i,t}| > \sigma; \\ & \text{if } \varepsilon_{i,t} > \max(0, \varepsilon_{i,t-1}, \varepsilon_{i,t-2}, ..., \varepsilon_{i,t-12}); \\ & \text{if } \varepsilon_{i,t} < \min(0, \varepsilon_{i,t-1}, \varepsilon_{i,t-2}, ..., \varepsilon_{i,t-12}); \\ 0, & \text{otherwise} \end{cases} \tag{3.3}$$

where i represents the oil supply, global demand, or oil-specific demand shocks derived from the oil market SVAR model. In the first rule, σ is the standard deviation of the structural shocks, which is equal to 0.849 across all structural oil market shocks. Any value outside this standard deviation band is characterised as an extreme shock. The second and third rules correspondingly detect the presence of net oil price positive increases and negative decreases over the previous 12 months. To acquire the extreme positive and negative oil market shocks, from the rule-based specification described by Eq. (3.3), involves a further filtering of all periods identified as 1 into episodes where $\varepsilon_{i,t} > 0$ and $\varepsilon_{i,t} < 0$, respectively. Considering both symmetric or asymmetric movements in the crude oil market are especially useful, given that the conclusions in applied studies tend to vary depending on which has been used (Degiannakis et al., 2018a). The months which are consistently identified as 0 by the rule-based specification in Eq. (3.3), across all three structural oil market shocks, form a relatively calm sample. Such a common calm sample is useful for identifying periods to compare how financial returns and the relationships between returns behave in calm times (0) to periods otherwise identified as extreme (1).

3.2.1.2 Bull and bear oil market phases

Much of the literature has been devoted to debating and testing the asymmetric effects of oil prices (see, *inter alia*, Kilian and Vigfusson (2011a,b), and Cheema and Scrimgeour

(2019)). In Chapter 2, we argued that a novel and interesting way to consider this issue in energy contagion analysis are with bull and bear market phases; which captures an environment when oil prices are increasing or decreasing, respectively. Rule-based algorithms are more appropriate for in-sample identification of bear and bull market states than Markov-switching models (Kole and Dijk, 2017). Two popular rule-based methods for identifying bull and bear phases in the literature are those described in Pagan and Sossounov (2003) and Lunde and Timmermann (2004) (Hanna, 2018). We also found, as documented in Table 2.2 of Chapter 2, that the bear and bull oil price phases identified with the Pagan and Sossounov (2003) method calibrated for oil markets as suggested in Gil-Alana et al. (2016) yields a 97% similarity using the Lunde and Timmermann (2004) approach on a dataset of the same range and frequency. As the former is the most popular rule-based algorithm for the identification of bull and bear market phases in the empirical literature, and to avoid the duplication of almost identical results, we proceed to make use of the Pagan and Sossounov (2003) approach to proxy oil price booms and slumps in this present chapter as well. Therefore, we are able to test whether an environment where oil prices are increasing influence the relationships between oil and financial variables differently when compared to a period of decreasing oil prices. Phases in the Pagan and Sossounov (2003) are determined based on maxima and minima in real crude oil prices by applying rules. A peak (trough) is based on whether the oil price in month t is above (below) other months within the interval $t - \tau_{window}$ and $t + \tau_{window}$. Furthermore, the turning points which trigger a switch between phases are restricted with a minimum duration rule, τ_{censor}, to prevent extrema values towards the end of the interval from distorting the identification of market states. We set $\tau_{window} = 8$ months and $\tau_{censor} = 6$ months, which are feasible combinations given in Pagan and Sossounov (2003). Thus, we acquire an oil price dummy variable where bear (bull) phases are coded as 1 (0).

3.2.2 Oil-finance dynamic correlations

We specify a DCC model to obtain the three pairs of time varying correlations between oil, exchange rate, and stock returns. The DCC model uses oil market data, as well as exchange rate and stock market indicators for Trinidad and Tobago. For crude oil prices, we again use European Brent crude oil prices in constant 2010 US dollars from the preceding section. For the exchange rate indicator we use the real effective exchange rate (REER)[6], where a rise (fall) in this index implies currency appreciation (depreciation). We also use real stock prices, which are represented by the Trinidad and Tobago Stock Exchange (TTSE) Composite Stock Price Index (CSPI) adjusted for inflation, with a 2010 base year, using the RPI [7]. These three variables are first expressed as returns[8]. As in Chapter 2, in order to avoid the issue of omission of relevant variables (see, for example, Rigobon (2019)), we the pre-filter the return series before approaching the DCC model. We work with residuals (ε_t) from Eqs. (3.4), (3.5), and (3.6), respectively, as our adjusted returns[9]. Our specifications for these regressions are driven by the exogeneity of international oil prices for a small economy like Trinidad and Tobago. Adjusted oil returns is acquired from the single equation model specified in Eq. (3.4):

$$\Delta \ln OP_t = \alpha_0 + \alpha_1 \Delta \ln OP_{t-1} + \alpha_2 SSR_{t-1} + \varepsilon_t \tag{3.4}$$

where $\Delta \ln OP_t$ are real Brent crude oil returns, α_0 is a constant, $\Delta \ln OP_{t-1}$ is an autoregressive term, and SSR_{t-1} are the US interest rates. An optimal lag order of 1

[6]Data are sourced from the International Monetary Fund (IMF) International Financial Statistics and retrieved via Thomson Reuters Eikon, accessed in May 2018.

[7]These data are calculated using data from the Central Bank of Trinidad and Tobago (CBTT), and are available from www.central-bank.org.tt/statistics/data-centre and accessed in May 2018.

[8]Returns are calculated as the first difference in the natural logarithm for each series, times 100.

[9]The regression output from these models, together with a short commentary, are provided in the Appendix of Chapter 2.

month is determined by information criteria and there is no residual autocorrelation based on a Lagrange multiplier test at the conventional levels of significance.

As neither exchange rates nor stock returns from Trinidad and Tobago can affect international crude oil returns, we use the residuals from Eqs. (3.5) and (3.6) from a VARX(1) system to obtain these adjusted financial returns.

$$\Delta \ln REER_t = \alpha_{10} + \alpha_{11}\Delta \ln REER_{t-1} + \alpha_{12}\Delta \ln CSPI_{t-1} + \alpha_{13}IR_{t-1} + \alpha_{14}\Delta \ln OP_{t-1} + \alpha_{15}SSR_{t-1} + \varepsilon_{1t} \quad (3.5)$$

$$\Delta \ln CSPI_t = \alpha_{20} + \alpha_{21}\Delta \ln CSPI_{t-1} + \alpha_{22}\Delta \ln REER_{t-1} + \alpha_{23}IR_{t-1} + \alpha_{24}\Delta \ln OP_{t-1} + \alpha_{25}SSR_{t-1} + \varepsilon_{2t} \quad (3.6)$$

where $\Delta \ln REER_t$ is the growth rate of the REER, $\Delta \ln CSPI_t$ is real composite stock returns, IR_{t-1} denotes domestic interest rate for Trinidad and Tobago, along with exogenous variables for oil returns ($\Delta \ln OP_{t-1}$) and US interest rates (SSR_{t-1}). An appropriate lag length of 1 month is selected using information criteria and a Lagrange multiplier test shows there is no statistically significant residual serial correlation.

Following Forbes and Rigobon (2002), interest rates are included in Eqs. (3.4), (3.5), and (3.6) to account for macroeconomic and monetary performance. To these ends, we use US Shadow Short Rates (SSRs) as a foreign interest rate measure relevant to this small-island economy. US SSRs adjusts the conventional policy rate to accommodate for unconventional monetary authority actions characterising much of the post GFC era, see Krippner (2016). The commercial banking median basic prime lending rate is used to account for activity from the real and financial sectors, as well as the policy environment in Trinidad and Tobago. Additionally, we allow exchange rate and stock returns to enter each other's regression functions endogenously to account for potential lead-lag interactions.

The DCC estimation consists of a two-step process. Step 1 involves the estimation of univariate generalised autoregressive conditional heteroskedastic (GARCH) processes for all three adjusted returns. Step 2 uses the residuals from the first stage to estimate the three pairs of conditional correlations between these three variables.

In step 1, we aim to optimally estimate each individual return series. Due to the pre-filtering of the data, the mean equation for each return series (r_t) takes the form of a constant only, as no autoregressive terms are necessary, as defined in Eq. (3.7):

$$r_t = a_0 + \epsilon_t \tag{3.7}$$

To estimate the conditional variances, we commence with the parsimonious GARCH(1,1) process given by Eq. (3.8) for each series:

$$h_t = \omega_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{3.8}$$

where ω_0 is the intercept of the variance, ϵ_t are ARCH innovations with a conditional distribution that has a time dependent variance h_t, and h_{t-1} are lags of the conditional variance. Further, ϵ_t follows the Student's t-distribution and the solver used is a non-linear optimisation with augmented Lagrange method. The GARCH(1,1) models for all returns are stable in variance as the condition $\alpha + \beta < 1$ is met (see Table 3.2). Additionally, the Ljung-Box and ARCH Lagrange multiplier (LM) tests indicate no concerns regarding autocorrelation and ARCH effects, respectively, in the residuals of the GARCH(1,1) specification for all three returns. Moreover, Engle and Ng (1993) sign bias tests provide no substantive evidence of asymmetric responses to positive and negative news in the three financial returns[10]. Hence, the parsimonious univariate

[10]We find no statistically significant asymmetric responses to positive and negative news for exchange rates and stock returns. However, in the case of oil returns, the asymmetric volatility tests show that the individual sign bias tests convey no asymmetric volatility in the standardised residuals, but the joint effects test is statistically significant. Therefore, we consider asymmetric GARCH variants for this particular series to accommodate for this artefact. Yet, an EGARCH(1,1) for oil returns, which we find

GARCH(1,1) process is an optimal representation of the conditional variance for each return series.

Step 2 of the DCC model follows Engle (2002). The k x k conditional covariance matrix of returns, H_t, is decomposed as:

$$H_t = D_t P_t D_t \tag{3.9}$$

where D_t are the standard deviation diagonal matrices derived from the GARCH(1,1) models suggested in Eq. (3.8) and P_t is the correlation evolution of the (possible) time varying correlation matrix which takes the form:

$$P_t = diag\left(q_{1,t}^{-1/2}, q_{2,t}^{-1/2}, q_{3,t}^{-1/2}\right) Q_t diag\left(q_{1,t}^{-1/2}, q_{2,t}^{-1/2}, q_{3,t}^{-1/2}\right) \tag{3.10}$$

where Q_t defined in Eq. (3.11) is a symmetric positive definite matrix whose elements follow the GARCH(1,1) specified in Eq. (3.8):

$$Q_t = S(1 - \lambda_1 - \lambda_2) + \lambda_1 \frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}} \left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}\right)' + \lambda_2 Q_{t-1} \tag{3.11}$$

where S is the unconditional correlations matrix, and the adjustment parameters λ_1 and λ_2 are time invariant non-negative scalar coefficients related to the exponential smoothing process that is used to construct the dynamic conditional correlations. The constraint $\lambda_1 + \lambda_2 < 1$ indicates that the process is stationary. Finally, the time-varying correlations are estimated by:

to be the most suitable alternative GARCH specification for this series, shows that the leverage effects term is not significant. Further, the differences in dynamic correlations estimated from a model where oil returns follows either a GARCH(1,1) or an EGARCH(1,1) specification is negligible. As such, we revert to the parsimonious GARCH(1,1) model for oil returns.

$$\rho_{i,j,t} = q_{i,j,t}/\sqrt{q_{i,i,t}q_{j,j,t}} \tag{3.12}$$

3.2.3 Comparing dynamic correlations by oil market conditions

Using the discrete oil market conditions identified with the rule-based specifications and the time varying correlations obtained from the DCC model, it becomes straightforward to perform oil contagion tests. We use the Welch (1947) two-sample t-test to compare the equality of means for the three pairs of market correlations under the relatively calm periods versus extreme structural oil market shock conditions, and bullish versus bearish oil market phases. Welch's t-test has desirable properties over the Student's t-test when comparing the equality of means between to samples. In particular, the former is robust to unequal variances and unequal sample sizes relative to the latter, reducing the incidence of a Type I error (Fagerland and Sandvik, 2009).

3.3 Application to the international crude oil market and a small oil-exporter

3.3.1 Discrete calm and crisis oil market conditions

In Figure 3.1, the blue dots show the extreme positive shocks and red stars show the extreme negative shocks identified by our novel rule-based specification, described in Eq. (3.3), for classifying oil market shocks into discrete calm and extreme conditions. Graphs (A), (B), and (C) illustrate the result of this filtering process applied to each of the structural oil supply, global demand, and oil-specific demand shocks, respectively, obtained from the global oil SVAR model described in Eq. (3.2). With reference to Figure 3.1 (A) and (C), extreme oil supply and oil-specific demand shocks, respectively, are seen to occur intermittently over the entire sample. On the other hand, when compared to the latter half of the 1990s, extreme global demand shocks in Figure 3.1 (B) appear to increase in frequency from the 2000s and especially so in the 2008 Global Financial Crisis (GFC) and post-GFC eras.

Bear phases in the real Brent crude oil prices are shown by grey vertical panels in Figure 3.1. Graph (D) conveys that the contemporary oil slumps identified coincide with international crises such as the Asian financial crisis (1997), the internet bubble burst and the 9/11 terrorist attacks (2001) in the US, and the GFC (2008). Additionally, Baumeister and Kilian (2016a,b) find that the stark oil decline between June 2014 and January 2015 can be explained partly due to a negative oil-specific demand shock from a slowdown in the global economy, and positive oil supply shocks coming from the US shale boom and other major oil producers.

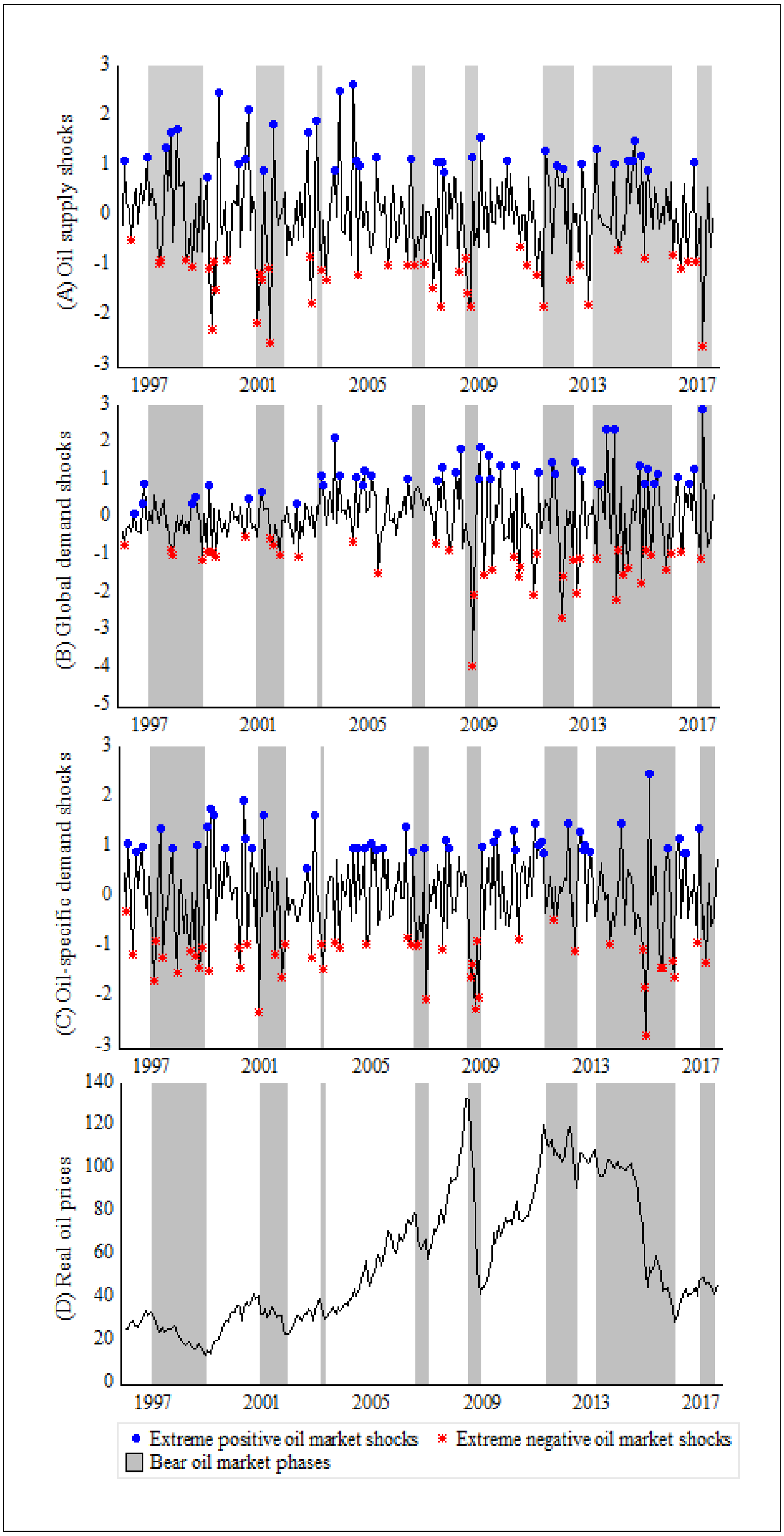

Figure 3.1: Extreme oil market shocks and bear phases. *Caption continues on the next page.*

Graph (A), (B), and (C) shows the oil supply, global demand, and oil-specific demand shocks, respectively, from the international crude oil market which are derived from the SVAR model specified in Eq. (3.2). For each of these three graphs, the extreme positive and negative conditions for a particular shock which are identified by our novel rule-based specification in Eq. (3.3) are shown in blue dots and red stars, respectively. To gain an illustrative perspective of our procedure for identifying discrete calm and extreme oil market conditions, consider that the extreme positive (negative) shocks in the three structural oil market shocks in graphs (A), (B), and (C) are either values greater (less) than the standard deviation band of +0.850 (-0.850) or the largest (smallest) value over the preceding 12 months. Bear oil market phases identified by the Pagan and Sossounov (2003) algorithm are shown in grey vertical panels in graphs (A) to (D). For reference, graph (D) shows real Brent crude oil prices in US dollars per barrel.

3.3.2 Performance of returns under alternative oil market conditions

Table 3.1 shows simple summary statistics which captures the behaviour of the monthly adjusted returns under calm and extreme structural oil market shocks, and during bullish and bearish oil market phases, for the full and GFC-censored samples[11]. The relatively calm oil market condition is that time period in the international oil market where no extreme structural shock is identified by our non-linear rule-based specification. Such a common calm period can be used as a basis for comparing how financial returns from the oil, exchange rates, and stock markets and the relationships between them behave during genuinely tranquil oil market conditions in comparison to periods when there are extreme oil supply, global demand, and oil-specific demand shocks. This relatively calm period is computed as the periods which are consistently identified as 0 in Eq. (3.3) across all three structural oil market shocks.

[11]The National Bureau of Economic Research defines the timespan of the Great Recession in the US from December 2007 to June 2009. See www.nber.org/cycles. We use this dating for coverage of the main adverse events associated with GFC crisis in international markets, which incorporates the infamous collapse of Lehman Brothers in September 2008.

Table 3.1: Descriptive statistics of monthly adjusted returns under calm and extreme structural oil market shocks, and during bullish and bearish oil market phases, for the full and GFC-censored samples. $***$, $**$, and $*$ associated with the mean returns indicate where such mean returns are significantly different from zero at the 1%, 5%, and 10% levels, respectively, evaluated against the Student's t distribution. Test statistics and accompanying significance levels, where appropriate, from two sample Welch's t-tests for Testing the Equality of Means (TEM) with unequal variances and sample sizes, for the average adjusted returns during calm vs. extreme and bullish vs. bearish oil market conditions, are noted as $***$, $**$, and $*$ for the 1%, 5%, and 10% levels of significance, respectively. The Welch's t-tests are evaluated against the Student's t distribution using Welch's degrees of freedom (see Welch (1947)). The abbreviations are obs. for observations, SD for standard deviation, Min for minimum, and Max for maximum. The descriptive statistics for the adjusted returns are based on the residuals of the regressions specified in Eqs. (3.4), (3.5), and (3.6), and can be interpreted as percentages. The relatively calm period is that time period which are consistently identified as 0 in Eq. (3.3) across all three structural oil market shocks and is the base sample in the tests for equality of the means.

