Tests for Identifying Financial Contagion: New Theoretical Approaches and Empirical Evidence

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Abstract

This thesis explores the impact of financial contagion following the outbreak of the recent global financial crisis. It provides a new and unified approach to identify contagion. The first aim is to investigate for financial contagion by accounting for the existence of trends in linkages between markets, due to progressing globalisation, and allows for a description of the progress of contagion across the crisis period. Based on different reactions of domestic markets to financial shocks originating abroad, the occurrence of contagion is categorised into three types: “shock”, “recoupling”, and “kink” contagion. The results for a sample of 25 stock markets show that the impact of the 2007-9 crisis was largely heterogeneous and countries were not uniformly affected: those markets, which experienced contagion, were affected in various ways, and those, which did not suffer from contagion, experienced the crisis episode in various ways, too. The second objective is to examine contagion effect at a sectoral level from the world and domestic financial sectors across 25 countries and the findings show that the impact of the 2007-9 crisis was largely heterogeneous and the real economy was not uniformly affected. At least one sector of all countries in our sample was affected during the crisis, either by global or their local financial sectors. Moreover, there is also evidence of more instances of contagion effects in non-financial sectors of developed economies as compared to emerging ones, and the Basic Material sector was more vulnerable to shocks from both global and domestic financial sector relative to other sectors. The final part of this thesis proposes a new approach to test for financial contagion, which accounts for the existence of day-of-the-week effects in returns. The existence of day-of-the-week effects in contagion form the U.S. for twelve European countries before and during recent financial crisis using synchronised data is examined. The results show that countries did not experience contagion consistently during every day of the week; rather, excess co-movements happened only during certain days of the week. This model has the potential to disclose otherwise unobserved contagious effects, and to offer a more detailed picture of those, which could be identified using a more traditional approach.

I dedicate this thesis to my little angel Shyamal who is in heaven.

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Declaration

I declare that this thesis is my own work. Chapter 3 and 5 have been formalized after the completion of my thesis into journal articles with the help of my supervisors, Dr. Bartosz Gebka and Dr. Robert Anderson. As a result, the formalized version of Chapter 3 has been published in the Journal of International Financial Markets, Institutions and Money and Chapter 5 has been published in Finance Research Letters. Moreover, Chapter 3 has been presented at 3 conferences and has been posted online for review by conference attendees. The methodological framework of Chapter 4 is based on Chapter 3 and is currently being finalized as a journal article.

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Chapter 1. Introduction

1.1.Research Background and context

This thesis is dedicated towards a novel approach to identify financial contagion. There have been numerous research studies conducted on this topic since financial crises have been unfolding across the globe. The international financial market has experienced several financial crises since the U.S. stock market crash in 1987, such as the Mexican peso crisis in 1994, the Asian Crisis in 1997, the Russian Crisis in 1998, the U.S. dot-com crisis in 2000, the U.S. sub-prime crisis in 2007, and the European debt crisis in 2010. A common feature of these financial crises is that the dramatic shocks in the equity markets of the crisis-originating country can quickly spillover to other economies of different structures, sizes and development stages across the world. The dynamics of dependence in international equity markets have led economists to raise the question whether the high cross market co-movements during a crisis provide evidence of contagion. Hence the main motivation of studying contagion comes down to one basic question: If one economy sneezes, does the rest of the world catch a cold? And if yes, what is the best way to test for it.

For the purpose of this thesis, I will be focusing on financial contagion during the 2007-2009 financial crisis, which has led to the worst economic collapse since the Great Depression of 1929 (Temin, 2010). The subprime mortgage market in U.S. where the crisis originated, was less than 4 percent of the financial system, according the Bank of International Settlement (2009). Yet, this had a substantial impact in the U.S and around the world. The crisis rapidly spread across the economic sectors of both emerging and advanced economies around the world, mainly due to the interdependency of financial markets which has been stimulated by growing economic integration for the last 30 years. This interrelationship amongst markets has been fostered through a gradual liberalization of capital movements, deregulation of financial markets and new technologies in both developed and developing countries. And, despite the numerous benefits of financial globalisation, it can lead to crises affecting not only countries with weak fundamentals but can also have an impact on countries with sound fundamentals since crises can spillover to other economies through real links, financial links or market imperfections such as herding behaviour or panics. The severity of the 2007-2010 financial crisis affected both financial activities and macro-economic conditions around the globe, with long term consequences for economic development and growth. Hence a detailed understanding of the processes driving the Global Financial Crisis (GFC), and how this is transmitted, is both topical and has important policy development implications for measures to deal with future crises.

There have been several research studies which have proposed to capture the rational and irrational aspects of the spread of the financial crisis, following the seminal paper by King and Wadhwani (1990) and contagion is the term which mainly represents this stream of research. And until now there has not been a clear consensus on what precisely contagion signifies. For instance, King and Wadhwani (1990) defines contagion as "an increase in correlation during a crisis period relative to a stable one". But the mostly commonly used definition is the one given by Forbes and Rigobon (2002) who describe contagion as "a significant increase in the cross-market linkages after a shock to one or a group of countries" and use the term 'shift contagion' to describe this situation.

Together with the disagreement on the definition of contagion, there is also controversy regarding the best method to empirically test for contagion, which can be summed up into two different categories, namely direct and indirect measurement. The first method involves measuring the presence of contagion by observing the fundamentals that drive spillovers. In other words, it requires economists to observe macroeconomic fundamentals (such as interest rates, financial constraints, policy responses, trade and financial openness) together with risk appetite, contingent contracts, amongst others (see for example, Baele et al., 2011; Bekaert et al. 2014). However, in practice, it is quite difficult to implement this method, as firstly, it is quite challenging to agree on which economic fundamental is more important and it is also impossible to measure certain fundamentals at the required level of granularity. Moreover, it is also difficult to obtain these data at high frequency level which is desirable to investigate for contagion.

The second method involves observing and evaluating the symptoms of financial contagion. This is done by looking at the co-movement during a "normal" and the excess co-movement during a crisis, above the non-crisis period. In other words, it involves the examination of how different the propagation is during a contagious event, from the shock transmission that exists in normal times. The question which arises while employing the indirect procedure is that what defines "normal"? Previous research studies on financial contagion literature consider the period before the crisis occurred as normal, i.e. the pre-crisis period. And the standard approach in the literature is to test whether an empirical measure of linkages between markets differs significantly between tranquil and crisis periods (see for example, Baur, 2012; Kenourgios and Dimitriou, 2012). However, my observation is that those tests typically do not allow for those linkages to vary within each market state or account for the fact that they can vary across different days of the week. Hence, existing results could be misleading or biased as they might falsely identify contagion where a higher level of spillovers in a crisis period would have been observed anyway, even in the absence of a crisis, due to long-term trends in financial integration among markets (e.g. globalisation). In addition to this, contagion does not occur consistently across the whole crisis period and it does not propagate to other economies simultaneously.

Given the severity of the recent financial crisis and its impact across equity markets, and the real economy around the world, it is important to understand how to identify genuine contagion for effective portfolio management, risk management and policy market decision during a financial crisis. Consequently, this study uses a unique approach while employing widely acknowledged empirical methods to address the controversies and ambiguities regarding the identification of financial contagion.

1.2.Research Objectives and Contribution

Given the above arguments, this study follows three main research directions. The first one is to investigate contagion within an international market perspective. More precisely, this thesis explores how international market linkages evolve during a crisis and post-crisis period, and test whether there is evidence of genuine contagion. I am proposing a method to empirically discriminate between genuine contagion and changes in linkages due to long-term processes such as globalisation, by looking at the propagation of the 2007-2009 financial crisis in the equity markets, financial sectors and non-financial sectors of 25 developed and emerging countries. This method enables to determine the difference between spillovers and contagion effect, in order to test whether the higher co-movements are driven by globalisation or result from the shock inflicted by a crisis episode. By showing the integration process of the world market with other economies across a period of 27 years, this method allows to determine whether there has been a positive integration (globalisation) before the crisis, and how was this relationship affected after a crisis was triggered (whether there was contagion or decoupling). In addition to this, the integration process is also examined during the post crisis period. As a result, I suggest a new meaning of contagion, whereby it refers to an excess co-movement between equity markets during a turmoil period, as compared to what the integration process between these two markets would have been if the crisis had not struck.

The second research direction is detection of contagion at different phases of a crisis. Contagion has a heterogeneous impact on equity markets, financial and non-financial sectors, depending on various factors (for instance the regional proximity and the trade and financial linkages with the crisis originating country, their current account deficit, amongst others). Consequently, I hypothesise that the timing which a shock originating from one country affects other economies differs significantly, whereby some can experience contagion immediately after the outbreak of a crisis whereas others might not face any distress until a later stage of the crisis. Further, the impact of a shock might only be transitory for certain markets, while for others it might have a permanent impact. As a result, in this thesis, evidence of contagion is categorised into three types, namely, 'shock', 'recoupling' and 'kink' contagion. This characterisation allows to determine whether an economy or a particular sector experienced contagion on the onset of the crisis or at a later stage.

The third major objective of this paper is to investigate the hypothesis that contagion occurs only intermittently, and not steadily across a turmoil period, as postulated by most research studies in financial contagion literature. The average increasing co-movement during a crisis have been examined in previous literature. However, contagion is not a phenomenon that happens consistently across the crisis period. It might be more persistent on certain days of the week, due to short selling activities during the crisis, strengthening of the blue Monday effect following the crisis outbreak, and the surge in the number of investors taking a short view due to liquidity needs during the recent financial crisis might all lead to changes in the day of the week effect domestically, but also affect cross-border investment decisions. Moreover, announcements of macro-economic data on taking place on different days of the week might lead to contagion effect being different across weekdays, too.

1.3.Structure of the thesis

This thesis has been divided into six distinct chapters, with an appendix section at the end of chapter 3, 4 and 5. The first chapter illustrates a brief overview on financial contagion and the recent global financial crisis. Moreover, the aims and contribution of this thesis are also elaborated.

Chapter 2 expands on the different definitions given to the term financial contagion. Moreover, various methods, ranging from a simple probability analysis to more complex and robust technique such as the dynamic conditional correlations model used to investigate contagion are discussed. The potential channels (including both fundamental and behavioural aspects) through which contagion are transmitted across economies are reviewed in detail. The factors that have contributed to the intensification of these channels are also discussed in this chapter.

Chapter 3 is the first empirical chapter of this thesis and proposes a new approach to model contagion. It accounts for the existence of trends and linkages between markets, due to progressing globalisation, and allows for a description of the progress of contagion across the crisis period. Based on different reactions of domestic markets to financial shocks originating abroad, the occurrence of contagion is categorized into three types: 'shock', 'recoupling', and 'kink' contagion. The results for a sample of 25 stock markets show that the impact of the 2007-9 crisis was largely heterogeneous and countries were not uniformly affected: those markets which experienced contagion were affected in various ways, and those which did not suffer from contagion experienced the crisis episode in various ways, too. Contagion was also less common than could be expected based on the more commonly employed model with market interdependencies assumed constant within sub-periods.

Chapter 4 investigates the impact of the crisis on the real economy of 25 countries. Studying contagion effect at a sectoral level is important mainly because the returns dynamics of sectors are not all identical and some are more vulnerable to shocks compared to others because of their industrial structures. In this chapter, the same contagion model as in chapter 3 is employed and also classifies contagion into three distinct types. Following the fact that the 2007-2009 financial crisis has not only affected equity markets, but also financial and non-financial sectors across the global, this chapter sets out to examine contagion effect at a sectoral level from the world and domestic financial sectors across 25 countries. The findings show that despite there might be no evidence of contagion at a country-level, the real economies of a country might be showing signs of contagion effects. In addition to this, I also look at whether the real economy of emerging or developed country are mostly affected and which sectors are more vulnerable to crises.