Oil Market Condition	Obs.	Adjusted returns														
		Oil					REER					Stock				
		Mean	TEM	SD	Min	Max	Mean	TEM	SD	Min	Max	Mean	TEM	SD	Min	Max
Full sample																
Overall	260	-0.04	-	8.90	-26.54	24.39	0.01	-	0.96	-2.50	4.79	-0.05	-	2.82	-13.29	11.29
Structural shocks																
Relatively calm	85	0.60	-	4.88	-9.79	13.06	0.06	-	0.83	-2.22	2.61	0.07	-	2.76	-5.60	10.51
Extreme oil supply	83	-1.40	1.578	10.44	-26.54	19.18	0.17	-0.754	1.05	-2.50	4.79	-0.35	0.951	2.90	-13.29	7.72
Positive	39	-1.91	1.536	9.63	-26.54	15.74	0.26	-1.089	1.04	-1.47	4.79	-0.23	0.519	3.07	-13.29	6.12
Negative	44	-0.94	0.869	11.20	-24.89	19.18	0.08	-0.134	1.05	-2.50	2.52	-0.46	1.011	2.78	-5.28	7.72
Extreme global demand	88	-0.37	0.797	10.20	-26.54	24.39	-0.02	0.526	1.15	-2.50	4.79	-0.32	0.890	2.95	-13.29	7.72
Positive	46	1.70	-0.736	9.47	-24.55	19.18	-0.02	0.428	1.02	-2.17	2.80	0.02	0.092	2.75	-9.88	7.72
Negative	42	-2.63	1.875*	10.61	-26.54	24.39	-0.03	0.392	1.30	-2.50	4.79	-0.69	1.329	3.15	-13.29	4.69
Extreme oil demand	96	-1.47	1.484	12.62	-26.54	24.39	0.06	-0.067	1.01	-2.16	4.79	-0.40	1.039	3.26	-13.29	11.29
Positive	48	9.25***	-8.621***	5.91	-1.03	24.39	-0.28**	2.123**	0.88	-2.16	1.33	-0.50	0.114	2.51	-9.88	5.75
Negative	48	-12.19***	10.903***	7.25	-26.54	1.11	0.41***	-2.024**	1.02	-1.37	4.79	-0.30	0.567	3.90	-13.29	11.29
Oil market phases																
Bull	155	3.00***	-	7.34	-21.41	23.22	-0.11	-	0.94	-2.50	2.80	-0.09	-	2.49	-5.60	10.51
Bear	105	-4.52***	7.031***	9.14	-26.54	24.39	0.19**	-2.475**	0.96	-2.22	4.79	0.02	-0.290	3.27	-13.29	11.29
GFC-censored sample																
Overall	241	0.09	-	8.52	-24.89	24.39	-0.01	-	0.90	-2.50	2.80	0.05	-	2.68	-9.88	11.29
Structural shocks																
Relatively calm	81	0.47	-	4.94	-9.79	13.06	0.06	-	0.82	-2.22	2.61	0.18	-	2.75	-5.60	10.51
Extreme oil supply	77	-0.74	0.941	10.18	-24.89	19.18	0.06	0.020	0.88	-2.50	1.81	-0.12	0.724	2.37	-5.03	7.72
Positive	37	-1.25	1.089	8.98	-22.71	15.74	0.11	-0.289	0.71	-1.47	1.43	0.17	0.018	2.23	-4.51	6.12
Negative	40	-0.27	0.397	11.27	-24.89	19.18	0.02	0.242	1.02	-2.50	1.81	-0.38	1.126	2.48	-5.03	7.72
Extreme global demand	78	-0.51	0.810	9.53	-24.55	24.39	-0.08	0.976	1.04	-2.50	2.80	-0.23	0.945	2.68	-9.88	7.72
Positive	40	0.54	-0.046	9.37	-24.55	19.18	0.00	0.365	0.98	-2.17	2.80	-0.02	0.356	2.86	-9.88	7.72
Negative	38	-1.62	1.254	9.69	-22.71	24.39	-0.17	1.140	1.10	-2.50	2.43	-0.45	1.243	2.50	-8.33	4.69
Extreme oil demand	89	-0.75	0.879	12.00	-24.89	24.39	0.01	0.431	0.86	-2.16	2.80	-0.21	0.874	2.98	-9.88	11.29
Positive	46	9.05***	-8.312***	5.93	-1.03	24.39	-0.25*	1.930*	0.89	-2.16	1.33	-0.58	1.578	2.50	-9.88	5.75
Negative	43	-11.23***	9.945***	6.82	-24.89	1.11	0.28**	-1.470	0.75	-1.37	2.80	0.19	-0.021	3.40	-8.33	11.29
Oil market phases																
Bull	142	2.76***	-	7.42	-21.41	23.22	-0.11	-	0.93	-2.50	2.80	-0.09	-	2.45	-5.60	10.51
Bear	99	-3.74***	6.107***	8.58	-24.89	24.39	0.13	-2.030**	0.83	-2.22	2.61	0.26	-0.958	2.98	-9.88	11.29

As anticipated, average oil returns are negative (positive) and volatility is higher (lower) under extreme (calm) structural oil market shocks and bearish (bullish) oil market phases. The highest volatility in the crude oil market occurs during oil-specific demand shocks. As we might expect, oil returns are negative under extreme positive oil supply shocks and positive under extreme positive oil-specific demand shocks. Moreover, we find that the mean adjusted oil returns are highly significantly different from zero under extreme positive and negative oil demand shocks, and under bearish and bullish oil market phases. Also, Welch's t-test for the equality of means show that average adjusted oil returns under extreme negative global demand shocks, and positive and negative oil demand shocks are significantly different from the relatively calm period; and average adjusted returns in the bearish oil market phases are statistically different to bullish oil market conditions.

The mean exchange rate appreciations are higher (lower) during extreme (relatively calm) oil market shocks and bearish (bullish) oil market phases. Additionally, the periods of highest exchange rate volatility are exhibited under global demand shocks. There are two particularly surprising observations for this small oil-exporter. First, the highest exchange rate appreciations occur during episodes of extreme negative oil-specific demand shocks and bearish oil market phases, and both these mean adjusted REER returns are significantly different from zero. Second, exchange rate depreciations are observed during extreme positive oil-specific demand shocks, which is also statistically significantly different from zero. Both artefacts contradicts the Dutch disease and positive wealth effects propositions, at least from a contemporaneous perspective. The Welch's t-test for the equality of means convey that there are statistically significant differences in the mean adjusted REER returns under extreme positive and negative oil demand shocks compared to relative calm periods, and bearish compared to bullish oil market conditions.

Prima facie average stock returns behaviour appears to be particularly sensitive to the GFC, as noted by the marked differences in the mean, volatility, and range of returns obtained between the full and GFC-censored samples. Upon closer inspection, it can be seen that none of the mean adjusted stock returns are found to be statistically different from zero, which implies low market activity. Furthermore, the Welch's t-test for the equality of means show that there are no statistically significant differences in the mean stock returns of Trinidad and Tobago in calm versus extreme oil market conditions, or in bullish versus bearish oil market phases.

3.3.3 Oil-finance time varying correlations under alternative oil market conditions

The DCC parameters are shown in Table 3.2; while the evolution of the dynamic oil-REER, oil-stock market, and REER-stock market relationships over the sample period of January 1996 to August 2017 are graphed as the solid black lines in Figures 3.2, 3.3, and 3.4, respectively[12]. These time varying correlations are illustrated under extreme positive (blue dots) and negative (red stars) oil supply, global demand, and oil-specific demand shocks, as well as under bearish (grey vertical bars) oil market phases. All three pairs of dynamic correlations exhibit contagion effects during the GFC, as all relationships deepen in this period. The GFC is hallmarked by extreme negative global demand and oil demand shocks, an artefact that is well-documented in the literature (see for example, Baumeister and Kilian (2016a); Kim (2018)), and is a bear phase in the crude oil market.

Figures 3.2 and 3.4, which respectively show the time-varying correlations between oil and the REER of Trinidad and Tobago, as well as Trinidad and Tobago's REER and real stock returns, convey that these are both negative and relatively moderate

[12]The DCC model coefficients and dynamic correlations are estimated with the rmgarch package in R (see Ghalanos (2019)).

associations across the two decade sample period. Apart from the marked stronger negative relationship in these two DCCs during the GFC period, there is also additional observational evidence for oil market contagion as these relationships also deepen during the 2014/2015 oil market crash. In the 2014/2015 oil price plummet, the increase in the magnitude of the relationship for these pair of DCCs can be seen to coincide with multiple shocks in the international crude oil market, i.e. extreme positive oil supply, negative global demand shocks, and negative oil-specific demand shocks, which are expected to adversely impact an oil-exporter. For Trinidad and Tobago, these relationships during crisis imply that as oil prices fell due to such disturbances in the crude oil market, the currency appreciated and appreciations are associated with negative stock returns.

Figure 3.3 show that the oil-stock market association is typically weak with distinct punctuated phases where the correlation strengthens. The negative oil-stock market relationship prior to 1999 is reversed thereafter to a positive association, which is in line with the inferences of Miller and Ratti (2009) who examine a selection of OECD countries. They argue that the positive association is likely due to the existence of stock and oil market bubbles which have characterised 21^{st} century financial markets. Indeed, we observe that there are two distinct periods where the time-varying oil-stock market correlation increase in the 2000s, which coincide with the dot-com and sub-prime bubbles and crashes.

Table 3.3 conveys the average financial correlations during relatively calm and extreme structural oil market shocks, and during bullish and bearish oil market phases, in the full sample and a GFC-censored sample for robustness analysis. The relatively calm period in the crude oil market forms the sample which is used as basis for comparing each of the extreme structural shock periods. First, we observe a moderate and inverse oil-

REER interdependence. This relationship suggests that oil price increases (decreases) are associated with exchange rate depreciations (appreciations), and is inconsistent with the Dutch disease conjecture and the positive wealth effect spillovers expected for an oil-exporter which implies the opposite outcome. In Chapter 2, we also find evidence for such a contradiction and explain this is likely due to the peg of the Trinidad and Tobago dollar to the US dollar. In the full sample, we find statistically significant results that the oil-REER relationship marginally deepens during extreme global demand shocks when compared to the relatively calm period. This conforms with the findings of Atems et al. (2015) for the responses of exchange rate indexes to this demand-side shock. However, such evidence of oil market contagion in the oil-REER correlation is primarily associated with the GFC period.

Looking at the oil-stock market correlation in Table 3.3, this association is generally weak. Therefore, we find no evidence of either interdependence or contagion. We also observe that oil-stock returns correlation in bullish oil market phases becomes weaker under bearish conditions. These results can be linked to the relatively underdeveloped stock market of Trinidad and Tobago, and the fact that there is only one energy security listed on the stock exchange, which subdues the spillover effects from the international oil market. The minimal effect of the oil market on the stock market is consistent with evidence from other oil-exporters such as the Gulf Cooperation Council countries (Al Janabi et al., 2010), Mexico (Basher et al., 2018), and Trinidad and Tobago (from Chapter 2 of this thesis); but can be contrasted against the findings of the positive oil-stock market relationship from other oil-exporters such as Canada (Kang and Ratti, 2013), Norway (Park and Ratti, 2008; Bjørnland, 2009), and Russia (Ji et al., 2018).

Turning to the REER-stock market association, the inverse interdependence suggests that an exchange rate appreciation (depreciation) is correlated with a downturn (uptick) in stock returns. There is also indication of this dependence strengthening since the GFC, which is consistent with Caporale et al. (2014). It can be useful to consider this result in tandem with the aforementioned oil-REER relationship. Although the oil-stock returns relationship is weak, it is possible for crude oil to have indirect spillovers for the stock market performance through the exchange rate channel. We also find that the REER-stock returns relationship becomes somewhat stronger under the global demand shocks, but this result is sensitive to the omission of the GFC period. This is in line with Wei et al. (2019), who find that compared to other macroeconomic fundamentals, the exchange rate market plays the most significant role in transmitting the impacts of oil prices on the emerging Chinese stock market, especially in the GFC aftermath.

Altogether, there is subtle evidence for oil market contagion channels in the financial markets of Trinidad and Tobago outside of the GFC period. This is primarily attributed to the oil market contagion effects noted in the oil-REER (Figure 3.2) and REER-stock market (Figure 3.4) DCCs. While Table 3.3 shows that there are some statistically significant results from the equality of means tests in our full sample, these do not necessarily imply economic significance as they do not appear to satisfy the typical definition of contagion. The averaged correlations in Table 3.3 do not convey a *marked* increase in cross market linkages under extreme or bearish oil market conditions, as these variations are relatively small.

Correlations during the calm period versus periods of extreme oil supply shocks across all three dynamic relationships appear less sensitive when compared to correlations under demand-side shocks. This resonates with Atems et al. (2015) and Basher et al. (2016) who find limited evidence that oil supply shocks affect exchange rates and with Filis et al. (2011) who find that supply-side oil price shocks do not influence the oil-stock market relationship. In fact, many studies are alluding to the notion that the role of oil supply shocks on the real and financial sectors is no longer consequential (see Broadstock and Filis (2014) and references therein.).

Our results also align with Antonakakis et al. (2017), who find that global demand innovations are the main source of shocks to stock market during economic turbulence; as well as Aloui and Aïssa (2016), who find that the dependence structure between oil, exchange rates, and stock returns are sensitive over the 2007-2009 GFC and Great Recession period. Indeed, we also find that shocks associated with the GFC appear to deepen cross market linkages between these three returns more than oil market shocks outside of this period in Trinidad and Tobago.

Table 3.2: DCC(1,1) parameter estimates. The coefficients are from the mean and variance Eqs. (3.7) and (3.8), respectively, from the first step of the DCC model. The univariate GARCH models are stable as the condition $\alpha_1 + \beta_1 < 1$ is met. λ_1 and λ_2 are the scalars which take the same value for all the all the time series from the second step of the DCC model. The process is stationary as the condition $\lambda_1 + \lambda_2 < 1$ is satisfied.

	Coefficient	Std. error	t value	Prob.
a_0^{Oil}	0.1212	0.4896	0.2475	0.8045
ω_0^{Oil}	8.0666	7.9570	1.0138	0.3107
α_1^{Oil}	0.1832	0.0677	2.7082	0.0068
β_1^{Oil}	0.7246	0.1295	5.5944	0.0000
a_0^{REER}	-0.0187	0.0526	-0.3558	0.7220
ω_0^{REER}	0.0252	0.0194	1.3017	0.1930
α_1^{REER}	0.0874	0.0433	2.0172	0.0437
β_1^{REER}	0.8873	0.0497	17.8693	0.0000
a_0^{Stock}	-0.0832	0.1184	-0.7028	0.4822
ω_0^{Stock}	0.0000	0.0000	0.0044	0.9965
α_1^{Stock}	0.0467	0.0249	1.8752	0.0608
β_1^{Stock}	0.9523	0.0206	46.1906	0.0000
λ_1	0.0261	0.0154	1.6936	0.0903
λ_2	0.8980	0.0466	19.2627	0.0000

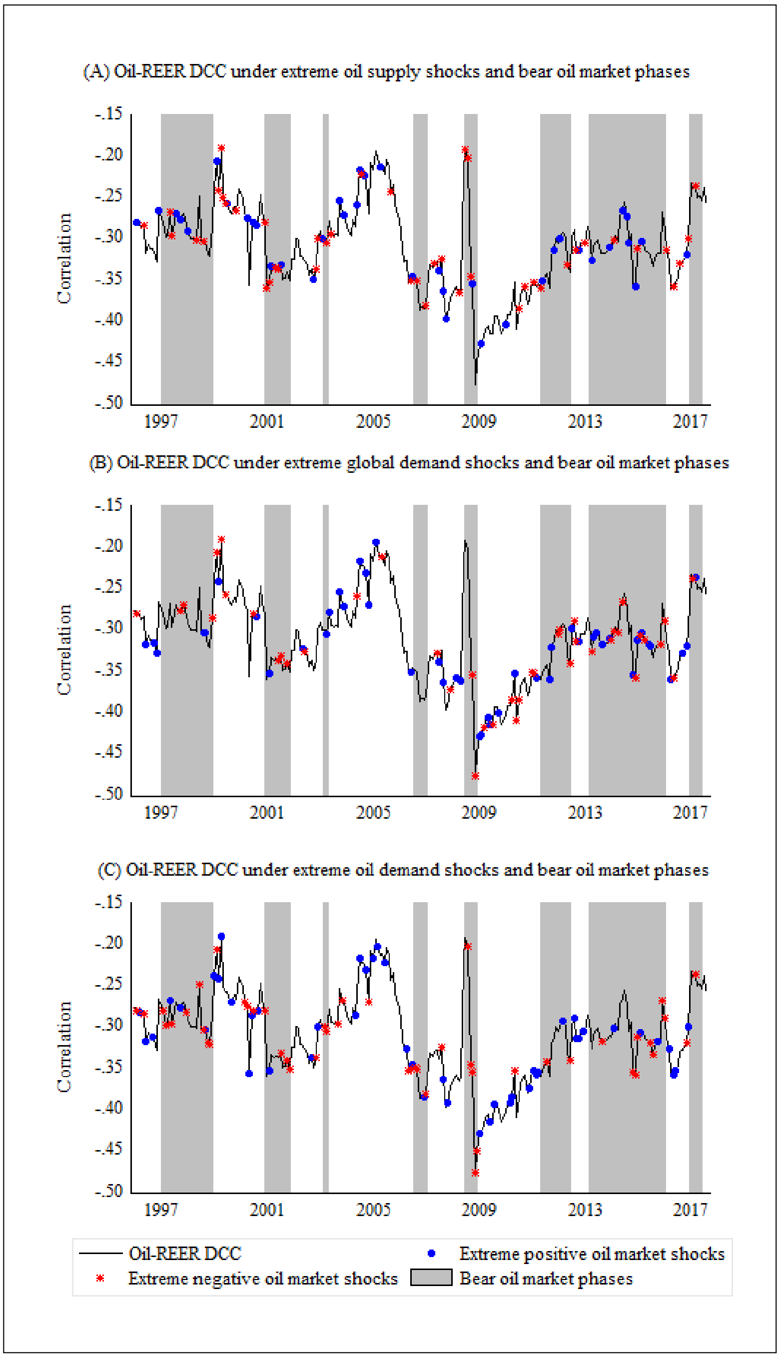

Figure 3.2: Oil-REER DCC under extreme shocks and bear phases in the international crude oil market. In each graph, the black solid line is the dynamic conditional correlation (DCC) between the real Brent crude oil returns and the real effective exchange rate (REER) returns of Trinidad and Tobago estimated from the DCC(1,1) model with oil, exchange rates, and stock returns. Graph (A), (B), and (C) show oil-REER DCC under periods of extreme oil supply, global demand, and oil-specific demand shocks, respectively. These extreme periods are obtained from Eq. (3.3) applied to the structural shocks estimated from the global crude oil SVAR model in Eq. (3.2). In graphs (A), (B), and (C) blue stars show the extreme positive episodes derived from each the particular shock, while red stars show the extreme negative shocks. For reference, the grey vertical bars in all graphs are bear oil market phases identified from the Pagan and Sossounov (2003) rule-based algorithm.