Chapter 5 on the other hand, combines insights from two vast but previously disjointed strands of the finance literature, on financial contagion and of days-of-the week effects in stock returns. I postulate that any conclusions on the existence and severity of financial contagion derived in the literature so far may be misleading or incomplete, as the prevailing testing approach fails to account for the existence of seasonalities in daily stock returns, as any approach treating all weekdays equally may fail to recognise those contagious but infrequent days. The chapter starts off with the examination of the Monday effect puzzle, whereby, stock returns are lower on average on Mondays as compared to other days of the week during the recent financial crisis across 13 developed economies. In addition to this, spillover and contagion effects from U.S. to 12 European economies across the days of the week are also explored. The findings show that there is substantial evidence of disappearing Monday effect. As far as the results regarding contagion effects are concerned, they show that contagion does not happen during all days of the week but may happen only during certain specific days of the week, which might be as a result of short selling activities, investors' perceptions and the announcements of macro-economic data taking place on different weekdays.

And the final chapter concludes the findings of all the empirical chapters and describes the potential future and limitation of this research.

Chapter 2. Literature Review

2.1. Definition and Theories of Contagion

The disagreement on whether there is any evidence of contagion or not, arises since there is a lot of disagreement on a definition of contagion and also on an appropriate technique. Regardless of the choice, whether to investigate in the first or second moment of market movements, it is crucial to precisely define the term contagion. And, there are numerous definitions attributed to the term contagion. The World Bank (2016), for instance summarizes the definitions into three categories. The first one is a broad definition by the World Bank, refers to the "cross-country transmission of shocks or the general cross-country spillover and that takes place both during good times and bad times". Under this definition, contagion can be transmitted through real or financial linkages, so that it is sometimes called fundamentals-based contagion (Calvo and Reinhart, 1996). These forms of co-movements may reflect normal interdependence, and do not need to be related to crises, despite they are emphasised during periods of crises.

The second definition is a more restrictive one, as it refers to the "transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks". And, lastly, the third definition of contagion given by the World Bank is a very restrictive one, and states that "contagion occurs when cross country correlations increase during crisis times relative to correlations during tranquil times" and is most commonly used in recent empirical analysis to identify and measure financial contagion (Dungey et al. 2005; Forbes and Rigobon, 2002), among others.

One of the very preliminary research studies on contagion was conducted by King and Wadhawani (1990) and they describe contagion as increase in correlations between markets after an idiosyncratic shock to one market because information is perfectly revealed. Pericoli and Sbracia (2001), on the other hand list five definitions of contagion, namely: "1) when there is an increased probability of crisis in a country, given the existence of a crisis in another country; 2) when volatility is propagated as a proxy for uncertainty from the crisis of a country to the financial markets of other countries; 3) when there is an increase in co-movements in prices and quantities between markets, given the crises in one or more markets; 4) when there is a change in the transmission mechanism or channel for contagion, with the intensification of the same after the crisis and 5) when there are co-movements that are not explained by the fundamentals."

However, the most common definition of contagion is the one given by Forbes and Rigobon (2002) who refers to contagion as a "significant increase in cross-market linkages after a shock to one country (or group of countries). According to this explanation, if two markets show a high degree of co-movement during periods of stability, even if the markets continue to be highly correlated after a shock to one market, this does not constitute contagion. It is only contagion if cross-market co-movement increases significantly after the shock." Forbes and Rigobon (2002) also used the term "shift contagion", which occurs when the normal cross-market channel intensifies after a crisis in one country. "It is only shift-contagion if the correlation between the two markets increases significantly. And if the co-movement does not increase significantly, then any continued high level of market correlation suggests strong linkages between two economies that exist in all states of the world." Forbes and Rigobon (2002) use the term interdependence to describe this situation. The advantage of their definition is that it provides a simple way to test for the existence of contagion occurs. The linkages between two markets just have to be compared (for instance, cross market correlation coefficients) during a relatively stable period with linkages directly after a shock. The second benefit is that it provides a straight-forward method of distinguishing between alternative explanations of how crises are transmitted across markets. A similar definition is proposed by Dornbush, Park and Claessens (2000), whereby contagion is a "significant increase in cross market linkages after a shock to an individual country (or group of countries), as measured by the degree to which asset prices or financial flows move together across markets relative to this co-movement in tranquil times."

Karolyi (2003) defines contagion as "irrational co-movements" which are the residual in a model, after controlling for "fundamentals-based co-movements" (from real and financial linkages) and "rational investor-based co-movement" (from rational investment decision making by financial agents). And, according to Hartmann et al. (2004), contagion relates to a "situation where there is a significant increase in the conditional probability of having a crash in one market, given one occurred in another." On the other hand, contagion is defined by Bekaert et al, (2014) as "the co-movement in excess of that implied by the factor model, i.e. above and beyond what can be explained by fundamentals taking into account their evolution in time."

It can be noted from the above descriptions of contagion that until now there has not been a universal definition for contagion adopted in the literature. Moreover, there is still an on-going debate on contagion transmission channels and the best way to identify this phenomenon.

2.2. Channels of Contagion

According to Forbes and Claessens (2004), the literature on international stock market co-movement can be divided in two broad groups, namely the fundamental causes and investors' behaviour. The fundamental causes explain the spillovers that arises because of normal interdependence among economies. This mechanism of contagion consists of trade and financial linkages, changing nature of businesses, and common shocks. And according to Kaminsky and Reinhart (1998) when a crisis originates in one country, this interdependence of economies becomes a carrier of crisis through real and financial linkages. Moreover, there have been numerous factors which have contributed to the increasing interdependence, for instance, innovations in information and communications technology, financial liberalisation, decreasing transaction costs, and availability of new financial instruments, such as futures and options. The increase in co-movement resulting from the channels of transmission mentioned above cannot be defined as contagion, unless they occur during a period of crisis and their impact is adverse.

And, on the other hand, the behavioural causes show how investors' behaviour is different in turbulent and tranquil times. Under this definition, contagion can occur during a crisis but is not linked to observed changes in macro-economic or other fundamentals but is only as a result of investors' behaviour. This type of contagion is often said to be caused by "irrational" phenomena, such as financial panics, herding behaviour, loss of confidence and change in risk perception. However, these phenomena can be rational individually but still exacerbate the severity of a crisis.

Distinguishing between the fundamental and behavioural based contagion is important as they have different implications (Gebka and Serwa, 2007; Forbes, 2012), as it enables economists and policy makers to know by which channel contagion is being transmitted to other economies, to take appropriate action to reduce the impacts of crises as far possible. The remainder of this section summarizes this extensive literature on channels of contagion.

2.2.1. Fundamental Causes

(a) <u>Trade Linkages and competitive devaluations</u>

Interdependence amongst countries or sectors are more likely to increase if there is the existence of trade linkages. For instance, if Country X exports a large amount of its production of cars to another Country, Y. A shock in Country Y, will have a negative impact on the revenues of the automobile industry in Country X, following a decrease in demand of cars and a fall in the stock prices of Country Y. And eventually the prices of automobile-rated stocks in Country X will decline. Forbes and Chinn (2004) found that "direct trade flows are important determinants of financial market co-movements while analysing emerging markets." Johnson and Soenen (2003), on the other hand, examined the U.S stock market in relation to eight Latin American markets, and came to similar conclusions. Forbes (2012) shows that since 1990, trade exposure has considerably increased globally. She also points out that there has been a substantial rise in trade, especially in Euro area countries, and hence these countries are now more exposed to trade relative to other developed economies. And the trends in trade exposure could lead to increasing interdependence over time, which might potentially accentuate contagion effect when an adverse shock hits the country.

Another contagion transmission channel is competitive devaluations. Devaluation of currency in a country affected by a crisis reduces the export competitiveness of the countries with which it competes, thus pressurising on the latter's currency, especially when those currency do not float freely (Zhang et al., 2013). According to Corsetti et al. (1999), "a game of competitive devaluation can prompt a sharper currency depreciation compared to that required by any initial deterioration in fundamental and a non-cooperative nature of this game might accentuate this depreciation relative to what could have been achieved in a cooperative equilibrium. If market participants expect that a currency crisis will lead to a game of competitive devaluation, this will result into them selling their holdings of securities of other countries and curb their lending." For instance, during the East Asian crisis whereby there was a considerable depreciation of the exchange rate even in economies that did not seem to be vulnerable, for example, Singapore, Taiwan and China to a speculative attack based on their fundamentals.

(b) Common Bank Lenders

This theory of common bank lenders was advanced by Kaminsky and Reinhart (2002). They assume that a single bank is lending to two countries, whose outputs are, in principal unrelated. In other words, it is assumed that there are no real linkages, but only financial linkages are present. The outbreak of a crisis in one country might affect its banks' balance sheet, thus curtail lending to the second country. This reduction in service (e.g. contraction direct lending, insurance, provision of liquidity, etc.) to the second country has real effects, and in the end, this affects asset prices and exchange rates. Hence, since both countries are receiving financial services from a common financial institution, they are interrelated. For example, Arvai et al. (2009) found evidence that Austria, Germany and Italy play the role of common lender to countries in Central, Eastern and South-East Europe.

The theory of common bank lenders can also be applied to margin calls, liquidity aspects or wealth effect. Instead of a banking sector, the financial intermediary in the latter cases is the capital market. An example has been given by Calvo (2002), whereby a shock in one country lowers the value portfolio holdings of the intermediary. The result of a fall in wealth would therefore induce the financial intermediaries to sell off assets in the same asset class due to either higher degree of risk aversion or they are subject to margin calls. These theories were developed after the Asian crisis in 1997 and Russian crisis in 1998, to better understand contagion transmission.

(c) Cross-market rebalancing

A financial shock in a country might prompt investors to rebalance their portfolios for liquidity, or risk management purposes. This happens since the outbreak of a crisis in a country will encourage investors who have positions in that country to reduce their risk exposures and as a result lead to a sale in assets whose returns have high correlations with those of the assets in the crisis originating country. For instance, consider an economy with three markets: X, Y and Z; assume that X and Y share exposure to one macroeconomic risk factor, whereas Y and Z share exposure to a different macroeconomic factor. A shock in market X may prompt investors to rebalance their portfolios in market Y (because of their common risk exposure), which in turns prompts investors to rebalance their portfolios in Z. As a result, the shock transmits itself from X to Z, although the two markets do not share exposure to the same risk factor (i.e., their fundamentals are independent).

Investors may also be tempted to sell liquid assets in such circumstances for other reasons. For instance, according to Kodres and Pritsker (2002) the diminishing value of assets of in crisis country lead to a need to raise cash to meet margin calls. Moreover, while conducting an experimental analysis to analyse cross-market rebalancing, Ciprani et al. (2013) confirmed the fact that the rebalancing channel is an important element in creating cross-market contagion.

(d) The global nature of businesses

Cavaglia et al. (2001) examined cross-border mergers and acquisition and show that mergers and acquisitions have grown from $40 billion per annum during the period from 1989 to 1993 to $400 billion per annum during the period from 1994 to 2000. By using a factor model, Brooks and Negro (2006) claim that "if a firm raises its international revenues by 10%, it will increase its exposure to global shock by 2% and simultaneously reduces exposure to local shocks by 1.5%." Moreover, a shock to the multinational firm influences the price of stocks of all its subsidiaries simultaneously around the world. Hence undoubtedly, an increase in mergers and acquisition and multination corporations around the world would aggravate the impact of a crisis.

(e) Common Shocks

The global phenomena or common shocks, such as changes in "U.S. interest rates, slowdown in world aggregate demand, a decline in commodity prices, or changes in the bilateral exchanges" between countries can have a negative impact on the economic fundamentals of several economies concurrently and may lead to the occurrence of a crisis (Rose and Wyplosz, 1996). An example of a common shock is the substantial dollar appreciation between 1991 and 1995 and the long-lasting slowdown in Japanese growth, which have contributed to the weakening of numerous sectors in Southeast Asian countries. Moreover, Babetskii et al. (2007) confirms that common shocks are indeed seen as a cause of stock market co-movements in their study of financial integration of four European Union members (the Czech Republic, Hungary, Poland, and Slovakia) with the Euro area.

2.2.2. Behavioural Aspect

From the previous section, i.e. the fundamental-based contagion, it could be observed that the spillover of a crisis to other economies depends of the degree of integration, whether it is in terms of financial markets or trade linkages. Therefore, it can be implied that more financial or economic integration will lead to a more extensive contagion effect to other countries or sectors. However, this does not mean that countries that are not financially or economically integrated (maybe due to capital controls or lack of access to international financing) are not immune to contagion. For example, even though there was no clear trade relationship between Mexico and Argentina, the later still suffered from the Mexican crisis in 1994.

Hence other than the fundamental causes for the international stock co-movement, there is the behaviour of investors, which is much harder to measure and dealt with. Even though, in economic theories, the behaviour of economic agents is assumed to be rational, it is a well-known fact that economic agents and investors behave rationally as well as irrationally. The last thirty years has witnessed major changes in financial globalisation, in terms of market liberalization together with a decline in familiarity and home bias, which meant that the importance of investors has also been growing as they have started to trade globally.

(a) Liquidity Problem and incentive problem

Another factor that can explain an increase in stock co-movement is the liquidity problem of investors. For instance, Frank and Hesse (2009) show that during the recent financial crisis, hedge funds that held asset-backed securities were induced to sell more liquid assets to meet margin calls, thus transmitting market stress.

Hence, if an institutional investor faces losses in a country, she might be motivated to dispose risky assets in other countries to meet the demands of her customer who offload their stake in the investor's company. Further, if the investor is more leveraged, she tends to sell riskier asset.

(b) Information asymmetries and Herd Behaviour

Imperfect information and differences in investors' expectations is another potential cause of contagion. For instance, where better information is absent, investors might have the belief that the existence of a financial crisis in one economy can lead to financial shocks in other nations. This behaviour which arises from information asymmetry is not necessarily irrational. Since investors are not fully informed about each country's true characteristics, they therefore make their decisions based on some known factors, which may not necessarily reflect the state of the vulnerabilities of the country.

Herd behaviour and general loss of confidence are other possible causes of stock market co-movements. According to Calvo and Mendoza (2000), "information asymmetries and fixed costs involved in gathering and processing country-specific information" could lead to herd behaviour which is rational. In their model, they differentiate between two types of financial, namely the uninformed and informed one.

The uninformed one, usually depicted by small and middle investors, incur more costs to gather relevant information and hence follow or consider the investment decisions of the better-informed investors, which they provide useful information. Moreover, in the case of informational cascades, trading by other parties can be considered to contain superior information about assets, hence it may be a rational strategy to suppress one's prior beliefs and follow the market.

(c) Wake-up calls

The wake-up-call hypothesis was first put forward by Goldstein (1998) to explain contagion from Thailand to other Asian countries in the Asian crisis. He argues that the other countries were affected by the same structural and institutional weaknesses as Thailand (for e.g. weak banking system) but investors ignored those weaknesses until the Thai "wake-up call".

According to Goldstein (1998), "wake-up calls may happen because investors are not focused on or aware of certain vulnerabilities, or because fundamentals only become problematic during a crisis thereby generating multiple equilibria. Weaker fundamentals or even just increased concern about a country's fundamentals could also strengthen various channels of contagion." For instance, a shock in the financial sector of Country X might lead to a fall in the funding given to banks in other countries, which can eventually lead to a wake-up call and countries with weaker fundamentals might even face bank runs.

Goldstein (1998) also states that "the wake-up calls can involve many forms of reassessment including not only the macroeconomic, financial or political characteristics of the country but also the functioning of financial markets or the policies of international financial institutions." For instance, a country's terms for debt restructuring could provide information on how other countries would be treated in similar circumstances. A re-examination of the functions of financial markets or policies taken by international institutions could cause investors to sell assets across countries, thereby causing contagion.

More recently, Bekaert et al (2014) confirms the "wake-up call" hypothesis, they that there has been evidence of contagion from domestic stock markets to individual domestic stock portfolios, with severity inversely related to the quality of the countries' economic fundamentals and polices.

2.2.3. Factors contributing to the intensification of contagion channels

As mentioned above, there are numerous channels through which contagion might occur, and they can be categorised into fundamental-based and behavioural aspect. In addition to this, there are various factors which have intensified the contagion channels among countries and they are as follows:

(a) Liberalization in Global trade of financial services

Financial markets have become more interdependent during the past 30 years. This has led to a steady liberalization of capital movements, deregulation of financial markets and new technologies in both developed and developing countries. Despite of the numerous advantages of financial liberalization, many research studies (e.g. Kaminsky and Reinhart, 1998 and Williamson et al. 1999) show that almost all banking crises have been associated with financial liberalization. This is because economies have become more interrelated, following the developments of the financial market and as a result domestic markets have become less isolated and react almost immediately to new information from the international market. This international linkage among markets are more likely to impact investors negatively, especially during a financial turmoil. According to Caprio et al. (2000) one possible explanation could be that financial liberalization exposes the risk and poor performance of pre-liberalization portfolios.

(b) Consolidation and Conglomeration

Financial institutions have been consolidating at a rapid pace over the past decade. In order to survive global competition, many banks are looking for strong partners in international markets. This bank consolidation process has been encouraged by both the governments and by the integration in the unified economic and monetary unions. For instance, according to Wilmarth (2008), policies taken by the government in the U.S., U.K. and Europe has encouraged consolidation and conglomeration within the financial services industry during the last two decades which consequently led to the formation of seventeen large complex financial institutions, known as the LCFIs, which dominated both domestic and global markets for securities underwriting, syndicated lending, asset-back securities, over-the-counter derivatives and collateralized debt obligations. Moreover, the countries mentioned above, and some European nations experienced an enormous credit boom between 1991 and 2007, and the LCFIs played a leading role as direct lenders and securitizers for nonprime home mortgages. And nonprime borrowers had to keep taking out new loans to pay off their old ones. Hence, when house prices stopped rising in 2006 and collapsed in 2007, defaults skyrocketed, as borrowers could not refinance, and this subprime financial crisis began.

(c) Globalisation and dependence on international capital inflows

As shown by Kaminsky and Schmukler (2003), during the last decades, restrictions have been lifted in both emerging and developed economies and there have been different factors contributing to the growing financial globalisation. For example, governments have been lifting restrictions on domestic financial institutions and the capital account of the balance of payment. There are indeed benefits of globalisation, such as financial development. However financial globalisation can also contribute of spillovers of crises, not only in economies with weak fundamentals, but also those with sound fundamentals, as countries have become more integrated into the world financial markets. For instance, globalisation can contribute to crises, if there are financial market imperfections. According to Schmukler et al. (2003), imperfections in financial market may lead to herding and irrational behaviour amongst investors and speculative attacks. Moreover, countries might be more prone to crises if they rely on foreign capital. For instance, a sudden shift in foreign capital flows might lead to financing problems and economic downturns. And according to Reinhart (1999), these shifts are not necessarily dependent on a country's fundamental but might be due to global factors such as world interest rates, economic cyclical movements, and a global drive towards diversification of investments in major financial centres, amongst others. Moreover, according to Broner et al. (2003) when countries depend on short term capital inflows relative to their ability to generate cash on short notice, they become more vulnerable if there are sudden reversals of capital flows and this might lead to liquidity crises.

(d) Financial Innovations

Financial innovations can hold unknown risks, because of their complexity and various ways used to measure risks. For instance, "the use of credit derivatives for hedging or speculative purposes imply numerous risks, such as: credit risk, counterparty risk, rating agency risk, and settlement risk" (Gibson, 2007). For the last two decades, financial innovation has facilitated the transfer of risk associated with mortgage risks, which has mostly been transferred via securitization and sold to investors globally. And since many financial institutions did not have an effective risk management during 2007-09 financial crisis, the turmoil on financial markets was widespread. And the problem was that risk management did not advance at the same pace as financial innovation. Hence the prevalence of complex and opaque financial instruments, fuelled at times by poor management and government interventions worsen the consequences of the crisis on both advanced and emerging economies.

(e) Development of new technologies.

"Constant technological improvements and the development of internet banking and brokerage services over the past decade has led to globalization to go beyond the limits of the ownership structure of financial conglomerates and reach the retail markets", (Balino and Ubide, 2000). Many banks are using their online operations in order to get into the foreign markets thus avoiding expensive establishment of overseas departments. "In addition, the emergence of virtual banking, e-service development has created the opportunity to develop non-bank financial institutions which carry out basic banking functions as well" (Račickas and Vasiliauskaitė, 2011).

2.3. Previous Findings

2.3.1. Testing for Contagion

There are numerous approaches that have been used to measure different features of contagion and/or interdependence. In this section, some of the most commonly used methods namely: probability analysis, cross market correlation, vector auto-regression (VAR), and dynamic factor analyses are discussed. Some research uses the combination of more than one of the above methods.

(a) Probability Models

One of the earliest approaches for testing contagion are probability models which assess the probability of a crisis conditional on information elsewhere, considering fundamentals or similarities.

The probability model tests were introduced by Eichergreen et al. (1996) and are used to examine channels of contagion by differentiating, among others, trade and financial links. Eichergreen et al. (1996) showed that financial contagion is more likely to spread through trade linkages compared to macro-economic similarities between countries by using a probit model and a panel of quarterly macroeconomic and political data covering 20 industrial economies from 1959 through 1993. This approach has been extended by Forbes and Warnock (2012) to test for the role of contagion in explaining sharp movements in capital flows and by Constancio (2012) to investigate probabilities of contagion resulting from credit default swaps. Probability models are commonly used as a method to test for contagion, as it readily allows for statistical evidence. However, the disadvantage is that they have limited success in controlling for endogeneity and omitted variables that could simultaneously cause events to occur in multiple countries.

(b) Correlation Coefficient

One of the most preferred method used by economists to capture and measure co-movement is correlation. "As per this approach, if two markets are closely and naturally correlated during stable periods, then, during a crisis, the impact of a shock from one market to another will lead to a considerable rise in the stock market co-movements which signifies contagion. And, on the other hand, if there is no major change in the relationships after a shock to one market, and the stability in the transmission system persists, then market co-movements can be assumed to be driven by strong real linkages between two economies. Such stability in parameters indicates interdependence over time. Therefore, based upon the above assumptions, contagion means that cross-country linkages are basically different after a shock to one market while interdependence means no real change in relationships" (Forbes and Rigobon, 2002).

King and Wadhwani (1990) and Lee, Kim and Park (1993) were the first one to carry out preliminary test for financial contagion. Their test was based on a simple comparative analysis of Pearson' correlation coefficient between market in the tranquil and turmoil periods, to assess the effect of the U.S stock crash in 1987 on the stock markets in the U.K., Japan, and various other countries. Their results support the evidence of contagion by depicting that the correlation coefficients between several markets significantly rose during the crash. Correlation tests were also used by Calvo and Reinhart (1996) whereby they find co-movement of weekly returns on equities in Asia and Latin America higher after the Mexican crisis relative to the pre-crisis period.