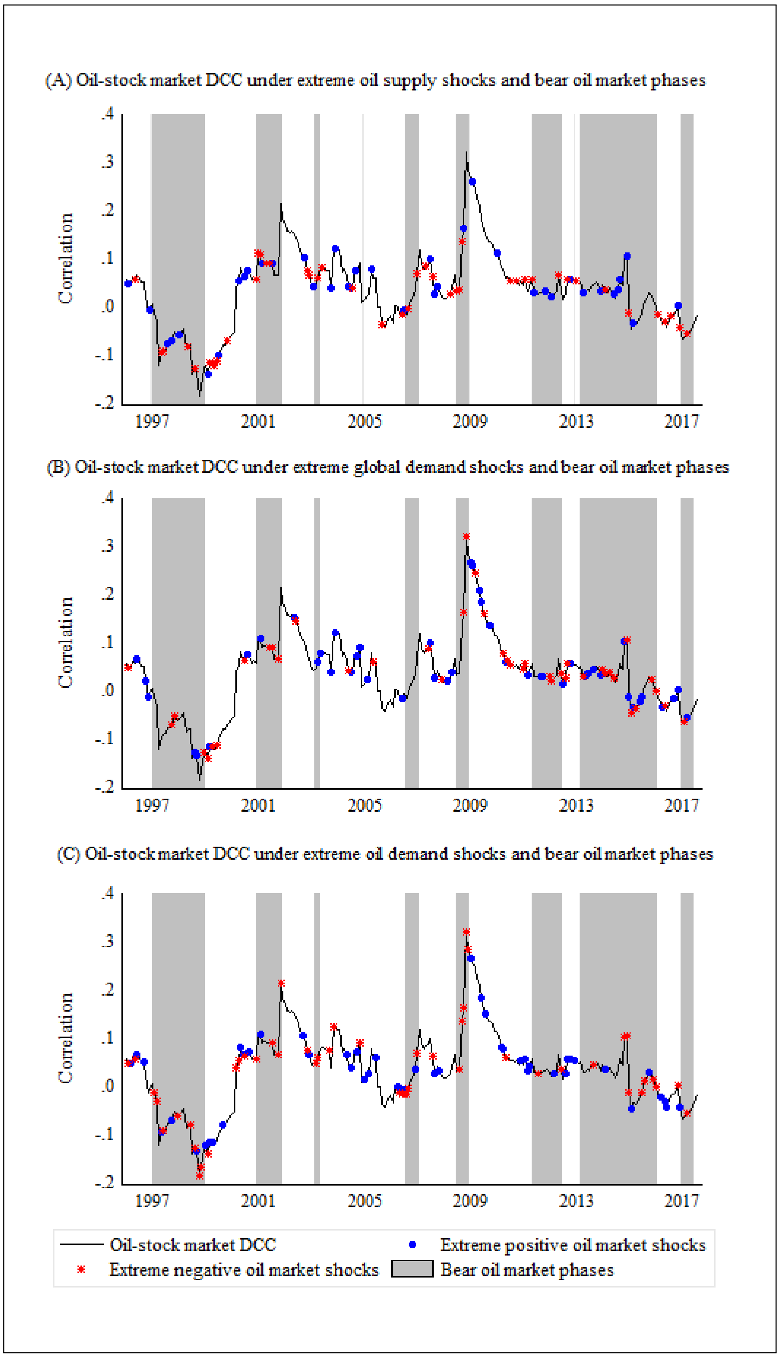

Figure 3.3: Oil-stock market DCC under extreme shocks and bear phases in the international crude oil market. In each graph, the black solid line is the dynamic conditional correlation (DCC) between the real Brent crude oil returns and the real composite stock returns of the Trinidad and Tobago Stock Exchange estimated from the DCC(1,1) model with oil, exchange rates, and stock returns. Graph (A), (B), and (C) show oil-stock market DCC under periods of extreme oil supply, global demand, and oil-specific demand shocks, respectively. These extreme periods are obtained from Eq. (3.3) applied to the structural shocks estimated from the global crude oil SVAR model in Eq. (3.2). In graphs (A), (B), and (C) blue stars show the extreme positive episodes derived from each the particular shock, while red stars show the extreme negative shocks. For reference, the grey vertical bars in all graphs are bear oil market phases identified from the Pagan and Sossounov (2003) rule-based algorithm.

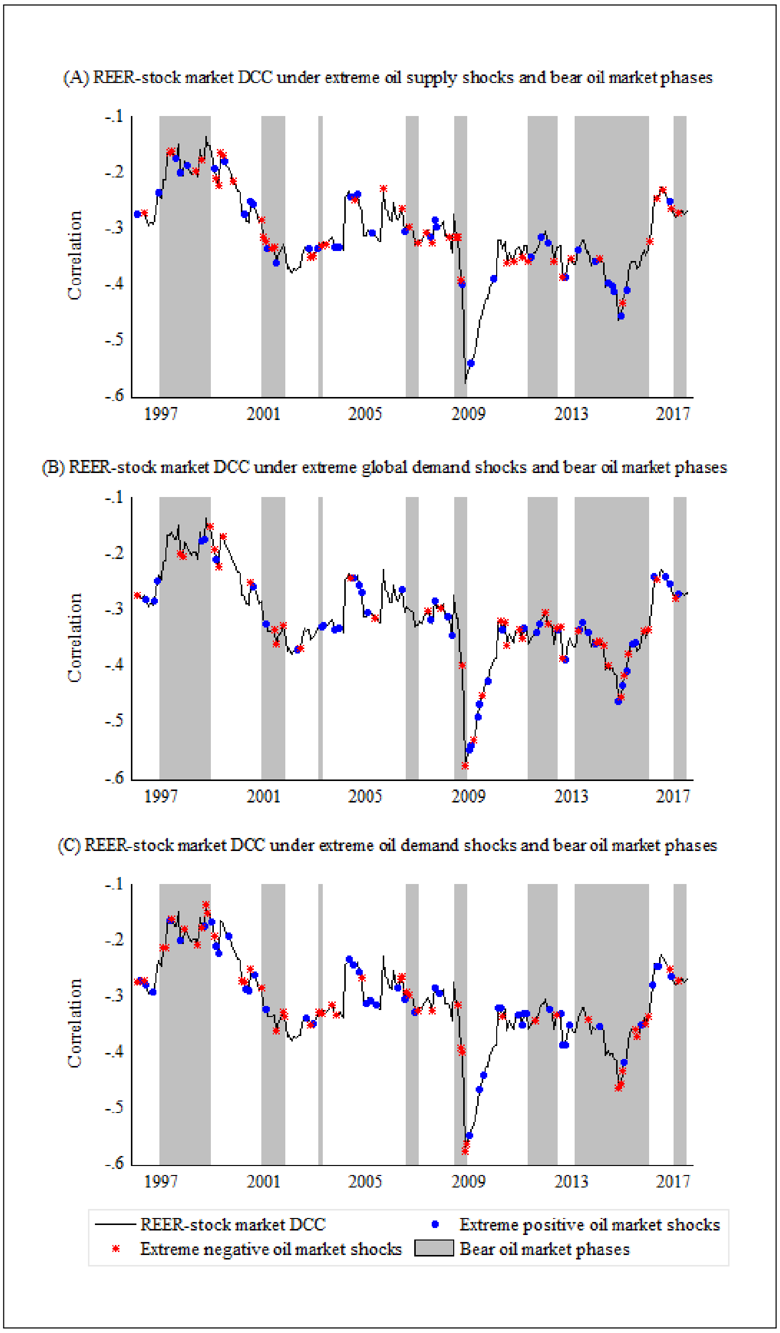

Figure 3.4: REER-stock market DCC under extreme shocks and bear phases in the international crude oil market. In each graph, the black solid line is the dynamic conditional correlation (DCC) between Trinidad and Tobago's real effective exchange rate (REER) returns and the real composite stock returns of the Trinidad and Tobago Stock Exchange estimated from the DCC(1,1) model with oil, exchange rates, and stock returns. Graph (A), (B), and (C) show REER-stock market DCC under periods of extreme oil supply, global demand, and oil-specific demand shocks, respectively. These extreme periods are obtained from Eq. (3.3) applied to the structural shocks estimated from the global crude oil SVAR model in Eq. (3.2). In graphs (A), (B), and (C) blue stars imply the extreme positive episodes derived from each the particular shock, while red stars imply the extreme negative shocks. For reference, the grey vertical bars in all graphs are bear oil market phases identified from the Pagan and Sossounov (2003) rule-based algorithm.

Table 3.3: Dynamic conditional correlations under relatively calm and extreme oil market shocks, as well as under bull and bear oil market phases, in both the full and GFC-censored samples. Significant results from two sample Welch's t-tests for Testing the Equality of Means (TEM) with unequal variances and sample sizes, for the monthly dynamic conditional correlations between calm vs. extreme and bullish vs. bearish oil market conditions, are noted as $***$, $**$, and $*$ for the 1%, 5%, and 10% levels of significance, respectively. The Welch's t-tests are evaluated against the Student's t distribution using Welch's degrees of freedom (see Welch (1947)). The abbreviations obs. is observations and SD is standard deviation. The relatively calm period is that time period where there are no atypical structural shocks in the international crude oil market as identified by discrete rule based specification. This calm period is used as the comparison sample for testing the equality of means in the dynamic correlations.

			Dynamic conditional correlations								
Sample	Oil Market Condition	Obs.	Oil-REER			Oil-stock			REER-stock		
			Mean	SD	TEM	Mean	SD	TEM	Mean	SD	TEM
Full	Overall	260	-0.31	0.05	-	0.03	0.08	-	-0.31	0.08	-
	Structural shocks										
	Relatively calm	85	-0.30	0.05	-	0.03	0.07	-	-0.31	0.07	-
	Extreme oil supply	83	-0.31	0.05	0.138	0.03	0.07	0.444	-0.30	0.08	-0.375
	Positive	39	-0.30	0.05	-0.020	0.04	0.07	-0.716	-0.31	0.08	0.457
	Negative	44	-0.31	0.05	0.234	0.01	0.07	1.350	-0.29	0.07	-1.087
	Extreme global demand	88	-0.32	0.06	2.047**	0.04	0.09	-0.850	-0.33	0.09	1.887*
	Positive	46	-0.32	0.05	1.876*	0.04	0.08	-0.937	-0.33	0.08	1.554
	Negative	42	-0.32	0.06	1.394	0.04	0.09	-0.412	-0.33	0.09	1.409
	Extreme oil demand	96	-0.32	0.05	1.444	0.03	0.09	0.018	-0.31	0.08	-0.012
	Positive	48	-0.31	0.06	1.030	0.03	0.08	0.210	-0.30	0.08	-0.257
	Negative	48	-0.32	0.05	1.313	0.03	0.10	-0.151	-0.31	0.09	0.203
	Oil market phases										
	Bull	155	-0.31	0.06	-	0.05	0.07	-	-0.31	0.07	-
	Bear	105	-0.31	0.04	0.140	0.01	0.08	3.502***	-0.31	0.09	0.406
GFC-censored	Overall	241	-0.31	0.05	-	0.02	0.07	-	-0.30	0.07	-
	Structural shocks										
	Relatively calm	81	-0.30	0.05	-	0.03	0.07	-	-0.31	0.06	-
	Extreme oil supply	77	-0.30	0.05	0.277	0.02	0.07	0.807	-0.30	0.07	-0.743
	Positive	37	-0.30	0.05	-0.337	0.03	0.06	-0.258	-0.31	0.07	0.029
	Negative	40	-0.31	0.05	0.777	0.01	0.07	1.438	-0.29	0.07	-1.199
	Extreme global demand	78	-0.31	0.05	0.981	0.02	0.07	0.363	-0.31	0.07	0.793
	Positive	40	-0.31	0.04	0.859	0.03	0.07	0.107	-0.31	0.07	0.491
	Negative	38	-0.31	0.05	0.728	0.02	0.07	0.483	-0.32	0.07	0.776
	Extreme oil demand	89	-0.31	0.05	1.044	0.02	0.07	0.984	-0.30	0.07	-1.034
	Positive	46	-0.31	0.05	0.759	0.02	0.07	0.710	-0.30	0.06	-0.872
	Negative	43	-0.31	0.04	0.997	0.01	0.08	0.895	-0.30	0.08	-0.810
	Oil market phases										
	Bull	142	-0.30	0.05	-	0.04	0.07	-	-0.30	0.06	-
	Bear	99	-0.31	0.03	0.972	0.00	0.07	4.122***	-0.31	0.08	0.626

3.4 Conclusion

We put forward a new approach to trace the sources of contagion in three pairs of financial market relationships, i.e. the crude oil-exchange rate, crude oil-stock returns, and exchange rate-stock returns correlations. The sources of international crude oil market contagion are determined using two rule-based specifications: A novel specification which combines established non-linear oil market rules to identify between relatively calm and extreme structural oil market shocks, as well as the Pagan and Sossounov (2003) rule-based algorithm to identify bull and bear oil market phases. We obtain the time-varying financial market relationships with a dynamic conditional correlations model. Then, we compare the correlations under calm versus extreme, and bullish versus bearish oil market conditions. The methodology proposed in this chapter is useful for financial stability analysis in economies susceptible to disturbances from the international crude oil market. Our empirical analyses are carried out on the financial markets of a small petroleum intensive economy of Trinidad and Tobago, from January 1996 to August 2017. We find a moderate interdependence in the oil-exchange rate and exchange rate-stock returns linkages in Trinidad and Tobago, with evidence of oil market contagion effects during the recent crude oil market crashes of the 2008 Global Financial Crisis (GFC) and 2014/2015. We also find that, outside of the GFC event, the oil-stock market relationship is generally weak, which suggests that the spillover risk from the international crude oil market to the Trinidad and Tobago Stock Exchange is low.

Chapter 3 Appendix

The VAR model estimates underlying the international crude oil market SVAR postulated in Kilian (2009) are presented in Table 3.4. Figure 3.5 illustrates that the VAR is stationary, as all eigenvalues of the companion matrix lie inside the unit disc. Further details are provided in the the table and figure captions. In addition, the just-identified SVAR model of the global oil market defined in Eq. (3.2) is estimated using EViews such that $A_0^{-1} = A'^{-1}B'$, where $A'e = B'\varepsilon$ and $E[\varepsilon\varepsilon' = I]$, as shown in Eqs. (3.13) and (3.14):

$$A' = \begin{bmatrix} 1 & 0 & 0 \\ -0.879 & 1 & 0 \\ 0.005 & -0.001^{*} & 1 \end{bmatrix} \tag{3.13}$$

$$B' = \begin{bmatrix} 0.760^{*} & 0 & 0 \\ 0 & 17.226^{*} & 0 \\ 0 & 0 & 0.086^{*} \end{bmatrix} \tag{3.14}$$

where * indicates statistical significance of the estimated parameter at the 1% level, evaluated against the normal distribution.

Table 3.4: Global oil market VAR model estimates. *Table notes continue on the next page.*

OS lags	OS	EA	OP	EA lags	OS	EA	OP	OP lags	OS	EA	OP
OS_{t-1}	-0.026701	1.411955	0.000569	EA_{t-1}	0.000142	1.236364	0.000697	OP_{t-1}	-0.113759	51.04140	1.154064
	(0.07011)	(1.59051)	(0.00806)		(0.00327)	(0.07422)	(0.00038)		(0.64267)	(14.5802)	(0.07387)
	[-0.38086]	[0.88773]	[0.07059]		[0.04342]	[16.6571]	[1.85287]		[-0.17701]	[3.50073]	[15.6225]
OS_{t-2}	-0.177484	1.812350	-0.006287	EA_{t-2}	0.008003	-0.456403	-0.000845	OP_{t-2}	0.546475	-36.37326	-0.181189
	(0.06954)	(1.57761)	(0.00799)		(0.00516)	(0.11710)	(0.00059)		(0.96419)	(21.8745)	(0.11083)
	[-2.55232]	[1.14880]	[-0.78655]		[1.55057]	[-3.89759]	[-1.42434]		[0.56677]	[-1.66281]	[-1.63484]
OS_{t-3}	-0.040713	0.760946	0.001079	EA_{t-3}	-0.010068	0.216516	0.000616	OP_{t-3}	-0.293462	-21.99173	0.039981
	(0.07072)	(1.60439)	(0.00813)		(0.00539)	(0.12234)	(0.00062)		(0.97374)	(22.0910)	(0.11193)
	[-0.57570]	[0.47429]	[0.13276]		[-1.86710]	[1.76982]	[0.99342]		[-0.30138]	[-0.99550]	[0.35721]
OS_{t-4}	-0.003905	-1.336737	0.002085	EA_{t-4}	0.008041	-0.230412	-0.000163	OP_{t-4}	0.184384	-10.73269	-0.069712
	(0.07043)	(1.59780)	(0.00810)		(0.00549)	(0.12458)	(0.00063)		(0.96902)	(21.9839)	(0.11138)
	[-0.05545]	[-0.83661]	[0.25761]		[1.46424]	[-1.84948]	[-0.25812]		[0.19028]	[-0.48821]	[-0.62587]
OS_{t-5}	-0.056905	-0.043332	-0.008123	EA_{t-5}	-0.005621	0.254083	-0.000397	OP_{t-5}	-0.444266	23.37323	-0.003049
	(0.06987)	(1.58506)	(0.00803)		(0.00556)	(0.12608)	(0.00064)		(0.96902)	(21.9840)	(0.11138)
	[-0.81448]	[-0.02734]	[-1.01142]		[-1.01149]	[2.01532]	[-0.62213]		[-0.45847]	[1.06319]	[-0.02738]
OS_{t-6}	-0.025338	-3.603742	-0.007561	EA_{t-6}	0.001592	-0.069518	0.000300	OP_{t-6}	0.767608	-15.12388	-0.011851
	(0.07057)	(1.60108)	(0.00811)		(0.00568)	(0.12891)	(0.00065)		(0.97261)	(22.0654)	(0.11180)
	[-0.35904]	[-2.25082]	[-0.93207]		[0.28013]	[-0.53927]	[0.45906]		[0.78923]	[-0.68541]	[-0.10600]
OS_{t-7}	-0.046927	-0.831743	0.004769	EA_{t-7}	-0.002513	-0.07955	-0.000678	OP_{t-7}	-1.46129	11.40381	0.122016
	(0.07107)	(1.61244)	(0.00817)		(0.00578)	(0.13119)	(0.00066)		(0.97225)	(22.0573)	(0.11176)
	[-0.66026]	[-0.51583]	[0.58371]		[-0.43464]	[-0.60639]	[-1.01971]		[-1.50300]	[0.51701]	[1.09181]
OS_{t-8}	0.011000	0.095043	-0.004882	EA_{t-8}	0.004314	0.080142	0.001321	OP_{t-8}	1.600234	-8.653166	-0.150223
	(0.07157)	(1.62372)	(0.00823)		(0.00577)	(0.13091)	(0.00066)		(0.97907)	(22.2120)	(0.11254)
	[0.15369]	[0.05853]	[-0.59347]		[0.74766]	[0.61221]	[1.99138]		[1.63445]	[-0.38957]	[-1.33486]
OS_{t-9}	0.054682	-1.375948	-0.010133	EA_{t-9}	-0.007161	0.158467	-0.000581	OP_{t-9}	-1.155275	-5.89235	-0.065276
	(0.07136)	(1.61897)	(0.00820)		(0.00582)	(0.13193)	(0.00067)		(0.99519)	(22.5778)	(0.11439)
	[0.76628]	[-0.84989]	[-1.23536]		[-1.23138]	[1.20114]	[-0.86871]		[-1.16086]	[-0.26098]	[-0.57063]
OS_{t-10}	0.005476	-2.573713	-0.006212	EA_{t-10}	0.006786	-0.133547	-3.15E-05	OP_{t-10}	1.427493	5.534891	0.221141
	(0.07109)	(1.61281)	(0.00817)		(0.00588)	(0.13335)	(0.00068)		(1.00549)	(22.8115)	(0.11558)
	[0.07702]	[-1.59579]	[-0.76026]		[1.15455]	[-1.00146]	[-0.04659]		[1.41969]	[0.24264]	[1.91337]
OS_{t-11}	-0.012424	-0.191666	-0.024019	EA_{t-11}	-0.009802	0.098733	-0.000138	OP_{t-11}	-2.364168	-16.81061	0.043076
	(0.07117)	(1.61468)	(0.00818)		(0.00590)	(0.13387)	(0.00068)		(1.01887)	(23.1150)	(0.11711)
	[-0.17456]	[-0.11870]	[-2.93602]		[-1.66104]	[0.73751]	[-0.20353]		[-2.32039]	[-0.72726]	[0.36782]
OS_{t-12}	0.072535	-0.841209	0.006892	EA_{t-12}	0.011551	-0.039947	-0.000287	OP_{t-12}	1.767069	37.61084	0.031200
	(0.07170)	(1.62669)	(0.00824)		(0.00594)	(0.13473)	(0.00068)		(1.02845)	(23.3324)	(0.11822)
	[1.01162]	[-0.51713]	[0.83620]		[1.94507]	[-0.29651]	[-0.42041]		[1.71818]	[1.61196]	[0.26393]
OS_{t-13}	-0.050167	-1.646162	-0.004689	EA_{t-13}	-0.013825	-0.09224	0.000423	OP_{t-13}	0.975994	-29.20736	-0.287455
	(0.07203)	(1.63407)	(0.00828)		(0.00593)	(0.13464)	(0.00068)		(1.04114)	(23.6201)	(0.11967)
	[-0.69650]	[-1.00740]	[-0.56638]		[-2.32949]	[-0.68507]	[0.61975]		[0.93743]	[-1.23655]	[-2.40200]
OS_{t-14}	0.039015	-2.209987	-0.01379	EA_{t-14}	0.012000	0.039752	-7.08E-06	OP_{t-14}	-1.406615	35.06649	0.133724
	(0.07130)	(1.61762)	(0.00820)		(0.00598)	(0.13574)	(0.00069)		(1.03651)	(23.5151)	(0.11914)
	[0.54718]	[-1.36619]	[-1.68257]		[2.00553]	[0.29285]	[-0.01029]		[-1.35707]	[1.49123]	[1.12240]
OS_{t-15}	0.051708	0.535280	-0.001824	EA_{t-15}	0.000740	-0.083851	-0.000657	OP_{t-15}	-0.471724	-34.64723	-0.018567
	(0.07205)	(1.63469)	(0.00828)		(0.00601)	(0.13633)	(0.00069)		(1.03052)	(23.3793)	(0.11845)
	[0.71763]	[0.32745]	[-0.22023]		[0.12320]	[-0.61507]	[-0.95070]		[-0.45775]	[-1.48196]	[-0.15675]
OS_{t-16}	0.031030	0.500816	-0.01677	EA_{t-16}	-0.006837	0.153922	0.001212	OP_{t-16}	0.393414	34.23341	0.006256
	(0.07174)	(1.62759)	(0.00825)		(0.00594)	(0.13487)	(0.00068)		(1.03294)	(23.4343)	(0.11873)
	[0.43253]	[0.30770]	[-2.03358]		[-1.15003]	[1.14125]	[1.77341]		[0.38087]	[1.46083]	[0.05269]
OS_{t-17}	-0.099766	0.544995	0.004772	EA_{t-17}	-0.0017	-0.222809	-0.000249	OP_{t-17}	0.377029	-26.53512	-0.025063
	(0.07277)	(1.65084)	(0.00836)		(0.00602)	(0.13659)	(0.00069)		(1.03777)	(23.5438)	(0.11929)
	[-1.37104]	[0.33013]	[0.57056]		[-0.28231]	[-1.63124]	[-0.35923]		[0.36331]	[-1.12705]	[-0.21011]
OS_{t-18}	-0.038521	-1.365828	0.009111	EA_{t-18}	0.002794	0.130608	-2.08E-05	OP_{t-18}	-0.016018	6.672988	-0.010642
	(0.07204)	(1.63430)	(0.00828)		(0.00604)	(0.13707)	(0.00069)		(1.04015)	(23.5978)	(0.11956)
	[-0.53474]	[-0.83572]	[1.10037]		[0.46240]	[0.95282]	[-0.02989]		[-0.01540]	[0.28278]	[-0.08901]
OS_{t-19}	-0.01672	-2.072927	-0.007268	EA_{t-19}	0.007376	0.030560	-0.000642	OP_{t-19}	-0.162322	14.49585	0.099058
	(0.07247)	(1.64423)	(0.00833)		(0.00599)	(0.13583)	(0.00069)		(1.03325)	(23.4412)	(0.11877)
	[-0.23070]	[-1.26073]	[-0.87239]		[1.23204]	[0.22499]	[-0.93244]		[-0.15710]	[0.61839]	[0.83405]
OS_{t-20}	-0.114791	-0.790658	0.006868	EA_{t-20}	-0.007023	-0.065722	0.000206	OP_{t-20}	-0.644926	-14.45345	0.053317
	(0.07175)	(1.62767)	(0.00825)		(0.00584)	(0.13257)	(0.00067)		(1.03904)	(23.5725)	(0.11943)
	[-1.59998]	[-0.48576]	[0.83285]		[-1.20186]	[-0.49574]	[0.30622]		[-0.62070]	[-0.61315]	[0.44642]
OS_{t-21}	-0.098839	-1.033819	-0.000281	EA_{t-21}	-0.000338	-0.046742	0.000357	OP_{t-21}	0.450379	-9.084092	-0.130682
	(0.07192)	(1.63162)	(0.00827)		(0.00582)	(0.13196)	(0.00067)		(1.02775)	(23.3164)	(0.11813)
	[-1.37431]	[-0.63362]	[-0.03404]		[-0.05812]	[-0.35421]	[0.53363]		[0.43822]	[-0.38960]	[-1.10621]
OS_{t-22}	-0.130925	1.612795	0.015612	EA_{t-22}	0.004245	0.081347	-0.000687	OP_{t-22}	-0.640184	22.71750	0.090432
	(0.07142)	(1.62022)	(0.00821)		(0.00580)	(0.13153)	(0.00067)		(1.00486)	(22.7971)	(0.11550)
	[-1.83326]	[0.99542]	[1.90183]		[0.73218]	[0.61849]	[-1.03130]		[-0.63709]	[0.99651]	[0.78293]
OS_{t-23}	-0.055106	-0.80738	0.011936	EA_{t-23}	-0.000565	-0.036768	0.000682	OP_{t-23}	-0.046118	-15.65828	-0.169855
	(0.07170)	(1.62659)	(0.00824)		(0.00556)	(0.12622)	(0.00064)		(1.00182)	(22.7282)	(0.11515)
	[-0.76859]	[-0.49636]	[1.44837]		[-0.10164]	[-0.29130]	[1.06672]		[-0.04603]	[-0.68894]	[-1.47502]
OS_{t-24}	0.277262	-0.843006	-0.005871	EA_{t-24}	-0.002692	0.053381	-0.000325	OP_{t-24}	0.751997	0.481991	0.113725
	(0.07188)	(1.63080)	(0.00826)		(0.00343)	(0.07783)	(0.00039)		(0.66156)	(15.0087)	(0.07604)
	[3.85713]	[-0.51693]	[-0.71052]		[-0.78474]	[0.68588]	[-0.82450]		[1.13670]	[0.03211]	[1.49553]
								C	0.071703	11.36830	0.070173
									(0.39861)	(9.04315)	(0.04582)
									[0.17988]	[1.25712]	[1.53156]