However, numerous researchers have pointed out some loopholes pertaining to the conventional "correlation" technique while structural changes are being tested. They state that significant increase in correlations among markets may not be sufficient proof of contagion. If markets are historically correlated, this means that a sharp change in one market will naturally lead to changes in other markets, and therefore correlation during a crisis will increase. For instance, Forbes and Rigobon (2002) states that "the correlation coefficient between markets is in fact conditional on market volatility and during a period of crisis when there is increasing stock market volatility, the unadjusted estimates of cross market correlations will be biased. This can wrongly lead to accept that contagion occurred. In addition to this stock prices mostly suffer from problems such as heteroscedasticity. More specifically, heteroscedasticity in movements of asset prices might cause the estimated cross-market correlations to rise after a crisis, although there is no rise in the underlying correlations."

(c) <u>Vector Auto-Regression (VAR) Analyses</u>

Unlike probability models, VAR analysis considers the endogeneity of different economic variables when examining interdependencies among economies and analyses the dynamic impact of random disturbances and describes the assessment of a set of endogenous variables in the system as a linear function of their past evolution. "VAR models are more often presented with impulse response functions that test for the effects of the different shocks in one variable on the other variables, and variance decompositions that measure the relative importance of the different shocks to the variation in the different variables" (Sims, 1980). Granger causality tests are often used in the VAR analysis to decide the endogeneity of the variables.

Kim, Lee, and Park (2009) used a VAR model to examine on the level of economic interdependence which exists between emerging Asian nations and developed countries including Japan and the U.S. Their findings show the evolution of macroeconomic interdependence between the developing and developed economies under study through changing trade and financial linkages at both the regional level and the global level. Moreover, using the VAR model, Angkinand, Barth, and Kim (2010) also employed a VAR model to examine the interdependence among developed countries. They point out a significant increase in interdependence over time and that the spillover effects from the U.S to other industrial countries have been substantial during the recent financial crisis. And more recently, a study by Zhang (2011) examines the effect of U.S. stock market movements on Asian markets during the recent financial crisis using VAR analysis and find that the U.S. equity market has a stronger impact on the Asian equity markets during the crisis.

Shortly, after the Asian crisis in 1997, an extension of the VAR model was developed, and it is referred to as the Global Vector Auto-regression approach. It was used to test the impact of macro-economic developments on the losses of major financial institutions, (Chudik and Pesara, 2016). It follows a two-step approach, whereby the country specific models are firstly estimated conditional on the rest of the world. Secondly, individual countries VAR model are put together and solved simultaneously as one large G-VAR model. Chudik and Fratzscher (2011a) have employed a G-VAR approach to examine the transmission of global liquidity shocks and shocks to investor's risk appetite on equity markets during the recent financial crisis. And more recently, Beirne and Gieck (2014) employ a G-VAR to analyse how the transmission mechanism between assets (equities, bonds and currencies) over 60 economies may change during periods of crises, over the period 1998 to 2011. Their findings indicate that emerging economy equity markets are much more integrated to global equity markets than the integration of emerging bond markets with global bond markets and the integration of emerging currency market with global currency markets.

As established earlier, one of the advantages of employing a VAR model for examining interdependence and contagion effect is that it provides a systematic approach that imposing restrictions and recognises endogeneity among variables and as a result, captures relationships which are often hidden to standard procedures such as OLS regressions. However, one of the downsides of this method is that the robustness of the VAR estimations depends on a plausible setup on the endogenous assumptions among variables.

(d) Copula Approach

Copula (Schweizer and Sklar, 1983) is a multivariate probability distribution which has uniform marginal distribution of variables are also a common method to test for contagion. This method is mostly employed to examine dependence structures after extreme events. Copulas are part of a joint distribution dependence structure and they model the dependence between variables in a flexible way and independently of the marginal distribution.

Over the past decade, they have been numerous research papers employing copula method to analyse the integration process between markets and contagion effects. For instance, Patton (2006a) developed the concept of time varying copulas which allows dependence to vary over time and also depend on a set of conditioning variables. Time-varying copulas was also adopted by Candelon and Manner (2007) in order to investigate asset market contagion during the Asian crisis. And, a two-step approach is employed by Rodriguez (2007). He uses a univariate SWARCH model firstly to determine two volatility regimes, namely the low and high volatility regime corresponding to a turmoil and normal period. In the second step, copula models are estimated, based on a dummy variable which represents representing the volatility regimes in the "ground-zero" country. The dependence parameters across the two volatility regimes are then compared using a standard likelihood ratio test. And more recently, Ye et al. (2012) have used the Archimedean copula method by examining the tail dependence coefficient for measuring the degree of financial contagion between the U.S and Asian markets during the recent banking crisis.

(e) ARCH/GARCH Framework

Engle (1982) and Bollerslev (1986) were amongst the first one to model financial time series through a univariate ARCH and GARCH models and stochastic volatility models as well. And Hamao et al. (1990) were amongst the first to use the ARCH/GARCH framework in order to test for contagion. They have looked at intraday stock market returns from 1985 to 1987, and by using a GARCH (1,1)-M model, they found evidence of volatility spillover effect from U.S and U.K. stock markets to the Japanese stock markets.

And since then, there have been various GARCH models used in literature to investigate for contagion. An extension of the GARCH model is the (Glosten, Jagannathan, and Runkle, 1993) GJR GARCH model, which has been used by Baur (2012) to investigate contagion effects, accounts for possible asymmetric impacts of positive and negative shocks on the volatility of the markets. Another variation of a GARCH model is the DCC (Dynamic Conditional

Correlations) – GARCH which has been developed by Engle (2002) provides time-varying correlation between economic variables. One of the benefits of using a DCC-GARCH models is that it accounts for heteroscedasticity and autocorrelation of the variables while conducting time-varying calculation of correlations. The “2008 Global Financial Stability Reports” (IMF, 2008) employs a DCC-GARCH to analyse the co-movements in stock markets between the U.S. and emerging economies and found increasing correlation levels during the past several years up to 2008. Overall, GARCH models has proved to be more robust than the static correlation models, especially for looking at financial variables which often face greatly changing volatility, and in this thesis, a GARCH model will be employed.

2.3.2. Integration and Time Varying Betas

In the third and fourth chapter of this thesis, the time-varying integration process amongst equity markets are also examined. Examination of time-varying dependence structures in international equity markets has attracted increasing attention of theorists, empirical researchers, and practitioners recently. This is mainly since over the past three decades, there have been major changes in the world financial markets, in terms of increasing globalisation, lesser trade barriers, growing economic relation around the world and competition and more cost effect transportation system and improved technology. And as a result, one could expect increasing financial market integration.

The literature on stock market interrelationships and integration is fairly rich (for e.g. Baele et al. 2014; Bekaert et al. 2014; Ibrahim and Brzesczynski, 2014). The deregulation of capital movements in the early 1990s has resulted into systematic interrelation of the major financial markets. This dependence shows the growing similarities in reactions towards macroeconomic policies or financial crises. However, the empirical evidence is diverse depending on the data, methodology and theoretical models used. Shabri Abd Majid and Kassim (2009), for instance, examined the stock market integration among the U.S. stock market and the Indonesian and Malaysian markets over the period from February 2006 to December 2008, and found that these three markets tend to show more integration during crisis period. Moreover, Wu et al. (2015) investigate interdependence based on daily data from July 1997 to July 2010, among nine Asian Stock Markets (Japan, Hong Kong, Taiwan, Singapore, South Korea, Indonesia, Malaysia, China, and India) and the U.S. market. Their empirical results show that during the recent financial crisis, the U.S. stock market was co-integrated with the Asian Stock market. On the contrary, Roca (1999) and Smyth and Nandha (2003) showed that global markets are weakly interlinked.

Baele et al. (2010) are one of the first to examine European market integration and contagion after the recent financial crisis. They use model with both structural instruments and a latent regime variable and finds that both global and regional market comovement have substantially increased over the last 30 years, indicating a considerable progress in the degree of European market integration. According to them, one of the factors that strengthened this integration process even further is the introduction of Euro and adds that the overall increase in integration with world for the European markets being studied is relatively larger than for regional integration. However, they do not find evidence of contagion during any of the crisis periods they consider, namely the Mexican crisis, the Asian crisis, the Russian crisis, the Nasdaq Rash, the 9/11 terrorist attacks, the (start of the) subprime crisis, and during periods of high market volatility. They claim that contagion test results are vulnerable to suboptimal specifications for the dynamic factor model. For instance, the specifications with constant global (regional) market exposures incorrectly identify contagion during the 1987 crash, Asian crisis, the 9/11 terrorist attacks, the (start of the) subprime crisis, and during periods of high global market volatility. Similarly, the findings show that contagion test results can differ substantially depending on how the time variation in both the structural and cyclical component of the factor exposures is modelled.

Bekaert et al. (2014) is another study that examined the integration process and contagion during the recent financial crisis. They develop a three-factor model to set a benchmark for what the global equity market co-movements should be, based on existing fundamentals, as compared to Baele et al. (2010), who uses a two-factor model. Their model distinguishes between a U.S specific factor, a global financial factor, and a domestic factor for pricing of 415 country-sector equity portfolios across 55 countries and define contagion as the co-movement in excess of that implied by the factor model. Their benchmark factor model is also referred to as an "interdependence" model, and it implies a transmission of shocks proportional to the factor exposures, as measured pre-crisis. Contrary to Baele et al. (2012), they find significant evidence of contagion during the 2007-2009 financial crisis. They also use their framework to differentiate amongst the channels of contagion and to explain the heterogeneity on contagion Moreover, they find that the globalisation process may have gradually increased the U.S and global banking sector factor exposures over time but it may have also led to decoupling during the crisis as globalisation reversed due to the substantial decrease of trade integration, capital flows, and financial integration. However, Bekiros (2014) results find that, there has been an increase in international integration for BRICS (Brazil, Russia, India, China and South Africa) during the financial crisis. Bekeart et al. (2012) also observe that countries with weak fundamentals (such as poor sovereign ratings, and high fiscal and current account deficits) were more vulnerable to shocks from both from U.S. and from the domestic market and were overall more severely affected by the global financial crisis than countries with good fundamentals. However, good government policies implemented during the financial crisis, such as debt and deposit guarantees and through capital injections into domestic banks have helped to protect the domestic banking sector, and hence reduced domestic contagion.

In the same line as Bekaert et al. (2014), Støve et al. (2014) also found financial markets have become more and more interlinked in the past decades while examining the impact U.S to other economies during the financial crisis of 2007-2009. Their results show that the dependence between U.S. and European markets have increased during the 2007-2009 crisis compared to the stable period.

As far as time-varying correlation, there are many recent literatures (for example, Aloui, Alissa, and Nguyen, 2011; Syriopoulos and Roumpis, 2009) that have investigated this issue among developed and emerging markets and analyse related diversification benefits. The main conclusions of these literatures are that the benefits of international diversification come from weak correlation between developed and emerging markets, and the time-varying correlation has significant impact on this benefit. Moreover, Bianconi et al. (2011), and Kenourgios et al. (2011) show that after the recent financial crisis, there has been a general trend of increasing correlations, but they fail to suggest if the impact of the crisis on correlation pattern was short or long lived. This is important, as a permanent change means that there will crucial implications for the management of the international stock portfolios.

As mentioned above, there are two contradicting views regarding how a financial crisis changes the existing links between international stock markets. The first one is that the effect a shock on correlation levels may be permanent. According to Minsky (1992) crises can have major impact on the fundamentals of an economy and a financial shock might lead to structural changes to the financial markets. The same conclusions are found by Whalen (2008). On the other hand, there is the view that there is only a temporary change in the correlation levels following the occurrence of a crisis. Forbes and Rigobon (2002) suggest the impact of crisis on correlation will often be short term and not long-lasting pattern. Additionally, while investigating the impact of the recent financial crisis on global banking, Shehzad and De Haan (2013) find there has only been a temporary shock in the stock prices of banks in emerging countries and the prices recovered fairly quickly. However, the stock prices of banks in industrial countries remained at a lower level, relative to the pre-crisis period.

2.4. Summary

In this chapter, the theoretical backgrounds of the contagion effect, the channels by which they are transmitted from the country where the crisis has originated to other economies were discussed. Additionally, the methods used by various research studies for assessing the presence of contagion are outlined. Moreover, previous literature on integration and time varying correlation of stock market are compared.

From the above literature and findings, it can be observed that there is still controversy which remains regarding the best method to empirically distinguish between contagion and interdependence, and whether markets are integrated. The standard approach in the literature is to test whether an empirical measure of linkages between markets differs significantly between tranquil and crisis periods. However, my observation is that those tests typically do not allow for those linkages to vary within each of market states. Hence, existing results could be biased and, e.g., falsely identify contagion where a higher level of spillovers in a crisis period would have been observed anyway, even in the absence of a crisis, due to long-term trends in financial integration among markets (e.g. globalisation). Another way by which exiting literature might be biased is by identifying contagion during the crisis period and assuming the transmission of shock during a crisis is identical across the whole crisis period and all days of the week. The model proposed in this study discriminates empirically between genuine contagion and changes in linkages due to long-term processes such as globalisation. Another issue that this research addresses is that whether the shock transmission mechanisms return to their previous state once a financial crisis has passed, as some studies suggest that a crisis changes the connectedness between markets permanently (Gebka and Karaglou 2012) while others assume that post- and pre-crisis linkages are identical (Baur, 2012). However, even those research studies which report a change seem to be ignoring the fact that linkages would have evolved even if there was no crisis. Hence, different spillovers before and after crises might simply illustrate the progressing globalisation rather than the impact of crises on interdependencies between markets. Another issue with previous literature is that they look at the average co-movement during a crisis period, and hence generating a yes or no answer to contagion. The findings pertaining to such research studies might be misleading for diversification purposes, as contagion is a phenomenon that occurs intermittently over a crisis period. As a result, instead of looking at overall contagion during a turmoil period, this study explores financial contagion at different stages of a crisis and over the different days of the week.

Chapter 3: Financial Contagion: A new approach robust to trends in globalisation and interdependence

3.1.Introduction

In this chapter, I propose an improved approach to identify financial contagion, by accounting for the existence of trends on the linkages between equity markets, due to continuing globalisation. One existing strand of the literature model contagion as an increase in otherwise constant linkages between markets, whereas another strand attempts to explicitly model the relationship between financial linkages and economic fundamentals. The proposed model is a straightforward method which accounts for trends in financial linkages without the need for explicit modelling of their dependence on changes in fundamentals and allows for a description of how contagion evolves during a crisis period, thus bringing together two strands of the existing literature.

The outbreak of the Global Financial Crisis in 2007 attracted vast interest of academics, practitioners, policy makers, and the public in the topic of financial contagion. And as discussed in the previous section of this thesis, there are several core issues that remain ambiguous and unresolved, even though there have been several academic studies on contagion. Firstly, there is no commonly accepted definition of contagion; for instance, the World Bank (2016), offers three different explanations, Pericoli and Sbracia (2003) identify no fewer than five definitions of contagion proposed in the literature, and Forbes (2012) lists eleven research studies, each with its distinctive definition of contagion. Secondly, and related, there are multiple distinct empirical methods proposed to test for the existence of contagion, including conditional probabilities (e.g., Rose and Wyplosz, 1996, Hartmann, et al., 2004), correlation analysis (e.g., Forbes and Rigobon, 2002, Brière et al., 2012, Støve et al., 2014), VAR models (e.g., Climent and Meneu, 2003, Rigobon, 2003, Gebka and Serwa, 2006, Blatt et al., 2015), multivariate GARCH models, often involving endogenous regimes in parameters (e.g., Hamao et al. 1990, Gebka and Serwa, 2007, Chiu et al., 2015, Dungey et al., 2015), etc.

Regarding the definition of contagion, a consensus appears to be forming that interrelationships, or return spillovers, among stock markets worldwide are a natural and rational phenomenon, as countries are linked to each other by economic fundamentals, such as foreign trade and FDI, common bank creditors, and actions of portfolio investors. These investors can rationally respond to common news, liquidity shocks, changes in wealth inducing risk aversion variations, or can hedge against macroeconomic risks. Hence, it can be rational for stock markets to move together over time, and for those co-movements to be stronger, e.g., in times of high volatility. Only if those co-movements become excessively high and cannot be attributed solely to changes in fundamental links between markets, can financial contagion be assumed (Forbes and Rigobon., 2002, Karolyi, 2003, Boyer et al., 2006, etc.).

One problem of such a definition immediately becomes apparent, however: how can one discriminate between fundamentals-based (i.e., rational) and contagious (i.e., excessive) spillovers? One branch of the literature proposes to explicitly model the dependence of inter-market linkages on observed variables which proxy economic fundamentals, such as exchange rates, foreign trade, state of the banking system, macroeconomic condition of the domestic economy, industry structure (mis-)alignment, informational links with the world, etc. (Ng, 2000, Bekaert et al., 2005,2014 and Baele, Inghelbrecht, 2010). Contagion is identified in this approach when, for example, idiosyncratic country shocks derived from such a factor model are still dependent on foreign markets during crisis, or when there is an unexpected increase in those residual correlations or factor loadings, that is, if changes in those fundamentals explicitly accounted for cannot fully capture the observed dependence of one market on another. However, firstly, it is not clear which precise variables should be included in such a model to fully capture the impact of fundamentals on interdependencies among markets, which will lead to possible model misspecifications due to omitted variable bias and potential incorrect inference about existence of contagion. Secondly, as many empirical proxies of fundamentals are only available at low frequencies, a researcher is left with either too few observations in the crisis period (when fitting the model to low frequency data), or high persistence and low volatility of explanatory variables (when regressing high frequency stock returns on low frequency economic variables), especially if the crisis period under investigation was short.

An alternative approach to capture contagion is to test for a significant increase in co-movements between markets in the crisis versus the pre-crisis period, so allowing utilisation of higher frequency data. Using raw correlations for this purpose, as in King, Wadhwani (1990), can result in biased inference, however, as correlations tend to rise simply due to an increase in volatility in one market, even if the strength of the links between markets' returns has not changed. Hence, either adjusted correlations are employed (Forbes and Rigobon, 2002), or, alternatively, a measure of co-movements, the slope coefficient from a regression of one market's return on another, is investigated for an increase during crisis. The latter approach appears very popular in the literature. The common feature of these approaches is that they assume constant co-movements within each sub-period.

However, empirical studies demonstrate that co-movements between markets' returns vary over time and tend to follow upward trends due to progressing globalisation (e.g., Brière et al., 2012, Baele and Inghelbrecht, 2010, Pukthuanthong and Roll, 2009, Carrieri et al., 2007, Bekaert et al., 2011).[1] In addition, linkages between markets during the crisis period are not time-invariant either, as several research studies identify different phases within crisis episodes (Chiang et al., 2007, Fry-McKibbin et al., 2014, Dungey and Gajurel, 2014, Dungey et al., 2015, Kenourgios and Dimitriou, 2015). Hence, a model with constant pre-crisis and crisis co-movements (betas) could lead to biased inference about existence of contagion, as it might falsely identify contagion where a higher level of spillovers at the end of the sample period would have been observed anyway, even in the absence of a crisis, due to long-term trends in financial integration among markets (e.g., globalisation). Further, it would fail to capture the time-varying nature of those movements and the possible contagion within the crisis period, as those would have been assumed to be constant throughout the crisis.

This chapter contributes to existing literature in several ways. Firstly, a new method to empirically discriminate between contagion and changes in linkages between financial markets which only occur due to long-term processes such as globalisation or disintegration is proposed. This approach does not require an identification of fundamental variables, and is applicable to easily available, higher-frequency return data. Secondly, the model employed in this paper allows contagion to occur only during specific stages of the crisis. Thirdly, rather than generating a yes/no answer to the contagion question, it allows us to distinguish among different types of contagion, which we term 'shock', 'recoupling' and 'kink' contagion. In addition to this, statistical tests for each of these forms is also conducted. Lastly, the empirical analysis of the 2007-9 episode shows that genuine contagion was less common than what could have been concluded using standard approaches, and that it occurred in different forms and at different phases of the crisis period in different countries.

The rest of this chapter is organised as follows. Section 3.2 describes the methodological framework to differentiate among different types of and test for financial contagion. Empirical methodology and data are presented in Sections 3.3 and 3.4, respectively, whereas Section 3.5 describes the results and Section 7 summarises our findings and concludes.

[1] Reversals of globalisation, or disintegration, and no trends in integration are also possible, but empirically less relevant in my dataset, as demonstrated in the empirical part. Even if I mostly give examples based on progressing globalisation, my model is flexible and allows for any trend, positive or negative, or lack of trends in the integration process.

3.2. Methodology Framework

3.2.1. The Sub-period Specific Constant Spillovers Model

The starting point is the following model of financial contagion which assumes spillovers parameters to be constant in sub-periods (as, e.g., in Baur (2012)):

$$R_{i,t} = \alpha_0 + \beta_1 R_{W,t} + \beta_2 R_{W,t} D_{t,CRISIS} + \epsilon_{i,t} \tag{3.1}$$

where $R_{i,t}$ denotes stock returns in country *i* at time *t*, $D_{t,CRISIS}$ is a dummy variable equal to one during the crisis period and zero otherwise, and $R_{W,t}$ is the return on the world stock market index at time *t*. The estimated coefficients β measure the average impact of world market returns on returns in country *i* during the non-crisis (β_1) and crisis ($\beta_1 + \beta_2$) period. Contagion is defined in this approach as a significant positive change in the impact of the world stock market returns on individual country's returns during the crisis period, i.e., $\beta_2 > 0$.

There are several implicit assumptions underlying this model. Firstly, it assumes pre- and post-crisis periods to be identical in terms of the effect the world market exerts on country *i* (i.e., β_1 is implicitly assumed to be identical pre- and post-crisis). Since in (3.1), β_2 captures the change in average return co-movement over and above the non-crisis period (i.e., both pre- and post-crisis), but contagion is defined as an increase in β as compared to the pre-crisis period, if the pre-crisis and post-crisis periods' βs are different, the coefficient β_2 as given by model (3.1) will be biased. This biasedness will increase with the length of the post-crisis period and/or the degree of difference between pre-and post-crisis periods. Secondly, this model imposes a restriction that the intercept term, α_0, is constant across subperiods, confining all the effects from the crisis to manifest themselves in the slope coefficient β_2. Hence, it rules out, for example, a level shift in conditional country's *i* returns caused by the crisis, which can result in biased estimates of parameter β_2 and incorrect inference about the existence of contagion.