Table 3.4 notes: The sample, after a 24 months lag length adjustment, consists of 260 observations; i.e. January 1996 to August 2017, inclusive. Standard errors are presented immediately below the estimated coefficients and in are curved "( )" parentheses, and t-statistics appear below these in squared "[ ]" parentheses. OS represents the percentage change in world crude oil production, EA represents the Kilian (2019) correction of the Kilian (2009) real global economic activity index, OP is the log of real Brent crude oil prices, and C is the VAR intercept in each of the three system of equations. The columns, OS, EA, and OP can be seen as the three equations the trivariate system of equations. Each row is the lag of one of the variables up to 24 lags, and this is estimated for each of the three variables.

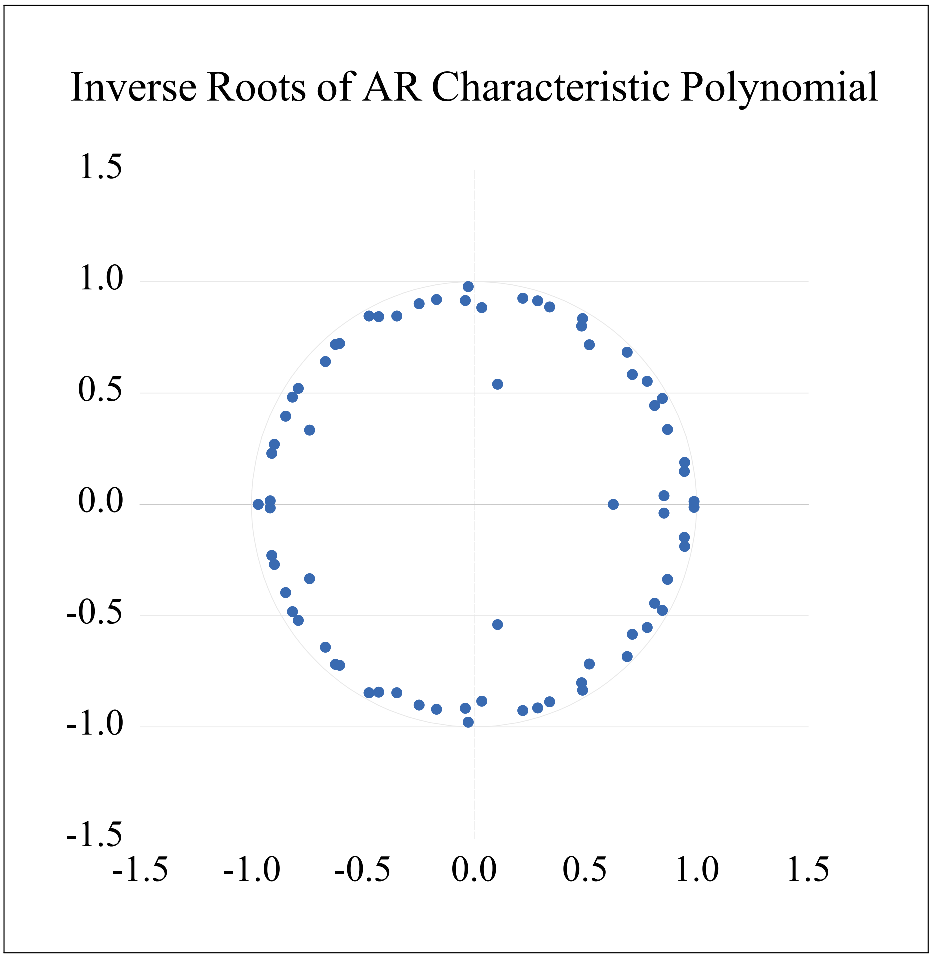

Figure 3.5: Eigenvalues of the companion matrix. While all the inverse roots of the AR characteristic polynomial reside inside the unit circle, many lie close to the limit, indicating that shocks in the global crude oil market do not die out quickly.

Chapter 4

Contagion testing in embryonic markets under alternative stressful US market scenarios

Abstract

We consolidate alternative ways for identifying stable and stressful scenarios in the S&P 500 market to construct contagion tests for recipient markets vulnerable to disturbances from this source market. The S&P 500 index is decomposed into discrete conditions of: (1) Tranquil versus turbulent volatility; (2) Bull versus bear market phases; (3) Normal periods versus asset bubbles and crises. We analyse the relationship between the S&P 500 market and major emerging Caribbean stock markets and find that, despite the prominent trade related exposure to the US, financial linkages are much less pronounced than might be expected outside of the Great Recession.

Keywords: Caribbean; contagion; correlation; S&P 500; stock market; United States
JEL classification: C58; G01

4.1 Introduction

If the linkages between markets only deepen during a crisis, then adverse shocks in a source market will be able to spread to a recipient market. This is the central idea behind contagion analysis. Typical financial contagion tests are designed around the comparison of market relationships in periods of so-called calm with a well-known crisis event. In this chapter, we offer a different perspective by considering various ways to decompose a source market into stable and stressful conditions for constructing financial contagion tests, which we illustrate using the S&P 500 index as the source market of financial stress. Because of share size and influence it exerts on financial markets around the world, the developments in the S&P 500 stock market are of vital interest for financial analysis (Phillips and Shi, 2020).

The first approach we use, classifies the VIX into tranquil and turbulent episodes using two alternative approaches: A practitioner's rule and a clustering algorithm. Stock volatility is a common proxy for market uncertainty (Bloom et al., 2007) and the VIX is widely considered to be an investor fear gauge (Min and Hwang, 2012), which motivates the development of contagion tests around low and high VIX regimes.

A second approach is based on identifying bullish and bearish market phases in the S&P 500 market with a rule-based algorithm suggested in Pagan and Sossounov (2003). Indeed, there is evidence to suggest that market correlations tend to rise and fall in bearish and bullish phases, respectively (see Syllignakis and Kouretas (2011) and references therein).

A third approach is based on asset bubbles and crises in the S&P 500 index identified in Phillips and Shi (2020). Asset bubbles, particularly those originating in the US financial market, are also important sources of contagion. For example, Hon et al. (2007) find that the dot-com bubble burst led to the collapse of the stock market in more than a dozen countries with close sectoral ties to the US technology, media, and telecommunications sector.

Altogether, these various lenses for examining stressful market conditions can help policy makers and investors understand the type of US financial environment during which shocks will be able to proliferate and propagate in recipient markets particularly exposed to developments in this source market. We use these identified stable and stressful conditions to evaluate the stock market relationships between the US and the Caribbean across various co-moment contagion channels, i.e. the correlation and co-skewness contagion tests presented in Fry et al. (2010), and the co-volatility contagion test introduced in Fry-McKibbin et al. (2014). Contagion analysis is an especially appropriate approach for an empirical exercise about how relationships are affected during suddenly changing conditions in a source market, as opposed to cointegration and interdependence tests which are more suitable for the assessment of long run relationships.

Our applications to Caribbean stock markets are valuable because small open island economies have a higher dependency on cordial trade relationships for survival than their larger counterparts (Briguglio, 1995). It is plausible for such a vulnerability to manifest in stock market relationships given that asset returns are assumed to reflect all available information, including developments in the real economy. Regarding the link between financial contagion and trade linkages, the evidence suggests that a financial crisis is amplified if the epicentre country is better integrated into the trade network of the recipient country (Kali and Reyes, 2010). Our focus is on the Trinidad and Tobago, Jamaica, and Barbados stock exchanges. These three financial markets are the most advanced of the Caribbean Community (CARICOM) region. Additionally, their economies represent 3 of the 6 More Developed Countries (MDCs) of the 15 full member states of the CARICOM. Moreover, the US is the uncontested most important trading partner for the three islands (see Table 1.1).

There is limited published research about the relationship between the US and Caribbean financial markets. Some studies have focused on the co-movement between these three Caribbean stock markets. For example, using cointegration analysis and common feature testing, Lorde et al. (2009) find no evidence of long run or short run relationships, or common features between these three stock exchanges. On the other hand, Harrison and Moore (2010) use principal component analysis and a VAR model to also investigate co-movements of Caribbean stock markets and find that there are only periodic linkages between the three markets.

Other works have considered the relationship between the US and Caribbean stock markets. Samarakoon (2011) looks at the transmission of shocks between US and foreign markets, including Trinidad and Tobago and Jamaica, to tests for contagion and interdependence associated with the Global Financial Crisis (GFC). Focusing on the contagion results, the author states that there is no contagion from the US to emerging stock markets. In addition, Cozier and Watson (2019) analyse co-movement, suggested by copula-GARCH models and correlation coefficients, to proxy financial integration between stock prices in Trinidad and Tobago, Jamaica, and Barbados as well as the US[1]. They conclude that while interdependencies exist between the three Caribbean stock markets, there is considerably less evidence of financial integration with the US market.

Our main contributions to the contagion literature are that we test for contagion using various sources of stress (i.e., turbulent volatility, bearish phases, and asset bubbles and crises) across various co-moment channels (i.e., correlation, co-volatility, and co-skewness).

[1] In particular, Cozier and Watson (2019) use the New York Stock Exchange.

Hence, our applications provide a fresh perspective for examining the market connectivity between the S&P 500 and Caribbean equity markets, by testing whether financial linkages change when conditions in the S&P 500 index change.

We find that the relationship between the US and Caribbean stock markets vary both under alternative source market conditions and by recipient country. There are many contagion channels from the US to Caribbean affiliated with the GFC in the cases of Trinidad and Tobago and Jamaica but not in Barbados. However, when the Great Recession is censored, we find that most of these intermittent market linkages disappear.

The rest of the chapter is structured as follows. Section 4.2 details our empirical procedures. In Section 4.3 we describe the data we use and the how the asset returns are adjusted. Then, in Section 4.4, we present and analyse the results. Subsequently, we conclude in Section 4.5.

4.2 Methodology

We use three different approaches to decompose a source market into discrete stable and stressful scenarios. Subsequently, we adapt four contagion channels to test how the relationship between a source and recipient market might change under the alternative source market conditions. This section documents these empirical procedures.

4.2.1 Approaches to decompose the US market into discrete stable and stressful conditions

We consider three alternative approaches to classify the S&P 500 market into stable and stressful scenarios, to determine which type of classification might be useful for financial risk analysis in emerging markets potentially vulnerable to the US market movements.

4.2.1.1 Tranquil and turbulent volatility

Our first approach identifies periods of high versus low volatility in the US stock market based on the Chicago Board Options Exchange Volatility Index, generally known under its ticker, VIX. The VIX measures the 30-day expected volatility of the US stock market derived from real-time, mid-quote prices of the S&P 500 call and put options. We adopt the practitioner's rule which associates low volatility to VIX values below 12, normal volatility to VIX values between 12 and 20, and high volatility to values above 20 (see, e.g. Edwards and Preston (2017)). The implied volatility of the VIX reflects market expectations regarding future price movements and provides a better forecast than the realised volatility, especially during turmoil periods (see, e.g. Kenourgios (2014)). As we are interested in comparing turbulent with non-turbulent volatility periods, we characterise all VIX values below 20 as tranquil and values otherwise as turbulent. One obvious advantage of applying the practitioner's rule on the VIX is that it is not sample sensitive. Given that the availability of data varies across the recipient Caribbean countries we consider, this is a particularly attractive feature.

For comparative purposes, we also juxtapose the results we obtain from the practitioner's rule with a non-hierarchical k-means cluster algorithm to sort the VIX into relatively low and high volatility episodes. The clustering employs Euclidean distance as the measure of similarity/dissimilarity in order to maximise between cluster variance and minimise within cluster variance of the two groupings. Unlike the more absolute blanket definition of high volatility implied by the practitioner's rule, the cluster analysis algorithm is sample sensitive and provides different clusters across the sample periods of the different Caribbean territories to give a perspective of *relatively* lower and higher volatility regimes.

4.2.1.2 Bull and bear market phases

Kole and Dijk (2017) apply both rule-based and Markov-switching methods for identifying bull and bear market phases to the S&P 500 index. They find that rule-based methods are preferred for in-sample identification of market states, whereas Markov switching models are better for forecasting. In particular, their results show that in-sample only the mean return of this market matters, which the rule-based methods precisely captures. The algorithms suggested in Pagan and Sossounov (2003) and Lunde and Timmermann (2004) are two frequently used rule-based approaches for identifying bull and bear phases in the literature (Kole and Dijk, 2017; Hanna, 2018), of which the former is the more popular of the two procedures according to Google Scholar citations. Although we find that there is strong congruence between the two measures[2], we observe that Lunde and Timmermann (2004) consistently understates historical bear market phases such as S&P downgrading of US sovereign debt in the summer of 2011 and the stock market selloff from the summer of 2015 up to the Brexit referendum result in early 2016. Figure 4.2 of the Chapter Appendix presents a graphical illustration of the omissions of key bear phases in the S&P 500 market produced by the Lunde and Timmermann (2004) rule-based algorithm when compared with the Pagan and Sossounov (2003) procedure. As such, our results are reported using the bull and bear phases in the S&P 500 market sorted using the algorithm suggested in Pagan and Sossounov (2003). This procedure involves the

[2]For instance, using our longest sample (i.e., from 1994m1 to 2018m11 for Trinidad and Tobago) we find an 89% similarity between these two rule-based algorithms for determining bear and bull market phases. This sensitivity analysis is performed using the feasible combinations for calibrating the Lunde and Timmermann (2004) algorithm suggested in Kole and Dijk (2017) and the calibration for the Pagan and Sossounov (2003) as we document in this chapter.

determination of local peaks and troughs in asset prices which are the highest or lowest values, respectively, within a specified interval on either side of a given month. Following Pagan and Sossounov (2003), we set this interval as 8 months for the S&P 500 market. Moreover, a minimum duration for individual phases and cycles restricts which turning points trigger a switch between phases. These minimum durations are set to 16 months in the case of cycles and 4 months in the case of phases. However, if a rise or fall in the asset price is greater than 20%, then the minimum phase rule is ignored and a switch of market phase is triggered. A 6 month censor, again suggested in Pagan and Sossounov (2003), is also used to prevent extreme values towards the end of an interval from distorting phases in the S&P 500 market. Pagan and Sossounov (2003) demonstrate that their rule-based algorithm identifies turning points which are synchronous to scenarios considered as bull and bear markets in the US stock market.

4.2.1.3 Normal periods, and asset bubbles and crises

We use the bubble and crises time-stamps in the S&P 500 market detected in Phillips and Shi (2020), which covers our sample period. Phillips and Shi (2020) contains an example of the *psymonitor* approach, postulated in Phillips et al. (2015a,b), for the S&P 500 market in the statistical package R. Psymonitor provides consistent real-time dating for the start and end of bubbles and market crashes (including flash crashes). Under the null hypothesis, a normal asset price behaviour follows a martingale process with a mild drift function. Rejection of the null implies a mild explosivity, which is indicative of an irregular asset market behaviour. The psymonitor test applies a rolling window right-tailed ADF test that has a double-sup window selection criteria to compute the ADF statistic in a double recursion over both feasible ranges of the window start points and a feasible range of window sizes. This procedure repeats the ADF test on a sequence of samples, steadily rolling the window frame throughout the sample. When the null of no mild explosivity in asset prices is rejected, this period is date-stamped. Psymonitor is globally recognised by policy-makers and the financial industry as an early warning device for crises (see, for example, the discussion in Phillips and Shi (2020)). Furthermore, such approach is considered to be particularly appropriate for the analysis of datasets which include the GFC period and its aftermath (see, for example, the discussions in Homm and Breitung (2012) and Figuerola-Ferretti et al. (2020)).