Furthermore, (3.1) assumes that the links between the world and the national market are constant within each sub-period (i.e., β_1 and β_2 are not time-varying). This feature does not allow for trends in financial linkages, as measured by β, prior to, during, and after the crisis period (due to, e.g., progressing globalisation), nor does it allow contagion to evolve during the crisis period. As mentioned in Section 3.1, contagion might be short-lived, and although perhaps being evident for part of the crisis period, model (3.1) will only capture contagion if its effect is strong enough to dominate the entire crisis period. And yet, if contagion is evident for even a short time, a robust test should be able to identify it. Below, I propose an extension to model (3.1) and provide a detailed demonstration of how a model such as (3.1), which assumes sub-period constant linkages, can mis-specify the existence of contagion.

3.2.2. The Globalisation Model

To address the potential issues identified with model (3.1), I propose a new model which is referred to as the 'Globalisation Model':

$$R_{i,t} = \alpha_0 + \alpha_1 D_{t,CRISIS} + \alpha_2 D_{t,POST-CRISIS} + \beta_{1t} R_{W,t} + \beta_{2t} R_{W,t} D_{t,CRISIS} + \beta_{3t} R_{W,t} D_{t,POST-CRISIS} + \varepsilon_{i,t} \quad (3.2)$$

where

$$\beta_{1t} = \delta_0 + \delta_1 t \quad (3.2A)$$

$$\beta_{2t} = \gamma_0 + \gamma_1 t \quad (3.2B)$$

$$\beta_{3t} = \theta_0 + \theta_1 t \quad (3.2C)$$

and $D_{t,POST-CRISIS}$ equals one in the post-crisis period and zero otherwise. Eq. 3.2 also contains an additional variable, the time trend "t"

If 3.2A, 3.2B and 3.2C are substituted into 3.2, it leads into the following model to be estimated:

$$R_{i,t} = \alpha_0 + \alpha_1 D_{t,CRISIS} + \alpha_2 D_{t,POST-CRISIS} + \delta_0 R_{W,t} + \delta_1 t R_{W,t} + \gamma_0 R_{W,t} D_{t,CRISIS} + \gamma_1 t R_{W,t} D_{t,CRISIS} + \theta_0 R_{W,t} D_{t,POST-CRISIS} + \theta_1 t R_{W,t} D_{t,POST-CRISIS} + \varepsilon_{i,t}$$

The resulting parameter estimates, δ_0, δ_1, γ_0, γ_1, θ_0, and θ_1, which are referred to in Figure 3.1 are then used to construct the "beta" estimates as defined in 3.2A, 3.2B and 3.2C. They also enable to obtain an estimate of any parameter "beta" at any point in time "t". For example, if the crisis starts in week $t = \tau 1$, the point estimate of β_{1t} at $t = \tau 1$ can be obtained by substituting $t = \tau 1$ into 3.2(A) to obtain $\beta_{1t} = \hat{\delta}_0 + \hat{\delta}_1 t$. This will assume a specific value (for week $\tau 1$) and the same procedure can be employed to estimate any "beta" at any given point in time "t".

The most important feature of model (3.2) is that it allows for a (linear) temporal development in the level of integration β between the stock market of country *i* and the world, a process which can be different in each sub-period. This is achieved by allowing each parameter β to be a function of time *t*.[2] In the pre-crisis state, δ_1 measures the pace of globalisation, while in the

[2] Here, long term trends in market integration are modelled as linear functions of time. More complex, non-linear processes could be imposed, but at a risk of capturing transitory variations in market integration trends rather than

crisis period, the difference in the pace of globalisation from its pre-crisis trajectory is given by γ_1; post-crisis, the difference in the pace of globalisation from the pre-crisis period is given by θ_1. Hence, the new model, (3.2), allows for temporal variation of β_t within each subsample, addressing an issue with (3.1) described above. Figure 3.1 shows an example of a diagrammatic representation of how these coefficients can be considered in terms of the temporal development of β_t parameters.

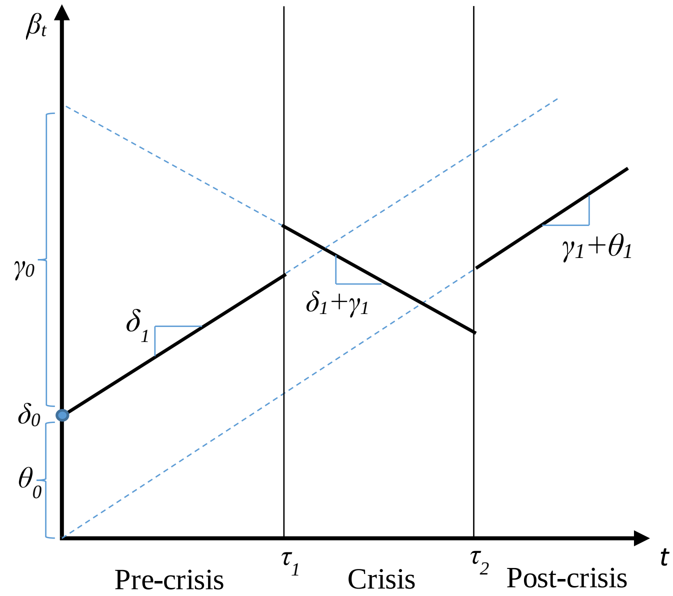

Figure 3.1: Coefficients of the Globalisation Model (3.2)

In summary, model (3.2) addresses all the main concerns identified with model (3.1) and is a more flexible specification than that those assuming sub-period specific constant integration levels, as represented by (3.1). It should be noted that model (3.2) nests (3.1): if α_1, α_2, δ_1, γ_1, and β_{3t} are all constrained to be zero, then model (3.1) results. Only where this is the case, would there be no potential misspecification bias in using (3.1) as opposed to (3.2). Model (3.2) differs from (3.1) in a number of respects. First, it allows for differences in the impact of the world on the national market between the pre- and the post-crisis period, as modelled by distinct coefficients β_{1t} and $\beta_{1t} + \beta_{3t}$, respectively. Hence, the post-crisis period is not assumed to be identical with the pre-crisis one (β_{3t} can be different from zero). β_{2t} in Model (3.1) represents change in co-movement over and above the non-crisis period. And if the pre-crisis and post-

genuine long-run processes. Moreover, the first week of the crisis period (i.e. Week 1451) is represented by $\boldsymbol{\tau_1}$ in this study. And $\boldsymbol{\tau_2}$ and $\boldsymbol{\tau_3}$ represents the last week of the crisis period and first week of the post crisis period, respectively.

crisis period are treated as the same, this might result into potential overestimation or underestimation of β_{2t}.

The underestimation of β_{2t} might arise if there is an increase in the co-movement between the World stock market portfolio and the individual countries' stocks during the post crisis. As it can be seen from Figure 3.2A below, if β_{3t} is higher during the post crisis period, it suggests that β_{2t} has been underestimated in the first model. The dashed line shows the level of co-movement between the World Stock Market portfolio with the stock returns of the individual countries during the pre-crisis period by using Model (3.1), where the pre and post crisis period were assumed to be identical. The solid lines, on the other hand, represent the level of co-movement between the World Stock Market portfolio and the individual markets, across the different regimes (i.e. pre-crisis, crisis and post crisis period), by using Model (3.2). Hence, treating the pre and post crisis as identical might lead to biased contagion result.

And on the other hand, if β_{3t} is lower on average during the post-crisis period, it might lead to potential overestimation of β_{2t} if the pre-crisis and post-crisis were treated as the same (i.e. by using Model (3.2.1)). This is displayed through Figure 3.2B below.

Figure 3.2: Underestimation and Overestimation of β_{2t} from model (3.1)

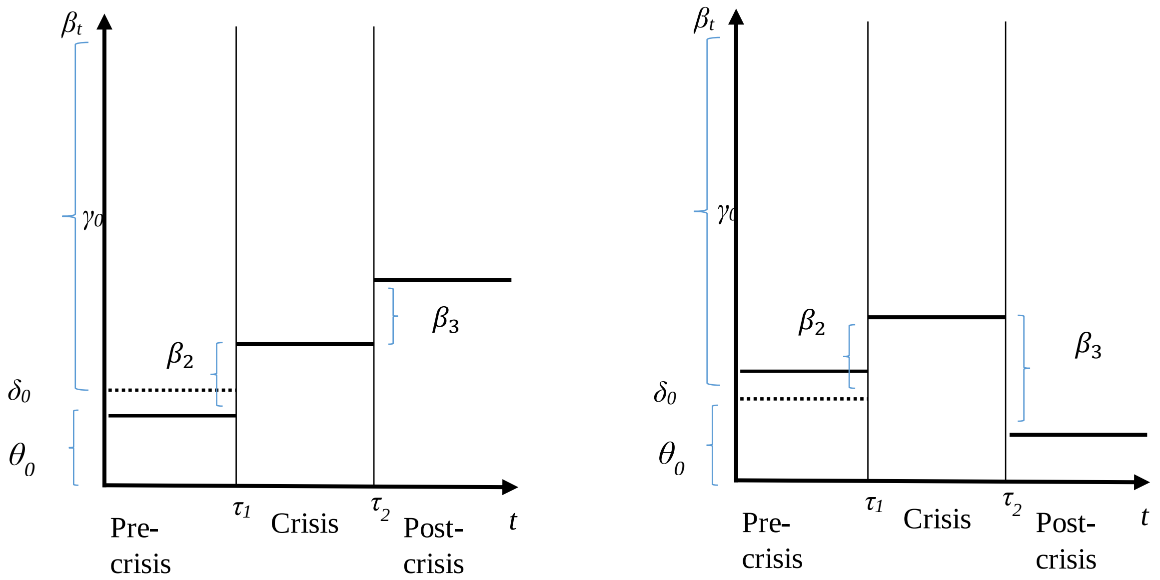

Figure 3.2A *Figure 3.2B*

The second advantage of model (3.2) over (3.2) is that it allows for changes in the intercept α across all sub-periods. In the former model, a non-time varying constant term was assumed. In other words, all changes were being captured by the β_t even if the intercepts were changing, which might lead biased β_t coefficients and contagion results. However, if the intercept is varied across time, i.e. a dummy is assigned for the constant term during the crisis and the non-crisis period, this might potentially lead to more reliable estimates of contagion.

And thirdly, given the specification of (3.2), the degree of stock market integration, β_t, is not assumed to be constant over time in each sub-period (as was the case in (3.1)), but can evolve over time as a result of, for instance, increasing globalisation in the pre-crisis period. In model (3.1) with constant sub-period betas, contagion was defined as a significant increase in β due to crisis' outbreak ($\beta_2 > 0$). However, if β is, for example, increasing over time due to progressing globalisation, then the average β_t in the later part of any sample will always be higher than the average β_t in the earlier part of the same sample, even if there was no crisis towards the end of the sample (or if the crisis was present but did not affect the financial integration process β_t). Hence, (3.1) will tend to find "contagion" (defined as an increase in average β_t) even when there is none, provided there is a process of increasing integration. Therefore, we define contagion not as an increase in average β_t but as existence of higher values of β_t in the crisis period compared to what would have been expected if the evolution of β_t observed pre-crisis continued unaffected into the crisis period.

To further explain this definition of contagion, which accounts for pre-crisis trends in financial interdependence as measured by β_t, as well as the difference between the identification of contagion in model (3.1) versus (3.2), Figure 3.3A and 3.3B provides examples of two hypothetical stock markets, assuming no post-crisis period for simplicity. The solid lines show values of β_t coefficients implied by model (3.2), in pre-crisis ($\hat{\beta}_{1t}$) and crisis ($\hat{\beta}_{1t} + \hat{\beta}_{2t}$) period. The dotted lines represent average values of β_t in both subperiods, as would have been measured by model (3.1): $\hat{\beta}_1$ and ($\hat{\beta}_1 + \hat{\beta}_2$). The dashed line in the crisis period indicates β values which should be expected in the "crisis period" if there had been no impact of the crisis on the process of market integration (i.e., no contagion), and is obtained by extrapolation of the pre-crisis process in β (i.e., $\beta_t = \beta_{1t} + \beta_{2t} = \delta_0 + \delta_1 t$, assuming $\gamma_0 = \gamma_1 = 0$ in (3.2)). In example A, $\delta_1 > 0$ but $(\delta_1 + \gamma_1) < 0$; in other words, the process of integration or globalisation reverses following the outbreak of the crisis at time $t = \tau_1$.

Figure 3.3: Difference between model (3.1) and (3.2)

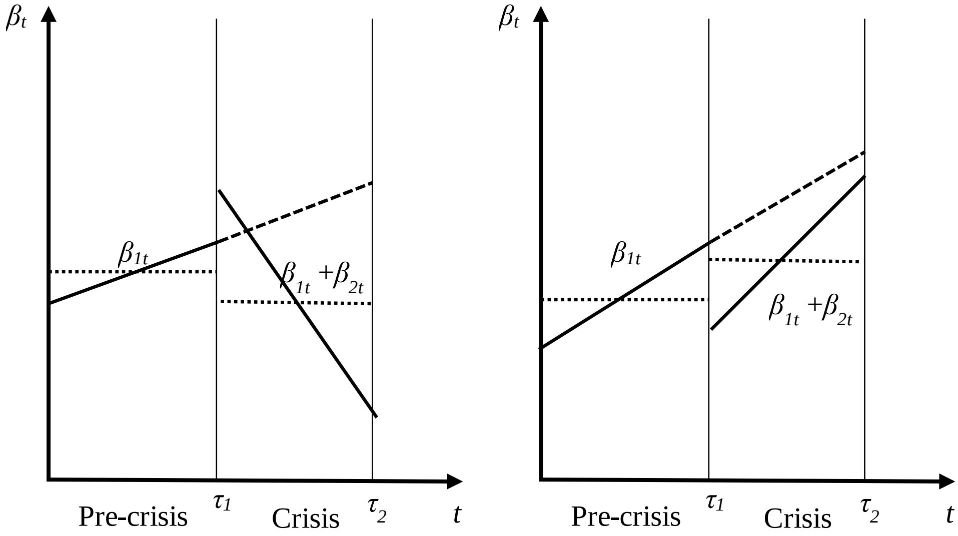

Figure 3.3A *Figure 3.3B*

It is evident that the outbreak of the crisis has affected the financial integration process (solid line), as, in example 3.3A, there is a discontinuity in β_t at crisis' start, and the intertemporal behaviour of β_t has changed in the crisis as well (market *i* increases its integration with the world market pre-crisis but is dis-integrating from it in the crisis period). In addition, β_t values in the first phase of the crisis are not only higher than pre-crisis but also higher than they would have been (dashed line) if the crisis had no effect on the financial integration process (β_t). Hence, one would conclude that there is evidence of contagion. However, using a definition of contagion that the *average* level of financial spillovers (β_t) is higher following the outbreak of a crisis (as in (3.1)), one would incorrectly conjecture that there was no contagion, as the average β_t during the crisis period is lower, not higher, than the average pre-crisis β_t (dotted lines).

Example 3.3B provides another demonstration of differences between model (3.1) and (3.2). This time, a negative shock to the financial integration process (β_t) at crisis' start (t=τ_1), followed by a higher pace of globalisation process during the crisis (as indicated by a higher slope of β_t) is demonstrated. If one defined contagion as a rise in the *average* level of financial spillovers (β_t) pre- vs during the crisis, the conclusion would be that contagion was observed here, as the *average* β_t is higher following the crisis' inception (dotted lines). However, it can also be observed that β_t values during the crisis (solid line) are lower, not higher, than they would have been if the pre-crisis process in β_t continued unchanged into the crisis period, i.e., if the crisis' outbreak did not affect the financial integration process (represented by the dashed line). Hence, the observed values of β_t are relatively too low during the crisis, which I suggest is to be interpreted as weaker, not stronger, co-movements in the crisis period, i.e., no contagion but rather decoupling.

In addition to the more robust identification of contagion, model (3.2) also allows for insights into the exact intertemporal nature of the financial integration process in each sub-period. For instance, in Figure 3.3A it would unveil a very high level of spillovers at the beginning of the crisis and a reversal of the financial integration process following the crisis' outbreak, both important features of financial integration which would remain unnoticed if one was employing a model of constant sub-period β_t coefficients, such as model (3.1). As a result, allowing the β_t to evolve across the different regimes might prove to be important to identify true contagion, as the latter may occur for only a short period of time (e.g., at the start or end) during the crisis period, and this is not captured by model (3.1).

Consequently, the "Globalisation Model" allows the linkages between the individual stock markets and the World Stock market portfolio to vary across time, is constructed to address the limitations of the model (3.1). The details on how evidence of contagion is captured by this model are explained below.

3.2.3. *Identifying Different forms of Contagion under the Globalisation Model*

Based on the "Globalisation Model" established the previous section, I propose a new definition of financial contagion. Contagion can be identified as an increase in β_t during the crisis period, over and above of what it would have been if the linkage between the individual country and world stock market portfolio was following the same process as in the pre-crisis period. Moreover, this increase in β_t can be at any point during the crisis and β_t is not necessarily higher during the whole crisis period, to provide for evidence of contagion.

Contagion can be identified in the following situations by estimating model (3.2):

a. <u>"Shock" Contagion</u>

The term "shock" contagion is defined as a positive jump in the co-movement (β_{2t}) between the stock market of the individual countries in this study and the world stock market portfolio, following the outbreak of the crisis. In other words, it means that $\beta_{2t} > 0$ at the starting point of the crisis period ($t = \tau_1$). Following this initial rise in the co-movements of stock returns with the world market portfolio (β_{2t}), there are different scenarios which may occur during the crisis period:

i. An increase in the slope of the linkages between the individual stock markets and the world market portfolio, during the crisis as compared with the pre-crisis period. (i.e. $\gamma_1 > 0$)

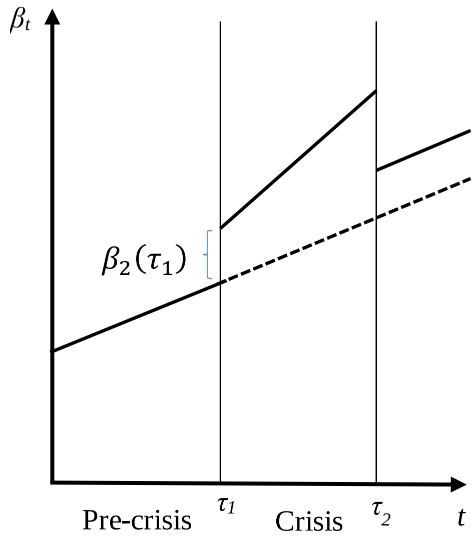

Figure 3.4A: Shock contagion ($\beta_2(\tau_1) > 0$ (Week 1451); $\delta_1 > 0$; $\gamma_1 > 0$)

ii) A decrease in the slope of the linkages between the individual stock markets and the world market portfolio, during the crisis as compared with the pre-crisis period. (i.e. $\gamma_1 < 0$)

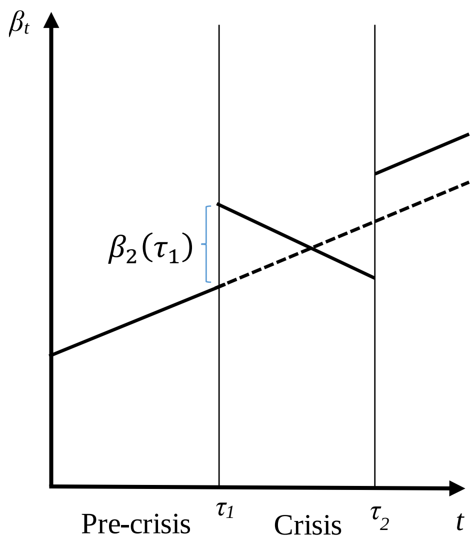

Figure 3.4B: Shock Contagion ($\boldsymbol{\beta}_2(\tau_1) > \mathbf{0}$ (Week 1451); $\boldsymbol{\delta_1} > \mathbf{0}$; $\boldsymbol{\gamma_1} < \mathbf{0}$, $\boldsymbol{\delta_1} + \boldsymbol{\gamma_1} < \mathbf{0}$)

iii) No change in the slope of the linkages between the individual stock markets and the world market portfolio, during the crisis as compared with the pre-crisis period. (i.e. and γ_1= 0)

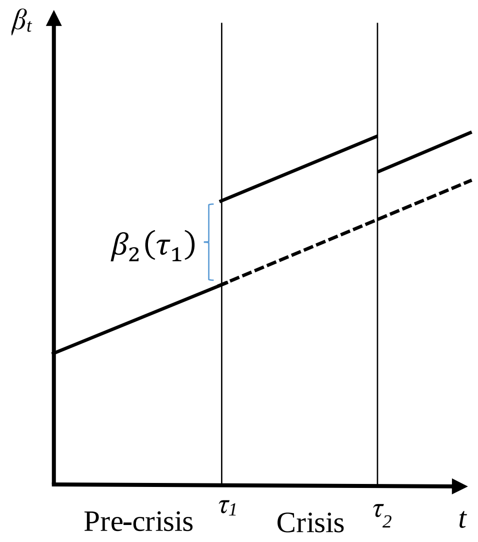

Figure 3.4C: Shock Contagion ($\boldsymbol{\beta}_2(\tau_1) > \mathbf{0}$ (Week 1451); $\boldsymbol{\delta_1}$ **> 0**; $\boldsymbol{\gamma_1}$**= 0)**

In all of these situations, "shock contagion" is identified if, following the outbreak of a crisis, the value of β_t at crisis' onset is higher than it would have been had the pre-crisis integration process still prevailed.

b. <u>"Recoupling" Contagion</u>

"Recoupling" contagion refers to a situation where there is an initial fall in the co-movement between the individual stock market and the world stock market ($\beta_{2t} < 0$ at $t = \tau_1$), followed by a subsequent rise in β_t above the level which would have prevailed had there been no impact due to the crisis. This situation can be defined as contagion only if there is an increase in the slope (γ_1> 0) during the crisis period, as this is a necessary condition for β_t to be higher at a certain point during the crisis than what it would have been if the shape of integration process had been the same as in the pre-crisis period. With this increase in slope, β_t must be higher at the end of the crisis period than what it would have been if the prior integration process had prevailed. For the "recoupling contagion" to exist, it is irrelevant whether the slopes of financial integration process β_t pre- and during crisis are positive or negative; but the latter period must have a higher slope than the former.