4.2.2 Contagion tests

Four contagion tests are employed to examine whether financial market relationships change across various co-moment channels. In the subsequent contagion tests, the S&P 500 index is the source market denoted as i and the recipient market is a given Caribbean stock exchange denoted as j. It is well-known that Pearson correlation is conditional on market volatility and becomes spuriously over-inflated when the volatility associated with a crisis increases, which leads to a false positive detection of contagion (Boyer et al., 1999; Loretan and English, 2000; Forbes and Rigobon, 2002). Hence, we follow the empirical literature[3] and correct for the potential heteroskedasticity bias in the stressful market periods as described in Eq. (4.1):

$$\hat{\rho}_{y|x_i} = \frac{\hat{\rho}_y}{\sqrt{1 + ((\sigma^2_{y,i} - \sigma^2_{x,i})/\sigma^2_{x,i})(1 - \hat{\rho}^2_y)}} \tag{4.1}$$

[3]See, for example, Boyer et al. (1999); Loretan and English (2000); Forbes and Rigobon (2002); Fry et al. (2010); Fry-McKibbin et al. (2014); Fry-McKibbin and Hsiao (2018).

where x represents the stable periods and y represents stressful scenarios, such that $\sigma^2_{x,i}$ and $\sigma^2_{y,i}$ are the return variances of the stable and stressful periods in the source market, respectively; and $\hat{\rho}_y$ is the correlation between the source and recipient markets during stressful scenarios. This adjusted linear correlation coefficient is used in each of the subsequent contagion tests to treat with possible heteroskedasticity bias in the co-moment channels.

4.2.2.1 Correlation channel

We use Fry et al. (2010) two-sided version of the Forbes and Rigobon (2002) significance test for a change in the adjusted stressful period correlation (i.e., $\hat{\rho}_{y|x_i}$) compared to the stable period correlation from the S&P 500 market to a Caribbean stock exchange given in Eq. (4.2):

$$CR_{\overline{FR}}(i \rightarrow j) = \left(\frac{\hat{\rho}_{y|x_i} - \hat{\rho}_x}{\sqrt{Var(\hat{\rho}_{y|x_i} - \hat{\rho}_x)}} \right)^2 \tag{4.2}$$

where $\hat{\rho}_x$ is the Pearson correlation in the calm sample and, under the null hypothesis of “no contagion”, the test statistic is asymptomatically distributed as $CR_{\overline{FR}}(i \rightarrow j) \xrightarrow{d} \chi^2_1$. In addition, the variance in the denominator of Eq. (4.2) is the standard error of the numerator and is decomposed in Eq. (4.3):

$$Var\Big(\widehat{\rho}_{y|x_i} - \widehat{\rho}_x\Big) = Var\Big(\widehat{\rho}_{y|x_i}\Big) + Var\Big(\widehat{\rho}_x\Big) - 2Cov\Big(\widehat{\rho}_{y|x_i}, \widehat{\rho}_x\Big) \tag{4.3}$$

where the second term on the right hand side of the equation is a sampling variance of the correlation coefficient. An approximation for large samples, and moderate or small correlations has been derived in (Hotelling, 1953, p. 212) as $Var\Big(\widehat{\rho}_x\Big) = \frac{1}{T_x}\Big(1 - \rho^2_x\Big)^2$. As the relevant population value ρ_x is unknown in practice, it is replaced in the calculation by the corresponding sample value[4].

4.2.2.2 Co-volatility channel

We apply the co-volatility contagion test in Eq. (4.4), suggested in Fry-McKibbin et al. (2014), to determine whether the volatility in S&P 500 is transmitted to the volatility of Caribbean stock exchanges during stressful S&P 500 market conditions:

$$CV(i \to j; r_i^2, r_j^2) = \left(\frac{\hat{\xi}_y(r_i^2, r_j^2) - \hat{\xi}_x(r_i^2, r_j^2)}{\sqrt{(4\hat{\rho}_{y|x_i}^4 + 16\hat{\rho}_{y|x_i}^2 + 4)/T_y + (4\hat{\rho}_x^4 + 16\hat{\rho}_x^2 + 4)/T_x}} \right)^2 \tag{4.4}$$

where T_x and T_y are the stable and stressful sub-samples, and the standardisation parameters $\hat{\xi}_x(r_i^2, r_j^2)$ and $\hat{\xi}_y(r_i^2, r_j^2)$ are respectively defined in Eq. (4.5) and (4.6):

$$\hat{\xi}_x(r_i^2, r_j^2) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left(\frac{x_{i,t} - \hat{\mu}_{xi}}{\hat{\sigma}_{xi}} \right)^2 \left(\frac{x_{j,t} - \hat{\mu}_{xj}}{\hat{\sigma}_{xj}} \right)^2 - (1 + 2\hat{\rho}_x^2) \tag{4.5}$$

$$\hat{\xi}_y(r_i^2, r_j^2) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left(\frac{y_{i,t} - \hat{\mu}_{yi}}{\hat{\sigma}_{yi}} \right)^2 \left(\frac{y_{j,t} - \hat{\mu}_{yj}}{\hat{\sigma}_{yj}} \right)^2 - (1 + 2\hat{\rho}_{y|x_i}^2) \tag{4.6}$$

and all other notation follows the aforementioned contagion test, and under the null hypothesis of "no contagion", the co-volatility test follows the same asymptotic distribution, i.e. $CV(i \to j) \xrightarrow{d} \chi_1^2$.

4.2.2.3 Co-skewness channels

In order to test whether the average S&P 500 returns affect the volatility of Caribbean stock returns under stressful S&P 500 scenarios, as well as whether the S&P 500 market

[4] For a further decomposition and computation of the other terms, see the Appendix in Fry et al. (2010, p. 435-436).

volatility affects the average Caribbean stock returns under stressful S&P 500 market scenarios, we employ the two variants of the co-skewness contagion test put forward in Fry et al. (2010) which are specified in Eqs. (4.7) and (4.8):

$$CS_1(i \to j; r_i^1, r_j^2) = \left(\frac{\hat{\psi}_y(r_i^1, r_j^2) - \hat{\psi}_x(r_i^1, r_j^2)}{\sqrt{(4\hat{\rho}_{y|x_i}^2 + 2)/T_y + (4\hat{\rho}_x^2 + 2)/T_x}} \right)^2 \tag{4.7}$$

$$CS_2(i \to j; r_i^2, r_j^1) = \left(\frac{\hat{\psi}_y(r_i^2, r_j^1) - \hat{\psi}_x(r_i^2, r_j^1)}{\sqrt{(4\hat{\rho}_{y|x_i}^2 + 2)/T_y + (4\hat{\rho}_x^2 + 2)/T_x}} \right)^2 \tag{4.8}$$

where r_i^1 and r_i^2 are the mean and standard deviation of the S&P 500 returns, correspondingly, and r_j^1 and r_j^2 are the same for a given Caribbean stock market returns. Furthermore, the standardisation parameters $\hat{\psi}_x(r_i^m, r_j^n)$ and $\hat{\psi}_y(r_i^m, r_j^n)$ take the form defined in Eqs. (4.9) and (4.10), respectively:

$$\hat{\psi}_x(r_i^m, r_j^n) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left(\frac{x_{i,t} - \hat{\mu}_{xi}}{\hat{\sigma}_{xi}} \right)^m \left(\frac{x_{j,t} - \hat{\mu}_{xj}}{\hat{\sigma}_{xj}} \right)^n \tag{4.9}$$

$$\hat{\psi}_y(r_i^m, r_j^n) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left(\frac{y_{i,t} - \hat{\mu}_{yi}}{\hat{\sigma}_{yi}} \right)^m \left(\frac{y_{j,t} - \hat{\mu}_{yj}}{\hat{\sigma}_{yj}} \right)^n \tag{4.10}$$

where $\hat{\mu}$ and $\hat{\sigma}$ are the mean and standard deviation, respectively, for a given market (i.e., i or j) under a given sample (i.e., x or y); and r^m (r^n) is the average returns for market i (j) in the CS_1 (CS_2) test version and squared returns in the CS_2 (CS_1) test version. The test statistics in Eqs. (4.7) and (4.8), when their associated null hypotheses of "no contagion" are true, are asymptotically distributed as $CS(i \to j) \xrightarrow{d} \chi_1^2$.

4.3 Data

The stock exchanges of the Caribbean region, akin to the capital markets of small and developing economies, are relatively illiquid due to the limited amount of companies listed on these exchanges in comparison to those of advanced markets (CBTT FSR, 2019). Hence, our analysis uses monthly data to control for spurious results created by sporadic trading spikes. The start dates of the individual samples we use for the analysis of the three Caribbean stock markets varies based on availability of local data required for adjusting the returns. For Trinidad and Tobago, the sample commences from January 1994; Jamaica, starts from March 2000; and Barbados begins from January 2003. All samples terminate in November 2018. Table 4.1 provides the sources and definitions of the data used in this chapter.

We follow the convention in the contagion literature and use returns net of market fundamentals in the contagion tests (see, for example, Forbes and Rigobon (2002); Fry et al. (2010); Fry-McKibbin and Hsiao (2018)). As such, we remove lead-lag effects from the real stock returns by working with the residuals in Eqs. (4.11), (4.12), (4.13), and (4.14). SBIC suggests an optimal lag length of 1 for each of these models. The LM test indicates an absence of serial correlation in the residuals of the S&P 500 and Trinidad and Tobago stock returns, but there is residual autocorrelation in the Jamaica and Barbados stock returns. The absence of serial correlation in the S&P 500 market returns, and the presence of this in the Jamaica and Barbados stock returns, are reasonable empirical results. Higher market liquidity tends to significantly lower returns autocorrelation as liquidity-driven trading benefits from more market information, which lowers serial correlation (Xue and Zhang, 2017), as is the case in the S&P 500 market. Emerging markets, which are relatively inefficient with infrequent trading, typically have high autocorrelation and are sluggish to absorb current information (Arjoon et al., 2016). While the residuals of the Trinidad and Tobago stock returns are serially uncorrelated, stock indices (as opposed to individual stocks) usually have lower autocorrelation (Campbell et al., 1993) and the empirical results of Arjoon et al. (2016) show that the majority of the disaggregated Trinidad and Tobago stock returns exhibit statistically significant first-order autocorrelation in daily data.

Table 4.1: Data definitions and sources

Series and abbreviations	Definition	Source
Real S&P 500 index	A S&P Dow Jones Indices maintained index measuring the performance of 500 large companies listed on US stock exchanges, expressed in constant 2015 USD using the composite US CPI.	Calculated using S&P 500 index data from Yahoo! Finance and CPI data from FRED.
VIX	A Chicago Board Options Exchange (CBOE) volatility index measuring near term implied volatility from price inputs of the S&P 500 index options.	Federal Reserve Economic Data (FRED).
Real Trinidad and Tobago Stock Exchange (TTSE) index	The composite stock price index is used, which is market value weighted and collectively measures the price movement of the ordinary shares for companies listed on the so-called First Tier market of the TTSE and adjusted for inflation using a composite RPI (100=2015).	Calculated using data from the Central Bank of Trinidad and Tobago.
Real Jamaica Stock Exchange (JSE) index	The JSE (Main) index is used, which measures the performance of all the ordinary shares listed on the so-called Main Market, adjusted for inflation using the composite CPI (100=2015).	Calculated using data from the Jamaica Stock Exchange and CPI data from the Central Bank of Jamaica.
Real Barbados Stock Exchange (BSE) index	The BSE local index is used, which measures all local companies listed on the so-called Regular Market, and adjusted for inflation using a composite RPI (100=2015).	Calculated using data from the Barbados Stock Exchange and RPI data from the Central Bank of Barbados.
US Shadow Short Rates (SSR)	SSR is the shortest maturity rate from the estimated US shadow yield curve. The rate can assume values below the zero lower bound to accommodate the unconventional monetary policy actions (i.e., rounds of quantitative easing) in the US (see Krippner (2016)).	Leo Krippner, Research Programme, Reserve Bank of New Zealand.
Real Oil Prices (OP)	European Brent crude oil spot prices in constant 2015 USD using the composite US CPI.	Calculated from FRED.
Trinidad and Tobago Interest Rates (TIR)	Commercial banking median basic prime lending rate in Trinidad and Tobago.	Central Bank of Trinidad and Tobago.
Jamaica Interest Rates (JIR)	Commercial banking domestic currency average weighted loan interest rate in Jamaica.	Central Bank of Jamaica.
Barbados Interest Rates (BIR)	Commercial banking upper bound prime lending rate in Barbados.	Central Bank of Barbados.

The S&P 500 returns are adjusted using the residuals of the regression function described in Eq. (4.11) times 100.

$$\Delta \ln S\&P\ 500_t = \alpha_0 + \alpha_1 \Delta \ln S\&P\ 500_{t-1} + \alpha_2 \Delta \ln OP_{t-1} + \alpha_3 SSR_{t-1} + \varepsilon_t \qquad (4.11)$$

where $\Delta \ln S\&P\ 500_t$ is the log difference of the real S&P 500 index, $\Delta \ln OP_{t-1}$ is the lag of the log difference of Brent crude oil prices, and SSR_{t-1} is the lag of the US shadow short rates. The returns of the Brent crude oil benchmark prices are used to account for developments in the oil market as there is an extensive empirical literature which seeks to explain the effects of oil price shocks on the US financial market (see, *inter alia*, Huang et al. (1996); Sadorsky (1999); Kilian and Park (2009); Kang et al. (2015a,b); Ready (2018); Thorbecke (2019)). Additionally, Forbes and Rigobon (2002) suggest using interest rates to adjust returns for the macroeconomic and policy environment. For this purpose we use the US shadow short rates which accommodates values below the zero lower bound to reflect the unconventional monetary policy actions pursued by the FED in the aftermath of the GFC.

Real Caribbean stock market returns are adjusted using the residuals of Eqs. (4.12), (4.13), and (4.14) times 100.

$$\Delta \ln TTSE_t = \alpha_0 + \alpha_1 \Delta \ln TTSE_{t-1} + \alpha_2 TIR_{t-1} + \alpha_3 \Delta \ln S\&P\ 500_{t-1} + \alpha_4 \Delta \ln OP_{t-1} + \alpha_5 SSR_{t-1} + \varepsilon_t \quad (4.12)$$

$$\Delta \ln JSE_t = \alpha_0 + \alpha_1 \Delta \ln JSE_{t-1} + \alpha_2 JIR_{t-1} + \alpha_3 \Delta \ln S\&P\ 500_{t-1} + \alpha_4 \Delta \ln OP_{t-1} + \alpha_5 SSR_{t-1} + \varepsilon_t \quad (4.13)$$

$$\Delta \ln BSE_t = \alpha_0 + \alpha_1 \Delta \ln BSE_{t-1} + \alpha_2 BIR_{t-1} + \alpha_3 \Delta \ln S\&P\ 500_{t-1} + \alpha_4 \Delta \ln OP_{t-1} + \alpha_5 SSR_{t-1} + \alpha_6 DUM_t + \varepsilon_t \quad (4.14)$$

where $\Delta \ln TTSE_t$ is the returns of the composite stock price index for the so-called First Tier Market, which is the primary market of the Trinidad and Tobago Stock Exchange

(TTSE); $\Delta \ln JSE_t$ is the returns of the Jamaica Stock Exchange (JSE) index measuring the performance of all the ordinary shares listed on the so-called Main Market; and $\Delta \ln BSE_t$ is the Barbados Stock Exchange (BSE) index for all locally listed companies. TIR_{t-1}, JIR_{t-1}, and BIR_{t-1} are the lags of the commercial bank lending rates to account for the domestic economic, policy, and financial activity in Trinidad and Tobago, Jamaica, and Barbados, respectively. In addition, DUM_t is a dummy variable included in Eq. (4.14) to account for a spike in Barbados stock returns in April 2005. Finally, lags of the S&P 500 returns, oil returns, and US shadow short rates are included in the Caribbean stock market regressions to account for international economic and financial fundamentals. The results of these regressions are presented in Table 4.3 in the appendix of Chapter 4.

4.4 Results

4.4.1 Alternative stressful S&P 500 market scenarios

Figure 4.1 shows the three types of stressful scenarios in the S&P 500 market shaded in grey vertical bars. Graph (A) highlights periods when the $\text{VIX}_t \geq 20$. Two distinct high volatility regimes in the sample are characterised by the practitioner's rule. The first corresponds to the run-up to and collapse of the internet bubble in the late 1990s and early 2000s. The second relates to the sub-prime mortgage crisis and the GFC.

Next, graph (B) illustrates the bear phases detected by the Pagan and Sossounov (2003) sorting procedure. Notable bearish market periods in the S&P 500 index coincide with the dot-com crash in the early 2000s, the GFC between late 2007 to mid-2009, the S&P downgrading of the US AAA credit rating in the summer of 2011, and the global turbulence associated with stock markets in 2015/2016.

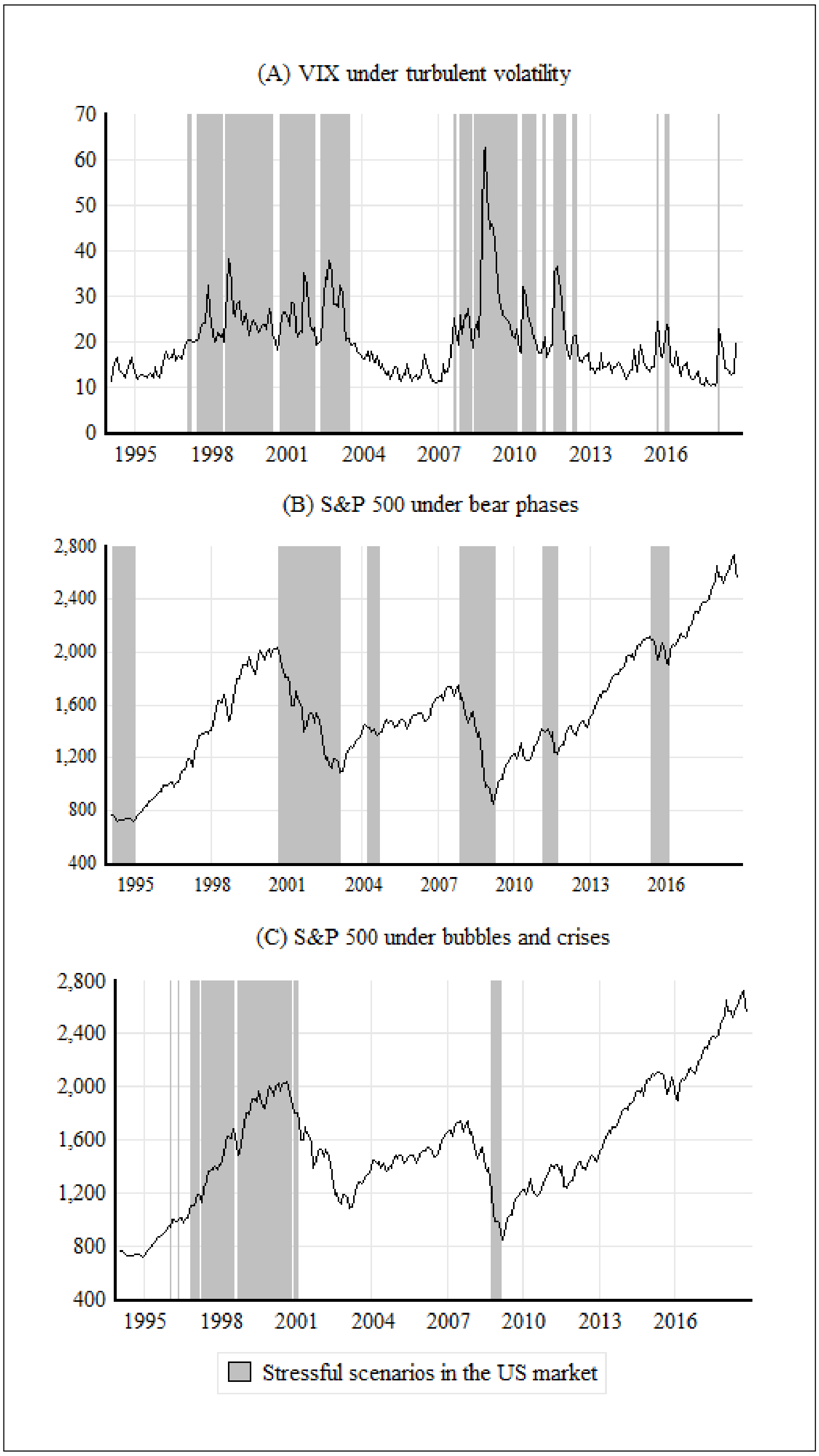

Figure 4.1: The VIX under turbulent volatility (A), the S&P 500 index under bearish market phases (B), and the S&P 500 index under the dot-com asset bubble and subprime mortgage crisis identified by the psymonitor approach (C).

Using the S&P 500 price dividend ratio, the relevant bubbles and crises periods identified in Phillips and Shi (2020) are: January 1996, May 1996, November 1996 to February 1997, April 1997 to July 1998, September 1998 to October 2000, December 2000 to January 2001, and October 2008 to February 2009. These periods are overlaid on the S&P 500 index and depicted in graph (C). Phillips and Shi (2020) argue that the psymonitor approach appropriately identifies the dot-com bubble of the late 1990s into the very early 2000s (with breaks) and the subprime mortgage crisis in late 2008 to early 2009. As Phillips and Shi (2020) analysis ends in July 2018, which is before our sample ends, we extend their application to November 2018 and find no bubbles or crises detected within this additional period. Due to sample size limitations in both Jamaica and Barbados, testing for contagion across the various co-moment channels with this approach is demonstrated with the S&P 500 and Trinidad and Tobago stock markets.

4.4.2 S&P 500 and Caribbean stock returns under alternative S&P 500 market conditions

In this section, we first examine how stock returns in both the source and recipient markets behave under the aforementioned identified stressful scenarios. We then analyse the correlations and the tests for contagion. Subsequent to this, we describe the sensitivity of the results to the Great Recession. The relevant statistics and estimates are presented in Table 4.2.

4.4.2.1 Source and recipient market performance, correlations, and contagion analysis

In the full sample for Trinidad and Tobago, the lowest monthly average returns and highest market volatility are noted under the psymonitor identified periods which capture the dot-com asset bubble and the GFC. Kurtosis values are higher for Trinidad and Tobago stock returns under stressful periods in the S&P 500 index when compared to stable periods. As high kurtosis values increases the likelihood of extreme values in the tail of an asset distribution, rising kurtosis are associated with crisis periods (Fry-McKibbin and Hsiao, 2018). In Jamaica, the highest monthly mean asset returns and volatility occur during bearish S&P 500 market conditions, while negative returns are observed when the source market is bullish. Turning to Barbados, average stock returns underperform the most during times when the VIX is turbulent, while both the highest returns and volatility are recorded in this recipient market when the VIX is tranquil[5]. Under stressful US market scenarios, kurtosis falls for Barbados asset returns while it rises for the S&P 500 returns. For all three Caribbean stock markets, there is no substantive empirical evidence provided from either t-tests for the significance of returns from zero or Welch's t-test[6] for the equality of means between stable and stressful conditions in the S&P 500 market.

Generally, the correlations between the S&P 500 and Caribbean stock returns are weak. The strongest positive correlations with the source market are noted for Trinidad and Tobago and Jamaica under bear market phases in the S&P 500 index. Correlation, co-volatility, and co-skewness contagion channels are detected from the S&P 500 market to the Trinidad and Tobago stock market, under the all alternative classifications of stable and stressful source market scenarios. In the case of Jamaica, one contagion channel which suggests that the S&P 500 market volatility affects average Jamaica stock returns is identified under both turbulent volatility and bear phases in S&P 500 market. There

[5]We note a general consistency in our results in Table 4.2 based on our two approaches, i.e. the practitioners rule and the non-hierarchical k-means cluster algorithm, for filtering the VIX into tranquil and turbulent volatility regimes.

[6]The Welch (1947) two-sample t-tests to compare the equality of means has desirable properties over the Student's t-test. In particular, the former is robust to unequal variances and unequal sample sizes relative to the latter, reducing the incidence of a Type I error (Fagerland and Sandvik, 2009).

is no evidence of contagion channels from the S&P 500 market to the Barbados stock market.

4.4.2.2 Robustness analysis

The NBER's Business Cycle Dating Committee determines that the Great Recession in the US occurred from December 2007 to June 2009[7], which captures the infamous collapse of Lehman Brothers and subprime mortgage crisis. Fry-McKibbin et al. (2014) show that, in a study of nine episodes of international financial turbulence between 1997 and 2013, the Great Recession stands out as a true global financial crisis. In the bottom half of Table 4.2, we check whether our main results are sensitive to this unparalleled event. The correlations between the source and recipient equity markets behave differently in the full and censored samples, which highlights the distorting effects of the Great Recession period and underscores the importance of using the latter sample as an important sensitivity check. Although we observe statistically significant contagion channels when the Great Recession is censored, these estimates are unaccompanied by a marked increase in correlations during stressful scenarios in the S&P 500 market. In fact, all three Caribbean stock market returns perform better during bearish conditions in the S&P 500 index, which indicates that the source and recipient markets are not well synchronised once we omit the Great Recession. Taken together, our analysis contradicts the finding of Kali and Reyes (2010) who show that financial contagion is stronger if the epicentre market has close trade ties with the recipient market, but complements those of Cozier and Watson (2019) who find little support for financial integration between the NYSE and Caribbean stock markets. Reasonable explanations for our results are that, despite strong US and Caribbean trade linkages, the stock markets of emerging

[7] See www.nber.org/cycles/recessions.html.

economies are relatively inefficient and illiquid which make them either sluggish to absorb current information (Arjoon et al., 2016) or generally insensitive. Further evidence of the illiquidity is indicated by the presence of residual autocorrelation (see the Breusch-Godfrey LM test in Table 4.3 of the chapter appendix) in the residuals of Eq. (4.13) for Jamaica and Eq. (4.14) for Barbados.

4.5 Conclusions

We contribute to the financial contagion literature by comparing alternative approaches to decompose a source market into dichotomous sub-samples of stable and stressful periods for the construction of contagion tests. Using the S&P 500 index, we consider three important ways to classify this market into discrete periods of: (1) Tranquil and turbulent volatility; (2) Bull and bear market phases; and (3) Normal periods and asset bubbles and crises. Then, with correlation, co-volatility, and co-skewness contagion tests, we compare whether the financial relationships between the S&P 500 market and Caribbean stock exchanges change during the various episodes identified in the S&P 500 market. Our application provides a new way of considering how the stock market relationship between the US and small-island emerging Caribbean economies are affected under alternative conditions in the US market. The main results show that there are both within and between country variations in the stock market relationships between the S&P 500 index and the Caribbean under different US market conditions. However, given the importance of the US trade relationships with the selected Caribbean territories, the financial market linkages are much less pronounced than might be expected outside of the events of the Great Recession in the US.

Table 4.2: S&P 500 and Caribbean stock returns summary statistics, correlations, and contagion estimates under alternative S&P 500 market conditions. The Mean is the monthly average adjusted returns (%), with standard deviation (S.D.), skewness (Skew.), and kurtosis (Kurt.) describing the second, third, and fourth moments of the adjusted return variables, respectively. For the mean adjusted returns, the $***$, $**$, and $*$ denote the conventional 1% (strong), 5% (moderate), and 10% (weak) levels of significance, respectively, of a t-test for the significance of these returns from zero, evaluated against the Student's t distribution. The stable and stressful S&P 500 months categorised using practitioner's rule on the VIX is given by the inequalities $VIX < 20$ and $VIX \geq 20$, respectively. The stable and stressful classifications of the VIX using the cluster analysis algorithm is given by the pair of inequalities that immediately proceed, where the threshold values for the inequalities are sum of the minimum of the high volatility cluster and the maximum of the low volatility cluster divided by two. Bull phase and bear phase are the S&P 500 market conditions identified by the Pagan and Sossounov (2003) rule-based algorithm. Bubble/crisis are the asset bubbles and flash crashes in the S&P 500 market identified in Phillips and Shi (2020) and normal periods are the conditions where there is relatively normal asset price behaviour. In the TEM columns, the test statistics from two sample Welch's t-tests for the equality of means are used to compare stock returns during the stable and stressful condition for the alternative approaches of characterising the S&P 500 market condition; where $***$, $**$, and $*$ are the 1%, 5%, and 10% levels of significance, respectively, evaluated against the Student's t distribution using Welch's degrees of freedom (see Welch (1947)). For the contagion tests, $***$, $**$, and $*$ denote the conventional 1% (strong), 5% (moderate), and 10% (weak) levels of significance, respectively, which corresponds to χ^2_1 critical values of 6.635, 3.841, and 2.706 of CR, CV, CS_1, and CS_2. The other abbreviations which apply are as follows: Obs. is the number of monthly observations; mkt. is market; TTSE is the Trinidad and Tobago Stock Exchange, JSE is the Jamaica Stock Exchange, and BSE is the Barbados Stock Exchange; GFC means Global Financial Crisis; C'bean means Caribbean; ρ is the Pearson correlation coefficient; $\bar{\rho}$ is the adjusted Pearson correlation coefficient; and CR, CV, CS_1, and CS_2 are the correlation, co-volatility, and the two variants of the co-skewness contagion tests, respectively.

	S&P 500 condition		Source (S&P 500) mkt.					Recipient (C'bean) mkt.					Correlation		Contagion test			
		Obs.	Mean	TEM	S.D.	Skew.	Kurt.	Mean	TEM	S.D.	Skew.	Kurt.	ρ	$\bar{\rho}$	CR	CV	CS_1	CS_2
Full sample																		
TTSE	Overall	299	0.02	-	3.48	-1.09	8.37	0.00	-	2.88	0.39	6.03	0.08	-	-	-	-	-
	VIX < 20	181	0.52***	-	2.26	0.18	3.83	0.00	-	2.56	0.48	5.25	0.04	-	-	-	-	-
	VIX ≥ 20	118	-0.74*	2.723***	4.69	-0.78	5.44	0.00	-0.003	3.33	0.31	5.83	0.10	0.05	0.010	72.352***	15.405***	15.420***
	VIX < 22.80	219	0.58***	-	2.44	0.03	3.34	0.07	-	2.69	0.58	5.03	0.04	-	-	-	-	-
	VIX > 22.80	80	-1.52***	3.533***	5.10	-0.59	5.08	-0.21	0.673	3.36	0.17	6.60	0.10	0.05	0.003	59.890***	13.794***	15.860***
	Bull phase	219	0.77***	-	2.65	0.26	5.49	0.03	-	2.94	0.76	5.54	-0.09	-	-	-	-	-
	Bear phase	80	-2.04***	5.235***	4.52	-1.05	5.91	-0.09	0.330	2.73	-0.91	7.52	0.38	0.23	12.387***	204.233***	9.781***	29.450***
	Normal	244	-0.02	-	3.22	-0.70	5.28	0.05	-	2.61	0.60	5.28	-0.01	-	-	-	-	-
	Bubble/crisis	55	0.21	-0.362	4.47	-1.72	10.92	-0.25	0.550	3.88	0.17	5.31	0.26	0.19	3.109*	113.742***	22.697***	34.422***
JSE	Overall	225	-0.24	-	3.58	-1.30	8.69	-0.02	-	4.05	0.65	5.78	0.17	-	-	-	-	-
	VIX < 20	141	0.41**	-	2.15	-0.07	3.17	0.14	-	4.21	0.62	5.78	0.17	-	-	-	-	-
	VIX ≥ 20	84	-1.33$**$	3.028***	5.00	-0.75	5.09	-0.28	0.775	3.76	0.65	5.50	0.19	0.08	0.839	0.142	2.065	3.917**
	VIX < 23.57	170	0.37**	-	2.37	-0.16	2.86	0.06	-	4.14	0.71	5.81	0.12	-	-	-	-	-
	VIX > 23.57	55	-2.10***	3.190***	5.56	-0.55	4.52	-0.25	-0.574	3.78	0.35	5.30	0.27	0.12	0.001	0.382	3.809*	2.601
	Bull phase	156	0.65***	-	2.42	0.39	6.28	-0.14	-	3.52	0.43	4.78	0.10	-	-	-	-	-
	Bear phase	69	-2.25***	4.763***	4.80	-0.91	5.23	0.25	0.514	5.06	0.69	5.15	0.28	0.14	0.167	0.063	0.422	6.035**
BSE	Overall	191	-0.04	-	3.35	-1.58	11.68	-0.03	-	2.63	-0.44	10.55	0.02	-	-	-	-	-
	VIX < 20	136	0.44**	-	2.08	-0.02	3.09	0.10	-	2.94	-0.53	9.52	0.04	-	-	-	-	-
	VIX ≥ 20	55	-1.23*	2.319**	5.17	-0.93	5.95	-0.37*	1.407	1.61	-0.20	2.82	-0.04	-0.02	0.269	1.403	0.141	0.096
	VIX < 24.12	158	0.43$**$	-	2.32	-0.36	3.31	0.07	-	2.78	-0.50	10.15	-0.02	-	-	-	-	-
	VIX > 24.12	33	-2.30$**$	2.653**	5.83	-0.65	5.40	-0.53*	-0.315	1.65	-0.43	2.61	0.05	0.02	0.120	0.978	0.736	0.000
	Bull phase	150	0.65***	-	2.42	0.42	6.44	-0.06	-	2.81	-0.48	10.17	0.04	-	-	-	-	-
	Bear phase	41	-2.56***	4.127***	4.82	-1.44	6.65	0.06	1.657	1.86	0.49	3.41	0.02	0.01	0.074	0.071	0.234	1.501
Censored sample (excludes the Great Recession)																		
TTSE	Overall	280	0.17	-	3.10	-0.68	5.21	0.07	-	2.78	0.72	5.75	-0.04	-	-	-	-	-
	VIX < 20	180	0.52***	-	2.26	0.18	3.81	-0.02	-	2.56	0.49	5.27	0.04	-	-	-	-	-
	VIX ≥ 20	100	-0.46	2.187**	4.15	-0.53	3.49	0.22	-0.638	3.14	0.87	5.62	-0.10	-0.06	1.114	0.005	1.419	0.137
	VIX < 20.80	194	0.62***	-	2.32	0.14	3.48	0.07	-	2.63	0.69	5.61	0.04	-	-	-	-	-
	VIX > 20.80	86	-0.85*	3.017***	4.23	-0.42	3.44	0.06	0.026	3.10	0.74	5.62	-0.13	-0.07	1.398	0.016	0.205	0.288
	Bull phase	216	0.71***	-	2.55	-0.06	4.58	0.05	-	2.95	0.74	5.50	-0.08	-	-	-	-	-
	Bear phase	64	-1.66***	4.477***	4.01	-0.45	3.54	0.11	-0.181	2.10	0.39	4.78	0.06	0.04	1.350	0.298	7.647***	0.936
	Normal	230	0.01	-	3.05	-1.03	5.44	0.11	-	2.57	0.63	5.59	-0.05	-	-	-	-	-
	Bubble/crisis	50	0.87*	-1.689*	3.28	0.49	3.37	-0.12	0.421	3.61	0.87	4.96	-0.01	-0.01	0.064	0.000	4.075**	0.970
JSE	Overall	206	-0.06	-	3.10	-0.98	5.25	0.11	-	3.92	0.68	6.06	0.08	-	-	-	-	-
	VIX < 20	140	0.41**	-	2.15	-0.07	3.15	0.14	-	4.23	0.62	5.74	0.17	-	-	-	-	-
	VIX ≥ 20	66	-1.06*	2.598**	4.35	-0.57	3.03	0.04	0.196	3.21	0.87	5.75	-0.03	-0.02	3.249*	3.082*	0.073	0.017
	VIX < 20.83	148	0.45**	-	2.18	-0.08	2.99	0.07	-	4.20	0.60	5.72	0.14	-	-	-	-	-
	VIX > 20.83	58	-1.37**	2.966***	4.46	-0.47	2.89	0.22	-0.274	3.13	1.19	6.01	0.02	0.01	1.568	1.576	0.304	0.018
	Bull phase	153	0.56***	-	2.25	-0.31	3.83	-0.14	-	3.51	0.45	4.88	0.07	-	-	-	-	-
	Bear phase	53	-1.86***	3.907***	4.33	-0.32	3.07	0.82	-1.306	4.90	0.69	5.71	0.17	0.09	0.031	1.449	0.099	0.082
BSE	Overall	172	0.20	-	2.67	-0.97	5.89	0.01	-	2.71	-0.47	10.42	-0.00	-	-	-	-	-
	VIX < 20	135	0.44**	-	2.09	-0.02	3.07	0.09	-	2.95	-0.52	9.48	0.03	-	-	-	-	-
	VIX ≥ 20	37	-0.70	1.651	4.06	-0.81	3.45	-0.27	0.990	1.55	-0.10	3.07	-0.20	-0.11	1.375	0.916	0.004	0.542
	VIX < 18.72	124	0.56***	-	2.00	0.10	3.07	0.06	-	2.95	-0.64	9.91	0.01	-	-	-	-	-
	VIX > 18.72	48	-0.75	2.288**	3.76	-0.76	3.64	-0.09	0.389	1.95	1.04	5.30	-0.07	-0.04	0.182	0.027	0.012	0.001
	Bull phase	147	0.56***	-	2.24	-0.31	3.91	-0.05	-	2.81	-0.48	10.26	0.03	-	-	-	-	-
	Bear phase	25	-1.94**	3.194***	3.81	-0.74	3.72	0.39	-0.975	1.96	0.59	3.17	-0.07	-0.04	0.265	0.116	0.772	0.441

Chapter 4 Appendix

Comparative analysis of rule-based algorithms for identifying bull and bear market phases

We compare the results of two popular rule-based algorithms for identifying bull and bear market phases. Figure 4.2, shows the results derived from employing feasible combinations for calibrating the Lunde and Timmermann (2004) algorithm suggested in Kole and Dijk (2017)[8] (bottom graph) and the calibration for the Pagan and Sossounov (2003) as we document earlier on in this chapter (top graph). There is an overlap between these two approaches of 219 months for bull markets and 47 months for bear markets in the real S&P 500 index for the 299 total observation months in our longest sample from 1994m1 to 2018m11. This indicates a similarity rate of 89%. The dissimilarity comes entirely from the 33 months which the Lunde and Timmermann (2004) approach classifies as bullish, where the Pagan and Sossounov (2003) method identifies as bearish. A comparison in Figure 4.2 of the results from the two approaches convey that the Lunde and Timmermann (2004) procedure is the more conservative of the two, understating historical bear market phases such as S&P downgrading of US sovereign debt in the summer of 2011 and the stock market selloff from the summer of 2015 up to the Brexit referendum result in early 2016. We, therefore, proceed with the main analysis of this chapter using the phases identified by the Pagan and Sossounov (2003) approach.

[8]In the Lunde and Timmermann (2004) semi-parametric rule-based algorithm, a shift in a market phase is determined by two threshold scalars: λ_1 and λ_2, where λ_1 (λ_2) activates a switch from a bear (bull) to a bull (bear) market. We set $\lambda_1 = 0.20$, which indicates a minimum increase of 20% in the market index since the last trough will activate a switch from a bearish regime to a bullish regime; and $\lambda_2 = 0.15$, which provides a rule that a minimum decrease of 15% since the last peak is needed to activate a switch from a bull phase to a bear phase. These feasible combination are suggested in Lunde and Timmermann (2004) and employed in Kole and Dijk (2017).

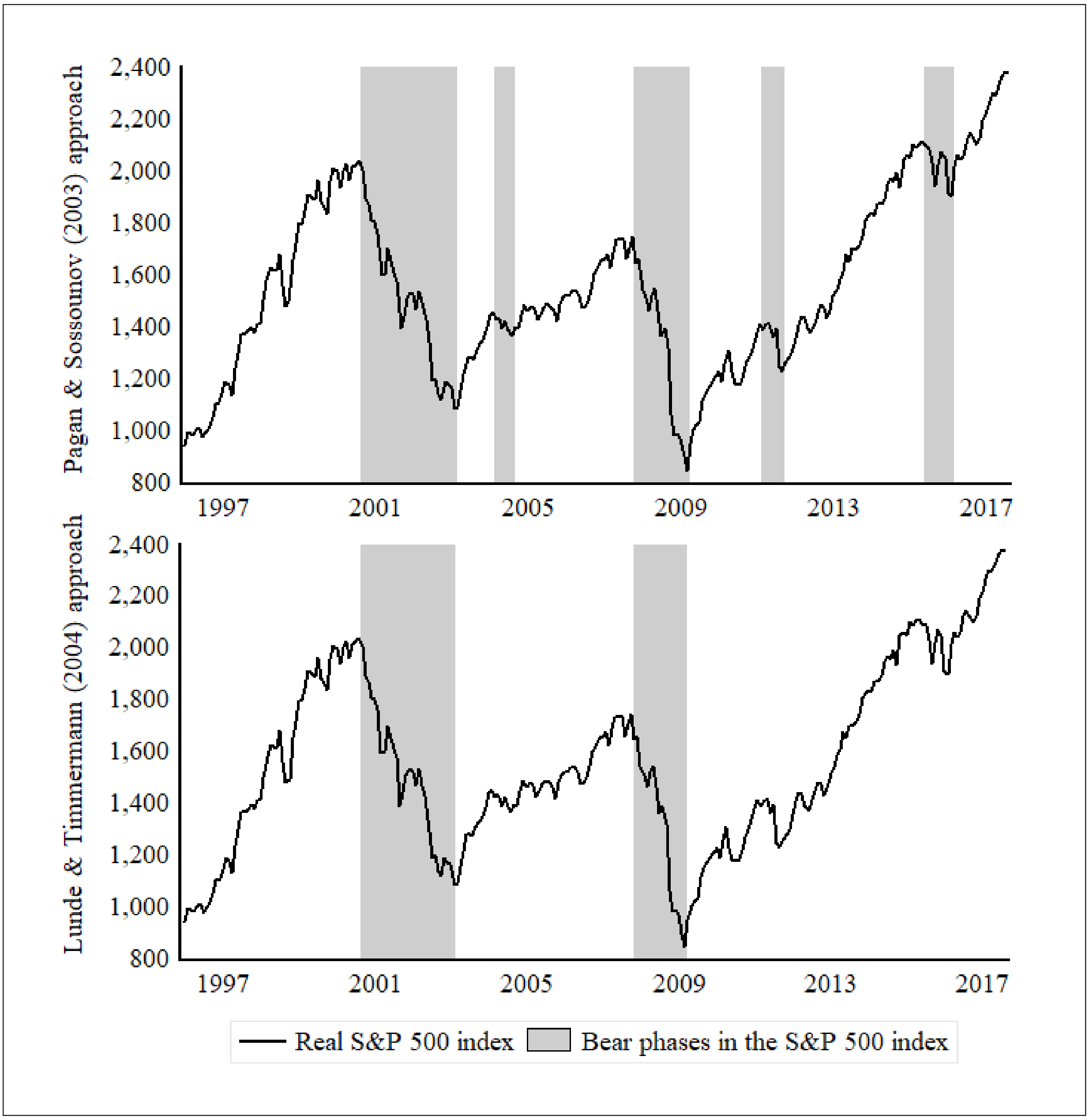

Figure 4.2: A comparison of bear phases in the real S&P 500 index using two semi-parametric rule based specifications.

Output from regression models for adjusting monthly stock market returns

Table 4.3 shows the output from the regression models for the adjusted monthly stock returns. Every row corresponds to the regression functions implied by Eqs. (4.11), (4.12), (4.13), and (4.14) for the S&P 500, Trinidad and Tobago, Jamaica, and Barbados stock markets, respectively, and the extreme right column (i.e., B-G test) provides the LM-test for autocorrelation. For each of the regressions, it can be seen that the lag dependent variables are highly statistically significant. The Oil returns coefficient is not significant in all of the models. Trinidad and Tobago is the only Caribbean stock market where the S&P 500 is significant. Here, the coefficient implies that a 1% increase in the S&P 500 returns leads to a 0.10% increase in Trinidad and Tobago's stock returns. In the Barbados stock returns model, the US shadow short rates is significant but the impact is negligible and the dummy variable associated with spike in April 2005 is statistically significant. The results of the autocorrelation tests are discussed within the data section of the chapter.

Table 4.3: Output from regression models for adjusting monthly returns. Each row corresponds to the regression functions implied by Eqs. (4.11), (4.12), (4.13), and (4.14) for the S&P 500, Trinidad and Tobago, Jamaica, and Barbados stock markets, respectively. Regression coefficients are presented beneath each term. The B-G test in the last column provides the F-statistic associated with the Breusch-Godfrey LM test for serial correlation for up to two lags, evaluated against the F-distribution. $***$, $**$, and $*$ associated with the coefficients stand for the 1% (strong), 5% (moderate), and 10% (weak) conventional levels of statistical significance, respectively, evaluated against the Student's t-distribution. For S&P 500 market and TTSE regressions, the sample commences from January 1994; JSE starts in March 2000; and Barbados begins in January 2003. All samples end in November 2018.

Dependent variable	Regression coefficients							B-G test
$\Delta \ln S\&P500_t$	α_0	$\alpha_1 \Delta \ln S\&P500_{t-1}$	$\alpha_2 \Delta \ln OP_{t-1}$	$\alpha_3 SSR_{t-1}$				
	0.004	0.230***	-0.002	0.000				1.685
$\Delta \ln TTSE_t$	α_0	$\alpha_1 \Delta \ln TTSE_{t-1}$	$\alpha_2 TIR_{t-1}$	$\alpha_3 \Delta \ln S\&P500_{t-1}$	$\alpha_4 \Delta \ln OP_{t-1}$	$\alpha_5 SSR_{t-1}$		
	-0.008	0.426***	0.001	0.095**	0.021	0.000		1.797
$\Delta \ln JSE_t$	α_0	$\alpha_1 \Delta \ln JSE_{t-1}$	$\alpha_2 JIR_{t-1}$	$\alpha_3 \Delta \ln S\&P500_{t-1}$	$\alpha_4 \Delta \ln OP_{t-1}$	$\alpha_5 SSR_{t-1}$		
	0.014	0.401***	-0.001	0.122	-0.020	0.001		3.156**
$\Delta \ln BSE_t$	α_0	$\alpha_1 \Delta \ln BSE_{t-1}$	$\alpha_2 BIR_{t-1}$	$\alpha_3 \Delta \ln S\&P500_{t-1}$	$\alpha_4 \Delta \ln OP_{t-1}$	$\alpha_5 SSR_{t-1}$	$\alpha_6 DUM_t$	
	0.062**	0.162***	-0.007**	0.004	-0.019	0.002**	-0.451***	7.461***

Chapter 5

Conclusion

5.1 Summary of main findings

A central theme of this thesis revolves around testing how the relationships between pertinent foreign markets and key financial variables in the small open petroleum economy of Trinidad and Tobago evolve under alternative conditions in external markets. In Chapter 2, the research question concerns whether the relationships between the oil market and key financial variables in Trinidad and Tobago strengthen during crises in the international crude oil market, and whether higher co-moment contagion channels exist. To address these questions the concept of energy contagion is proposed, i.e. a marked increase in source and recipient market correlations under crisis periods in energy markets. Further, energy contagion tests are constructed by augmenting the calm and crisis sample conditions of financial contagion tests based on high and low volatility periods, and bear and bull market phases in the crude oil market. Correlations between oil and financial returns are then compared using such tests. While evidence of contagion is detected and higher co-moment tests reveal additional channels of contagion, such findings are limited to the Global Financial Crisis (GFC).

Chapter 3 sets out to answer how the correlations between oil, exchange rates, and the stock market are affected during normal periods versus extreme structural oil market shocks. To consider this, a new rule-based specification is applied to structural oil market shocks to filter events in the international crude oil market into discrete calm and extreme periods for constructing contagion tests. The findings for Trinidad and Tobago show: (1) A relatively moderate and inverse interdependence in the oil-real effective exchange rate and real effective exchange rate-stock market relationships. (2) Evidence of oil market contagion effects from the crude oil market to financial returns in Trinidad and Tobago during the recent crude oil market crashes of the 2008 Global Financial Crisis (GFC) and 2014/2015. (3) Apart from the GFC the differences in the oil-stock returns correlation, regardless of the source of the oil market shock, are weak.

In Chapter 4, the question being asked is about how the relationships between the S&P 500 and three of the more advanced stock markets of the Caribbean region change during different conditions in the S&P 500 market. Three approaches for classifying the source market into stable and stressful conditions are utilised; which are based on low and high volatility regimes, bull and bear market phases, as well as calm periods and asset bubbles and crises. Altogether, the results suggest that the financial linkages between the US equity market index and the selected Caribbean stock exchanges are much less pronounced than might be expected outside the events of the Great Recession.

5.2 Synthesis and future research directions

The three main relationships this thesis considers include the oil and exchange rate correlation, the oil and stock market correlation, and the S&P 500 and Trinidad and Tobago stock market correlation. Each of these market linkages convey information about how this economy is connected to foreign markets. For instance, the oil-exchange rate interdependence is important to understand how oil markets might affect the trade competitiveness of an oil-exporter; while the oil-stock market relationship is a high data frequency proxy for the oil-macroeconomy connection; and the S&P 500 and Trinidad and Tobago stock market association can be used as a measure of financial integration between these two markets.

Furthermore, the thesis demonstrates alternative measures for filtering external market variables into stable and unstable conditions. For instance, in Chapter 2, oil price volatility is clustered into turbulent and tranquil states, and oil prices into bear and bull phases. In Chapter 3, structural oil market shocks are decomposed into extreme and typical periods using a novel rule-based specification, which is constructed from veteran non-linear oil price transformations, and the notion of bull and bear oil market phases is also revisited. On the other hand, Chapter 4 considers high and low volatility regimes, bear and bull market phases, as well as typical periods and bubbles and crises all in the S&P 500 market.

To achieve the overall aim of the thesis, contagion tests are designed to compare the many important market correlations under the aforementioned external market conditions to determine whether relationships change during such alternative scenarios. Together, these methodological innovations are expected to be the main research impact of the thesis. In particular, the results from the oil-exchange rate relationship show a relatively moderate inverse interdependence which implies exchange rate appreciations when oil prices fall and vice-versa. Such a result contradicts the positive wealth effects and Dutch disease hypotheses for oil-exporters, and is more expected for oil-importers.

Another general result of this PhD thesis is an insensitivity of the Trinidad and Tobago stock market to external markets, such as the international crude oil and the S&P 500 markets. This is despite the importance of oil and the US economy to the real sector of this small open economy. The contributions of this thesis to the field of contagion analysis are relevant for both academics and practitioners, such as policy makers and investors, interested in examining the vulnerability of financial markets in economies exposed to developments in the international crude oil market and the US stock market.

At the very start of this thesis, the direct transmission channel of external market shocks to the financial markets of a small open energy economy is defined as the scope of the research (see transmission mechanism A of Figure 1.2). Various tests on these direct linkages to key financial variables for Trinidad and Tobago yield a limited influence from foreign markets outside of the GFC event. Hence, the indirect channels characterising the domino effects from external markets to the real sector of Caribbean economies to their financial markets remain uncharted research avenues (see transmission channel $B \longrightarrow C$ of Figure 1.2). Unifying a framework to incorporate such knock-on effects holds promising research potential in the areas of early warning systems for financial instability and macroprudential surveillance in small open economies.

References

Aastveit, K. A., Bjørnland, H. C., Thorsrud, L. A., 2016. The world is not enough! Small open economies and regional dependence. The Scandinavian Journal of Economics 118 (1), 168–195.

Abdullah, M. B., 1990. On a robust correlation coefficient. The Statistician, 455–460.

Abeysinghe, T., 2001. Estimation of direct and indirect impact of oil price on growth. Economics Letters 73 (2), 147–153.

Abeysinghe, T., Yeok, T. L., 1998. Exchange rate appreciation and export competitiveness. The case of Singapore. Applied Economics 30 (1), 51–55.

Akram, Q. F., 2004. Oil prices and exchange rates: Norwegian evidence. The Econometrics Journal 7 (2), 476–504.

Akram, Q. F., 2009. Commodity prices, interest rates and the dollar. Energy Economics 31 (6), 838–851.

Al Janabi, M. A., Hatemi-J, A., Irandoust, M., 2010. An empirical investigation of the informational efficiency of the GCC equity markets: Evidence from bootstrap simulation. International Review of Financial Analysis 19 (1), 47–54.

Algieri, B., Leccadito, A., 2017. Assessing contagion risk from energy and non-energy commodity markets. Energy Economics 62, 312–322.

Aloui, R., Aïssa, M. S. B., 2016. Relationship between oil, stock prices and exchange rates: A vine copula based GARCH method. The North American Journal of Economics and Finance 37, 458–471.

Aloui, R., Aïssa, M. S. B., Nguyen, D. K., 2011. Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? Journal of Banking & Finance 35 (1), 130–141.

Aloui, R., Hammoudeh, S., Nguyen, D. K., 2013. A time-varying copula approach to oil and stock market dependence: The case of transition economies. Energy Economics 39, 208–221.

Antonakakis, N., Chatziantoniou, I., Filis, G., 2017. Oil shocks and stock markets: Dynamic connectedness under the prism of recent geopolitical and economic unrest. International Review of Financial Analysis 50, 1–26.

Arjoon, V., Bougheas, S., Milner, C., 2016. Lead-lag relationships in an embryonic stock market: Exploring the role of institutional ownership and liquidity. Research in International Business and Finance 38, 262–276.

Atems, B., Kapper, D., Lam, E., 2015. Do exchange rates respond asymmetrically to shocks in the crude oil market? Energy Economics 49, 227–238.

Auty, R., Warhurst, A., 1993. Sustainable development in mineral exporting economies. Resources Policy 19 (1), 14 – 29.

Auty, R. M., 2017. Natural resources and small island economies: Mauritius and Trinidad and Tobago. The Journal of Development Studies 53 (2), 264–277.

Baruník, J., Kocenda, E., 2019. Volatility spillovers on oil and forex markets. Routledge Handbook of Energy Economics, 405.

Basher, S. A., Haug, A. A., Sadorsky, P., 2012. Oil prices, exchange rates and emerging stock markets. Energy Economics 34 (1), 227–240.

Basher, S. A., Haug, A. A., Sadorsky, P., 2016. The impact of oil shocks on exchange rates: A Markov-switching approach. Energy Economics 54, 11–23.

Basher, S. A., Haug, A. A., Sadorsky, P., 2018. The impact of oil-market shocks on stock returns in major oil-exporting countries. Journal of International Money and Finance 86, 264 – 280.

Bastianin, A., Conti, F., Manera, M., 2016. The impacts of oil price shocks on stock market volatility: Evidence from the G7 countries. Energy Policy 98, 160–169.

Baumeister, C., Kilian, L., 2016a. Forty years of oil price fluctuations: Why the price of oil may still surprise us. Journal of Economic Perspectives 30 (1), 139–60.

Baumeister, C., Kilian, L., 2016b. Understanding the decline in the price of oil since June 2014. Journal of the Association of Environmental and Resource Economists 3 (1), 131–158.

Baumeister, C., Peersman, G., 2013. The role of time-varying price elasticities in accounting for volatility changes in the crude oil market. Journal of Applied Econometrics 28 (7), 1087–1109.

Beckmann, J., Czudaj, R. L., Arora, V., 2020. The relationship between oil prices and exchange rates: Revisiting theory and evidence. Energy Economics, Forthcoming.

Bekaert, G., Harvey, C. R., 2003. Market integration and contagion. Tech. rep., National Bureau of Economic Research.

Bjørnland, H. C., 2004. The role of the exchange rate as a shock absorber in a small open economy. Open Economies Review 15 (1), 23–43.

Bjørnland, H. C., 2009. Oil price shocks and stock market booms in an oil exporting country. Scottish Journal of Political Economy 56 (2), 232–254.

Bjørnland, H. C., Thorsrud, L. A., 2016. Boom or gloom? Examining the Dutch disease in two-speed economies. The Economic Journal 126 (598), 2219–2256.

Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and investment dynamics. The Review of Economic Studies 74 (2), 391–415.

Boldanov, R., Degiannakis, S., Filis, G., 2016. Time-varying correlation between oil and stock market volatilities: Evidence from oil-importing and oil-exporting countries. International Review of Financial Analysis 48, 209–220.

Bouri, E., 2015. Oil volatility shocks and the stock markets of oil-importing MENA economies: A tale from the financial crisis. Energy Economics 51, 590–598.

Boyer, B. H., Gibson, M. S., Loretan, M., 1999. Pitfalls in tests for changes in correlations. Federal Reserve Board. Tech. rep., IFS Discussion Paper.

Briguglio, L., 1995. Small island developing states and their economic vulnerabilities. World Development 23 (9), 1615 – 1632.

Broadstock, D. C., Filis, G., 2014. Oil price shocks and stock market returns: New evidence from the United States and China. Journal of International Financial Markets, Institutions and Money 33, 417–433.

Brooks, C., 2008. Introductory econometrics for finance. Cambridge University Press.

Campbell, J. Y., Grossman, S. J., Wang, J., 1993. Trading volume and serial correlation in stock returns. The Quarterly Journal of Economics 108 (4), 905–939.

Caporale, G. M., Hunter, J., Ali, F. M., 2014. On the linkages between stock prices and exchange rates: Evidence from the banking crisis of 2007–2010. International Review of Financial Analysis 33, 87–103.

CBTT, 2009. Economic Bulletin. Tech. Rep. July, Central Bank of Trinidad and Tobago (CBTT).

CBTT, 2015. Annual Economic Survey 2015. Tech. rep., Central Bank of Trinidad and Tobago (CBTT).

CBTT, 2015. Economic Bulletin. Tech. Rep. July, Central Bank of Trinidad and Tobago (CBTT).

CBTT, 2018. Annual Economic Survey 2017. Tech. rep., Central Bank of Trinidad and Tobago (CBTT).

CBTT FSR, 2019. Financial Stability Report 2018. Tech. rep., Central Bank of Trinidad and Tobago (CBTT).

CBTT MPR, 2019. Monetary Policy Report. Tech. Rep. November, Vol. XXI No. 2, Central Bank of Trinidad and Tobago (CBTT).

Chang, C.-Y., Lai, J.-Y., Chuang, I.-Y., 2010. Futures hedging effectiveness under the segmentation of bear/bull energy markets. Energy Economics 32 (2), 442–449.

Cheema, M. A., Scrimgeour, F., 2019. Oil prices and stock market anomalies. Energy Economics 83, 578–587.

Chen, S.-S., 2010. Do higher oil prices push the stock market into bear territory? Energy Economics 32 (2), 490–495.

Chen, W., Hamori, S., Kinkyo, T., 2014. Macroeconomic impacts of oil prices and underlying financial shocks. Journal of International Financial Markets, Institutions and Money 29, 1 – 12.

Chiang, T. C., Jeon, B. N., Li, H., 2007. Dynamic correlation analysis of financial contagion: Evidence from Asian markets. Journal of International Money and Finance 26 (7), 1206–1228.

Chkili, W., Nguyen, D. K., 2014. Exchange rate movements and stock market returns in a regime-switching environment: Evidence for BRICS countries. Research in International Business and Finance 31, 46–56.

Claessens, S., Kose, M. A., Terrones, M. E., 2012. How do business and financial cycles interact? Journal of International Economics 87 (1), 178–190.

Conover, W., 1999. Practical nonparametric statistics. Wiley Series in Probability and Statistics: Applied Probability and Statistics. Wiley.

Corden, W. M., 1984. Booming sector and Dutch disease economics: Survey and consolidation. Oxford Economic Papers 36 (3), 359–380.

Corden, W. M., 2012. Dutch disease in Australia: Policy options for a three-speed economy. Australian Economic Review 45 (3), 290–304.

Cozier, J. G., Watson, P. K., 2018. The evolution of stock markets in the CARICOM region (1969–2010): Lessons for other small emerging economies. Handbook of Small States: Economic, Social and Environmental Issues.

Cozier, J. G., Watson, P. K., 2019. Co-movement in stock prices in emerging economies: The case of the CARICOM region. International Economic Journal 33 (1), 111–127.

Creti, A., Joëts, M., Mignon, V., 2013. On the links between stock and commodity markets' volatility. Energy Economics 37, 16–28.

Degiannakis, S., Filis, G., Arora, V., 2018a. Oil prices and stock markets: A review of the theory and empirical evidence. Energy Journal 39 (5).

Degiannakis, S., Filis, G., Kizys, R., 2014. The effects of oil price shocks on stock market volatility: Evidence from European data. The Energy Journal, 35–56.

Degiannakis, S., Filis, G., Panagiotakopoulou, S., 2018b. Oil price shocks and uncertainty: How stable is their relationship over time? Economic Modelling 72, 42–53.

Diaz, E. M., Molero, J. C., de Gracia, F. P., 2016. Oil price volatility and stock returns in the G7 economies. Energy Economics 54, 417–430.

Diebold, F. X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal 119 (534), 158–171.

Diebold, F. X., Yilmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics 182 (1), 119–134.

Ding, Z., Liu, Z., Zhang, Y., Long, R., 2017. The contagion effect of international crude oil price fluctuations on Chinese stock market investor sentiment. Applied Energy 187, 27–36.

Downey, M., 2009. Oil 101. Wooden Table Press.

Drazen, A., 2000. Political contagion in currency crises. In: Currency crises. University of Chicago Press, pp. 47–67.

Edwards, S., Yeyati, E. L., 2005. Flexible exchange rates as shock absorbers. European Economic Review 49 (8), 2079–2105.

Edwards, T., Preston, H., 2017. A practitioner's guide to reading VIX®. S&P Global: S&P Dow Jones Indices (Education, Strategy 201), 1–10.

Elder, J., Serletis, A., 2011. Volatility in oil prices and manufacturing activity: An investigation of real options. Macroeconomic Dynamics 15 (S3), 379–395.

Elwood, S. K., 2001. Oil-price shocks: Beyond standard aggregate demand/aggregate supply analysis. The Journal of Economic Education 32 (4), 381–386.

Engle, R., 2002. Dynamic conditional correlation. Journal of Business & Economic Statistics 20 (3), 339–350.

Engle, R. F., Ng, V. K., 1993. Measuring and testing the impact of news on volatility. The Journal of Finance 48 (5), 1749–1778.

Ewing, B. T., Malik, F., 2016. Volatility spillovers between oil prices and the stock market under structural breaks. Global Finance Journal 29, 12–23.

Fagerland, M. W., Sandvik, L., 2009. Performance of five two-sample location tests for skewed distributions with unequal variances. Contemporary Clinical Trials 30 (5), 490–496.

Ferraro, D., Rogoff, K., Rossi, B., 2015. Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates. Journal of International Money and Finance 54, 116–141.

Figuerola-Ferretti, I., McCrorie, J. R., Paraskevopoulos, I., 2020. Mild explosivity in recent crude oil prices. Energy Economics, forthcoming.

Filis, G., 2010. Macro economy, stock market and oil prices: Do meaningful relationships exist among their cyclical fluctuations? Energy Economics 32 (4), 877–886.

Filis, G., Chatziantoniou, I., 2014. Financial and monetary policy responses to oil price shocks: Evidence from oil-importing and oil-exporting countries. Review of Quantitative Finance and Accounting 42 (4), 709–729.

Filis, G., Degiannakis, S., Floros, C., 2011. Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. International Review of Financial Analysis 20 (3), 152–164.

Flavin, T. J., Morley, C. E., Panopoulou, E., 2014. Identifying safe haven assets for equity investors through an analysis of the stability of shock transmission. Journal of International Financial Markets, Institutions and Money 33, 137–154.

Forbes, K., Rigobon, R., 2000. Contagion in Latin America: Definitions, measurement, and policy implications. Tech. rep., National Bureau of Economic Research.

Forbes, K. J., Rigobon, R., 2002. No contagion, only interdependence: Measuring stock market comovements. The Journal of Finance 57 (5), 2223–2261.

Frankel, J., Saravelos, G., 2012. Can leading indicators assess country vulnerability? evidence from the 2008–09 global financial crisis. Journal of International Economics 87 (2), 216–231.

Fry, R., Martin, V. L., Tang, C., 2010. A new class of tests of contagion with applications. Journal of Business & Economic Statistics 28 (3), 423–437.

Fry-McKibbin, R., Hsiao, C. Y.-L., 2018. Extremal dependence tests for contagion. Econometric Reviews 37 (6), 626–649.

Fry-McKibbin, R., Hsiao, C. Y.-L., Martin, V. L., 2019. Joint tests of contagion with applications. Quantitative Finance 19 (3), 473–490.

Fry-McKibbin, R., Hsiao, C. Y.-L., Tang, C., 2014. Contagion and global financial crises: Lessons from nine crisis episodes. Open Economies Review 25 (3), 521–570.

Gelb, A. H., 1988. Oil windfalls: Blessing or curse? Oxford University Press.

Gelos, R. G., Sahay, R., 2001. Financial market spillovers in transition economies. Economics of Transition 9 (1), 53–86.

Ghalanos, A., 2019. rmgarch: Multivariate GARCH models. R package version 1.3-6.

Ghosh, S., 2011. Examining crude oil price–exchange rate nexus for India during the period of extreme oil price volatility. Applied Energy 88 (5), 1886–1889.

Gil-Alana, L. A., Gupta, R., Olubusoye, O. E., Yaya, O. S., 2016. Time series analysis of persistence in crude oil price volatility across bull and bear regimes. Energy 109, 29–37.

Gogineni, S., 2010. Oil and the stock market: An industry level analysis. Financial Review 45 (4), 995–1010.

Gormus, N. A., Atinc, G., 2016. Volatile oil and the US economy. Economic Analysis and Policy 50, 62–73.

Güntner, J. H. F., 2014. How do international stock markets respond to oil demand and supply shocks? Macroeconomic Dynamics 18 (8), 1657–1682.

Guo, F., Chen, C. R., Huang, Y. S., 2011. Markets contagion during financial crisis: A regime-switching approach. International Review of Economics & Finance 20 (1), 95–109.

Hamilton, J. D., 1996. This is what happened to the oil price-macroeconomy relationship. Journal of Monetary Economics 38 (2), 215 – 220.

Hamilton, J. D., 2003. What is an oil shock? Journal of Econometrics 113 (2), 363–398.

Hamilton, J. D., 2009a. Causes and consequences of the oil shock of 2007–08. Brookings Papers on Economic Activity, 215–283.

Hamilton, J. D., 2009b. Understanding crude oil prices. The Energy Journal 30 (2), 179–207.

Hamilton, J. D., 2018. Measuring global economic activity. manuscript, University of California at San Diego.

Hanna, A. J., 2018. A top-down approach to identifying bull and bear market states. International Review of Financial Analysis 55, 93–110.

Harding, D., Pagan, A., 2003. A comparison of two business cycle dating methods. Journal of Economic Dynamics and Control 27 (9), 1681–1690.

Harrison, B., Moore, W., 2010. Stock market co-movement in the Caribbean. Economic Issues 15 (1), 1–15.

Hemche, O., Jawadi, F., Maliki, S. B., Cheffou, A. I., 2016. On the study of contagion in the context of the subprime crisis: A dynamic conditional correlation–multivariate GARCH approach. Economic Modelling 52, 292–299.

Henry, M., 2007. Formulating trade policy in a small hydrocarbon-dependent economy: The case of Trinidad and Tobago. World Economy 30 (8), 1222–1252.

Homm, U., Breitung, J., 2012. Testing for speculative bubbles in stock markets: A comparison of alternative methods. Journal of Financial Econometrics 10 (1), 198–231.

Hon, M. T., Strauss, J. K., Yong, S.-K., 2007. Deconstructing the Nasdaq bubble: A look at contagion across international stock markets. Journal of International Financial Markets, Institutions and Money 17 (3), 213–230.

Hotelling, H., 1953. New light on the correlation coefficient and its transforms. Journal of the Royal Statistical Society. Series B (Methodological) 15 (2), 193–232.

Hou, K., Mountain, D. C., Wu, T., 2016. Oil price shocks and their transmission mechanism in an oil-exporting economy: A VAR analysis informed by a DSGE model. Journal of International Money and Finance 68, 21 – 49.

Huang, R. D., Masulis, R. W., Stoll, H. R., 1996. Energy shocks and financial markets. Journal of Futures Markets: Futures, Options, and Other Derivative Products 16 (1), 1–27.

Inci, A. C., Li, H.-C., McCarthy, J., 2011. Financial contagion: A local correlation analysis. Research in International Business and Finance 25 (1), 11–25.

Ji, Q., Liu, B.-Y., Zhao, W.-L., Fan, Y., 2018. Modelling dynamic dependence and risk spillover between all oil price shocks and stock market returns in the BRICS. International Review of Financial Analysis.

Jiménez-Rodríguez, R., 2015. Oil price shocks and stock markets: Testing for non-linearity. Empirical Economics 48 (3), 1079–1102.

Jones, C. M., Kaul, G., 1996. Oil and the stock markets. The Journal of Finance 51 (2), 463–491.

Kali, R., Reyes, J., 2010. Financial contagion on the international trade network. Economic Inquiry 48 (4), 1072–1101.

Kang, W., Ratti, R. A., 2013. Oil shocks, policy uncertainty and stock market return. Journal of International Financial Markets, Institutions and Money 26, 305–318.

Kang, W., Ratti, R. A., Yoon, K. H., 2015a. The impact of oil price shocks on the stock market return and volatility relationship. Journal of International Financial Markets, Institutions and Money 34, 41–54.

Kang, W., Ratti, R. A., Yoon, K. H., 2015b. Time-varying effect of oil market shocks on the stock market. Journal of Banking & Finance 61, S150–S163.

Kayalar, D. E., Küçüközmen, C. C., Selcuk-Kestel, A. S., 2017. The impact of crude oil prices on financial market indicators: Copula approach. Energy Economics 61, 162–173.

Kenourgios, D., 2014. On financial contagion and implied market volatility. International Review of Financial Analysis 34, 21–30.

Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review 99 (3), 1053–69.

Kilian, L., 2016. The impact of the shale oil revolution on US oil and gasoline prices. Review of Environmental Economics and Policy 10 (2), 185–205.

Kilian, L., 2019. Measuring global real economic activity: Do recent critiques hold up to scrutiny? Economics Letters 178, 106–110.

Kilian, L., Park, C., 2009. The impact of oil price shocks on the US stock market. International Economic Review 50 (4), 1267–1287.

Kilian, L., Vigfusson, R. J., 2011a. Are the responses of the US economy asymmetric in energy price increases and decreases? Quantitative Economics 2 (3), 419–453.

Kilian, L., Vigfusson, R. J., 2011b. Nonlinearities in the oil price-output relationship. Macroeconomic Dynamics 15 (S3), 337–363.

Kilian, L., Zhou, X., 2018. Oil prices, exchange rates and interest rates. Unpublished.

Kim, M. S., 2018. Impacts of supply and demand factors on declining oil prices. Energy 155, 1059–1065.

Kojo, N. C., 2015. Demystifying Dutch disease. Journal of International Commerce, Economics and Policy 6 (02), 1–23.

Kole, E., Dijk, D., 2017. How to identify and forecast bull and bear markets? Journal of Applied Econometrics 32 (1), 120–139.

Korhonen, I., Juurikkala, T., 2009. Equilibrium exchange rates in oil-exporting countries. Journal of Economics and Finance 33 (1), 71–79.

Krippner, L., 2016. Documentation for measures of monetary policy. Reserve Bank of New Zealand. Wellington, New Zealand.

Kritzman, M., Li, Y., Page, S., Rigobon, R., 2011. Principal components as a measure of systemic risk. The Journal of Portfolio Management 37 (4), 112–126.

Kumar, S., 2019. Asymmetric impact of oil prices on exchange rate and stock prices. The Quarterly Review of Economics and Finance 72, 41–51.

Laeven, M. L., 2014. The development of local capital markets: Rationale and challenges. No. 14/234. International Monetary Fund.

Lee, K., Kang, W., Ratti, R. A., 2011. Oil price shocks, firm uncertainty, and investment. Macroeconomic Dynamics 15 (S3), 416–436.

Lee, K., Ni, S., Ratti, R. A., 1995. Oil shocks and the macroeconomy: The role of price variability. The Energy Journal, 39–56.

Li, F., Zhu, H., 2014. Testing for financial contagion based on a nonparametric measure of the cross-market correlation. Review of Financial Economics 23 (3), 141–147.

Lin, C.-H., 2012. The comovement between exchange rates and stock prices in the Asian emerging markets. International Review of Economics & Finance 22 (1), 161–172.

Liu, Z., Tseng, H.-K., Wu, J. S., Ding, Z., 2020. Implied volatility relationships between crude oil and the US stock markets: Dynamic correlation and spillover effects. Resources Policy 66, 101637.

Lizardo, R. A., Mollick, A. V., 2010. Oil price fluctuations and US dollar exchange rates. Energy Economics 32 (2), 399–408.

Lorde, T., Francis, B., Greene, A., 2009. Testing for long-run comovement, common features and efficiency in emerging stock markets: Evidence from the Caribbean. Economic Issues 14 (2).

Loretan, M., English, W. B., 2000. Evaluating correlation breakdowns during periods of market volatility. Board of Governors of the Federal Reserve System International Finance Working Paper (658).

Lunde, A., Timmermann, A., 2004. Duration dependence in stock prices: An analysis of bull and bear markets. Journal of Business & Economic Statistics 22 (3), 253–273.

Manescu, C., Van Robays, I., 2016. Forecasting the Brent oil price: Addressing time-variation in forecast performance. Tech. rep., CESifo Group Munich.

Melvin, M., 1985. The choice of an exchange rate system and macroeconomic stability. Journal of Money, Credit and Banking 17 (4), 467–478.

Miller, J. I., Ratti, R. A., 2009. Crude oil and stock markets: Stability, instability, and bubbles. Energy Economics 31 (4), 559–568.

Min, H.-G., Hwang, Y.-S., 2012. Dynamic correlation analysis of US financial crisis and contagion: Evidence from four OECD countries. Applied Financial Economics 22 (24), 2063–2074.

Mironov, V. V., Petronevich, A. V., 2015. Discovering the signs of Dutch disease in Russia. Resources Policy 46, 97–112.

Mohaddes, K., Pesaran, M. H., 2013. One hundred years of oil income and the Iranian economy: A curse or a blessing? In: Iran and the Global Economy. Routledge, pp. 28–61.

Mohanty, S. K., Nandha, M., Turkistani, A. Q., Alaitani, M. Y., 2011. Oil price movements and stock market returns: Evidence from Gulf Cooperation Council (GCC) countries. Global Finance Journal 22 (1), 42–55.

Mork, K. A., 1989. Oil and the macroeconomy when prices go up and down: An extension of Hamilton's results. Journal of Political Economy 97 (3), 740–744.

Ntantamis, C., Zhou, J., 2015. Bull and bear markets in commodity prices and commodity stocks: Is there a relation? Resources Policy 43, 61–81.

Obstfeld, M., Rogoff, K., 1995. The mirage of fixed exchange rates. Journal of Economic Perspectives 9 (4), 73–96.

Pagan, A. R., Sossounov, K. A., 2003. A simple framework for analysing bull and bear markets. Journal of Applied Econometrics 18 (1), 23–46.

Papapetrou, E., 2001. Oil price shocks, stock market, economic activity and employment in Greece. Energy Economics 23 (5), 511–532.

Paramati, S. R., Gupta, R., Roca, E., 2015. Stock market interdependence between Australia and its trading partners: Does trade intensity matter? Applied Economics 47 (49), 5303–5319.

Park, J., Ratti, R. A., 2008. Oil price shocks and stock markets in the US and 13 European countries. Energy Economics 30 (5), 2587–2608.

Parkinson, M., 1980. The extreme value method for estimating the variance of the rate of return. Journal of Business, 61–65.

Pericoli, M., Sbracia, M., 2003. A primer on financial contagion. Journal of Economic Surveys 17 (4), 571–608.

Phillips, P. C., Shi, S., 2020. Real time monitoring of asset markets: Bubbles and crises. In: Handbook of Statistics. Vol. 42. Elsevier, pp. 61–80.

Phillips, P. C., Shi, S., Yu, J., 2015a. Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. International Economic Review 56 (4), 1043–1078.

Phillips, P. C., Shi, S., Yu, J., 2015b. Testing for multiple bubbles: Limit theory of real-time detectors. International Economic Review 56 (4), 1079–1134.

Pollard, H., 1985. The erosion of agriculture in an oil economy: The case of export crop production in Trinidad. World Development 13 (7), 819 – 835.

Poon, S.-H., Granger, C. W., 2003. Forecasting volatility in financial markets: A review. Journal of Economic Literature 41 (2), 478–539.

Ram, J., 2005. Rates of return: Can natural resources sustain wealth? Edited by Dennis Pantin. Ian Randle: Jamaica, Ch. in The Caribbean Economy: A Reader.

Ready, R. C., 2018. Oil prices and the stock market. Review of Finance 22 (1), 155–176.

Reboredo, J. C., 2011. How do crude oil prices co-move?: A copula approach. Energy Economics 33 (5), 948–955.

Reboredo, J. C., 2012. Modelling oil price and exchange rate co-movements. Journal of Policy Modeling 34 (3), 419–440.

Reboredo, J. C., Rivera-Castro, M. A., 2013. A wavelet decomposition approach to crude oil price and exchange rate dependence. Economic Modelling 32, 42–57.

Reboredo, J. C., Rivera-Castro, M. A., Ugolini, A., 2017. Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. Energy Economics 61, 241 – 252.

Reboredo, J. C., Rivera-Castro, M. A., Zebende, G. F., 2014. Oil and US dollar exchange rate dependence: A detrended cross-correlation approach. Energy Economics 42, 132 – 139.

Rigobon, R., 2019. Contagion, spillover, and interdependence. Economía 19 (2), 69–99.

Riti, J. S., Shu, Y., Song, D., Kamah, M., 2017. The contribution of energy use and financial development by source in climate change mitigation process: A global empirical perspective. Journal of Cleaner Production 148, 882–894.

Rodriguez, J. C., 2007. Measuring financial contagion: A copula approach. Journal of empirical finance 14 (3), 401–423.

Saad-Filho, A., Weeks, J., 2013. Curses, diseases and other resource confusions. Third World Quarterly 34 (1), 1–21.

Sachs, J. D., Warner, A. M., 1995. Natural resource abundance and economic growth. Tech. rep., National Bureau of Economic Research.

Sadorsky, P., 1999. Oil price shocks and stock market activity. Energy Economics 21 (5), 449–469.

Samarakoon, L. P., 2011. Stock market interdependence, contagion, and the US financial crisis: The case of emerging and frontier markets. Journal of International Financial Markets, Institutions and Money 21 (5), 724–742.

Samuel, W., Viseth, A., 2018. Monetary transmission mechanisms in selected small island developing states with floating exchange rates. Handbook of Small States: Economic, Social and Environmental Issues.

Serletis, A., Xu, L., 2018. The zero lower bound and crude oil and financial markets spillovers. Macroeconomic Dynamics 22 (03), 654–665.

Syllignakis, M. N., Kouretas, G. P., 2011. Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. International Review of Economics & Finance 20 (4), 717–732.

Tang, X., Yao, X., 2018. Do financial structures affect exchange rate and stock price interaction? Evidence from emerging markets. Emerging Markets Review 34, 64–76.

Tanzi, V., 1982. Fiscal disequilibrium in developing countries. World Development 10 (12), 1069 – 1082.

Thorbecke, W., 2019. Oil prices and the US economy: Evidence from the stock market. Journal of Macroeconomics, 103–137.

Tiwari, A. K., Trabelsi, N., Alqahtani, F., Bachmeier, L., 2019. Modelling systemic risk and dependence structure between the prices of crude oil and exchange rates in BRICS economies: Evidence using quantile coherency and NGCoVaR approaches. Energy Economics 81, 1011–1028.

TTSE, 2006. Annual Report 2005. Tech. rep., Trinidad and Tobago Stock Exchange (TTSE) Limited.

TTSE, 2016. Annual Report 2015. Tech. rep., Trinidad and Tobago Stock Exchange (TTSE) Limited.

TTSE, 2017. Annual Report 2016. Tech. rep., Trinidad and Tobago Stock Exchange (TTSE) Limited.

TTSE, 2018. Annual Report 2017. Tech. rep., Trinidad and Tobago Stock Exchange (TTSE) Limited.

Turhan, M. I., Sensoy, A., Hacihasanoglu, E., 2014. A comparative analysis of the dynamic relationship between oil prices and exchange rates. Journal of International Financial Markets, Institutions and Money 32, 397–414.

van der Ploeg, F., 2011. Natural resources: Curse or blessing? Journal of Economic Literature 49 (2), 366–420.

Vo, M., 2011. Oil and stock market volatility: A multivariate stochastic volatility perspective. Energy Economics 33 (5), 956–965.

Wang, Y., Wu, C., Yang, L., 2013. Oil price shocks and stock market activities: Evidence from oil-importing and oil-exporting countries. Journal of Comparative Economics 41 (4), 1220–1239.

WEC, 2016. World energy resources 2016. Tech. rep., World Energy Council (WEC).

Wei, Y., Qin, S., Li, X., Zhu, S., Wei, G., 2019. Oil price fluctuation, stock market and macroeconomic fundamentals: Evidence from China before and after the financial crisis. Finance Research Letters 30, 23–29.

Welch, B. L., 1947. The generalization of ‘student’s’ problem when several different population variances are involved. Biometrika 34 (1/2), 28–35.

Wen, X., Wei, Y., Huang, D., 2012. Measuring contagion between energy market and stock market during financial crisis: A copula approach. Energy Economics 34 (5), 1435 – 1446.

Worrell, D., Moore, W., Beckles, J., 2018. A new approach to exchange rate management in small open financially integrated economies. In: Briguglio, L. (Ed.), Handbook of Small States: Economic, Social and Environmental Issues. Routledge.

Wu, C.-C., Chung, H., Chang, Y.-H., 2012. The economic value of co-movement between oil price and exchange rate using copula-based GARCH models. Energy Economics 34 (1), 270–282.

Xue, W.-J., Zhang, L.-W., 2017. Stock return autocorrelations and predictability in the Chinese stock market: Evidence from threshold quantile autoregressive models. Economic Modelling 60, 391–401.

Yang, L., Cai, X. J., Hamori, S., 2017. Does the crude oil price influence the exchange rates of oil-importing and oil-exporting countries differently? A wavelet coherence analysis. International Review of Economics & Finance 49, 536–547.

Zhang, D., Broadstock, D. C., 2018. Global financial crisis and rising connectedness in the international commodity markets. International Review of Financial Analysis, Forthcoming.

Zhang, Y.-J., Fan, Y., Tsai, H.-T., Wei, Y.-M., 2008. Spillover effect of US dollar exchange rate on oil prices. Journal of Policy Modeling 30 (6), 973–991.

Ziegler, A., 2012. Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for Germany. Transportation Research Part A: Policy and Practice 46 (8), 1372 – 1385.