The following show possible situations which might arise within the "recoupling" contagion:

i) $\beta_{2t}(\tau_1) < 0$ (β_t declines in week 1 of the crisis, but increases at higher pace than pre-crisis thereafter ($\gamma_1 > 0$), consequently β_t is higher during certain part of crisis period than what it would have been if the same globalisation process as in the pre-crisis period was being followed); increasing globalisation pre-crisis: $\delta_1 >$ 0

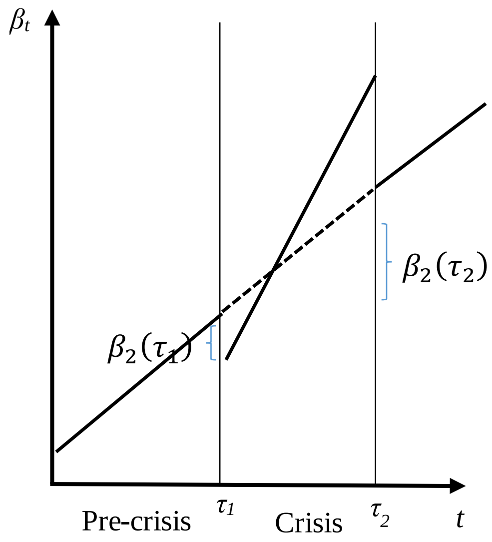

Figure 3.5A: Recoupling Contagion ($\beta_2(\tau_1) < 0$ (at Week 1451); $\delta_1 < 0$; $\gamma_1 > 0$)

ii) same as i) but decreasing globalisation during pre-crisis: $\delta_1 < 0$;

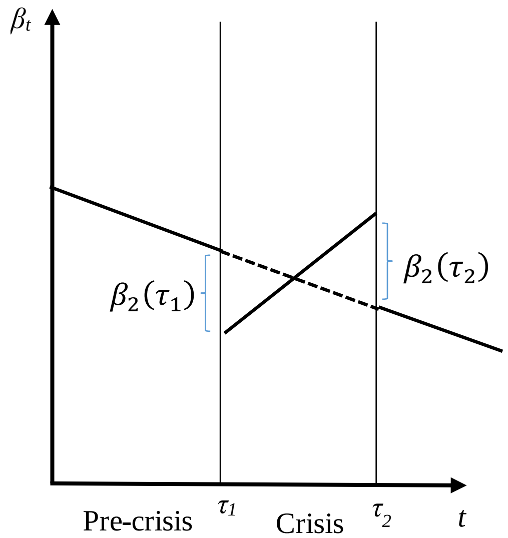

Figure 3.5B: Recoupling Contagion ($\beta_2(\tau_1) < 0$ (at Week 1451); $\delta_1 < 0$; $\gamma_1 > 0$)

iii) same as i) but constant globalisation during pre-crisis: $\delta_1 < 0$; In addition, the crisis period can be characterised by a negative, positive, or zero overall slope $(\delta_1 + \gamma_1)$

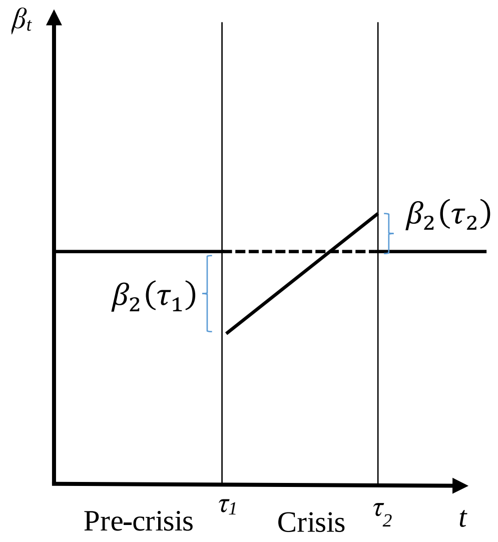

Figure 3.5C: Recoupling Contagion ($\beta_2(\tau_1) < 0$ (at Week 1451); $\delta_1 = 0$; $\gamma_1 > 0$)

c. <u>"Kink" Contagion</u>

Unlike in the previous two situations, "kink contagion" can occur when there is no abrupt change in co-movements between the individual country and the world stock portfolio during the first week of the crisis (i.e., $\beta_{2t} = 0$ at the starting point of the crisis, $t = \tau_1$). Instead, contagion is identified provided there is an increase in the slope ($\gamma_1 > 0$) during the crisis period and consequently β_t is higher during the crisis than what it would be if the process of integration process has been the same as in the pre-crisis period. For the "kink contagion" to prevail, it is irrelevant whether the slopes of financial integration process β_t pre- and during crisis are positive or negative; but the latter period must have a higher slope than the former.

The following graphs show the different situations that might arise within the "Kink Contagion".

i) No abrupt changes in $\beta_{2t}(\tau_1)$ (i.e. $\beta_{2t}(\tau_1) = 0$ in week 1 of the crisis, but the slope of β_t increases as compared to the pre-crisis period ($\gamma_1 > 0$), so that β_{2t} is higher at during the crisis period than what it would have been if the same globalisation process as the pre-crisis period was being followed); increasing pre-crisis globalisation ($\delta_1 > 0$)

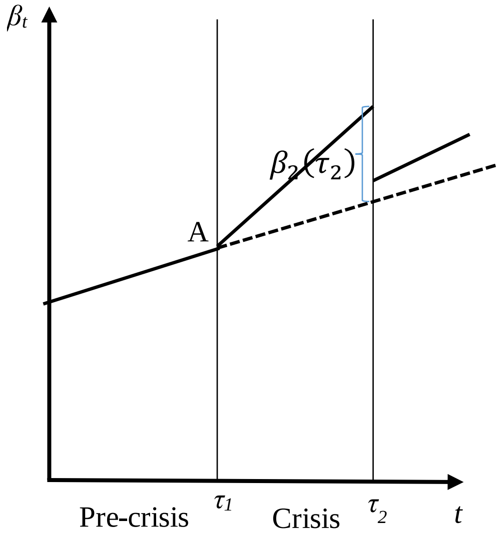

Figure 3.6A: Kink Contagion ($\beta_2(\tau_1)$ = 0 (at Week 1451); δ_1 >0; γ_1> 0)

ii) Same as in i) but constant pre-crisis globalisation (δ_1 = 0)

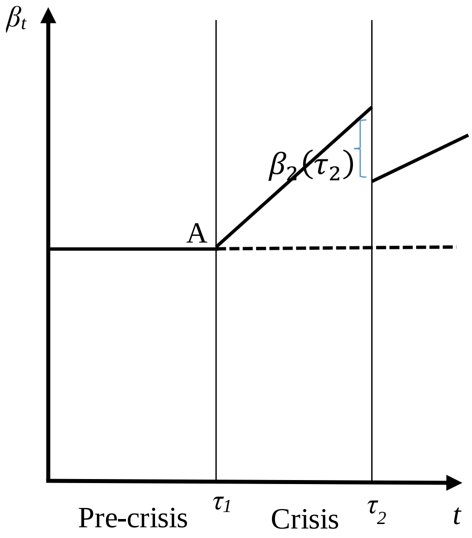

Figure 3.6A: Kink Contagion ($\beta_2(\tau_1)$ = 0 (at Week 1451); δ_1 =0; γ_1> 0)

iii) Same as in i) but decreasing pre-crisis globalisation (δ_1 < 0);

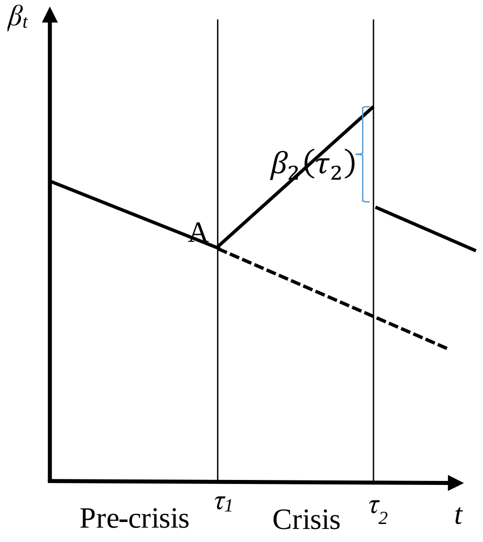

Figure 3.6C: Kink Contagion ($\beta_2(\tau_1)$ = 0 (at Week 1451); δ_1 <0; γ_1> 0)

3.2.4. Tests for Different Forms of Contagion under the Globalisation Model

As mentioned in the previous sub-section, the occurrence of contagion can be categorised into three scenarios, namely, "shock", "recoupling" and "kink contagion". The level of β_t at each point in time across the crisis period can easily be calculated from the estimated model (2), both the crisis-specific β_t values as well as those values which would be observed if the pre-crisis process in β_t continued unchanged into the crisis period. Specifically, the estimated value at each point in time within the crisis period can be calculated using: $\hat{\beta}_t = \hat{\beta}_{1t} + \hat{\beta}_{2t} = \hat{\delta}_0 + \hat{\gamma}_0 + (\hat{\delta}_1 + \hat{\gamma}_1)t,$ where the 'hats' represent estimated coefficient values, and *t* is in the range $\tau_1 \leq t \leq \tau_2$ (during the crisis period). If crisis outbreak had no effect of the process of β_t (i.e., $\hat{\beta}_{2t} = 0$), those crisis betas could be estimated using the coefficients governing the process in the pre-crisis period and would equal $\hat{\beta}_t = \hat{\beta}_{1t} = \hat{\delta}_0 + \hat{\delta}_1 t$, where *t* is the time variable from the crisis period.

Given the estimates of model (2) parameters as well as their variance-covariance matrix, a *t*-test can be performed to test for the significance of the difference in β_t between the crisis β_t values and those which would have been observed if crisis outbreak had had no effect on the intertemporal movement in β_t, at any point in time. Testing the significance of these differences between states is made easier by the fact that β_{2t} captures the difference in the level of β_t between the pre-crisis (β_{1t}) and the crisis ($\beta_{1t} + \beta_{2t}$) period. The form of the *t*-test will depend upon the type of contagion which is being tested for and can be summarised in the following diagram:

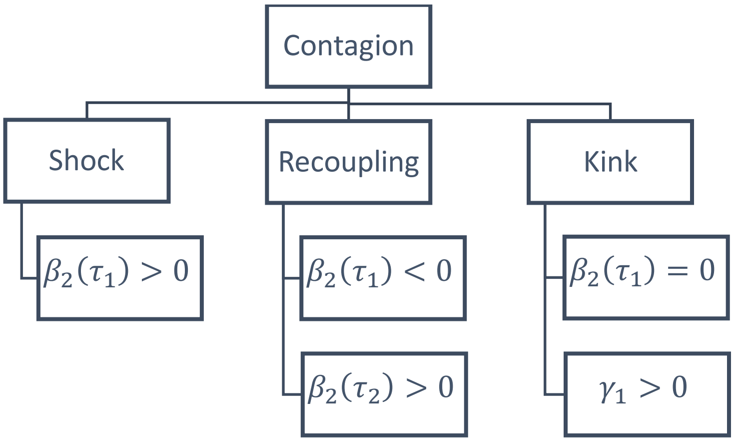

Figure 3.7: T-test to determine the type of contagion

a) *A test for "shock contagion"*

To test for "shock contagion", the level of β_{2t} at the start of the crisis period (t=τ_1) is analysed. In particular, "shock contagion" exists if there is a significant difference in co-movements at crisis' onset between model-implied crisis-specific $\hat{\beta}_t$ (= $\hat{\beta}_1(\tau_1) + \hat{\beta}_2(\tau_1)$) and what would be observed in absence of disruptions in the financial integration process ($\hat{\beta}_1(\tau_1)$). If there is a significant positive difference (i.e., $\hat{\beta}_2(\tau_1) > 0$), this provides evidence for the existence of shock contagion. Figures 3.4A, 3.4B, and 3.4C represent possible scenarios for the evolution of the β_t coefficients and how $\beta_2(\tau_1)$, if statistically significantly positive, would represent the degree of shock contagion. A test on $\beta_2(\tau_1)$ is a one-tailed *t*-test:

$$H_0: \beta_2(\tau_1) \leq 0, \qquad H_A: \beta_2(\tau_1) > 0$$

with $\beta_{2t} = \gamma_0 + \gamma_1 t,\ t = \tau_1$ and where the standard error of the coefficient β_{2t}at time *t*, $SE(\beta_{2t})$, is calculated as: $SE(\beta_{2t})^2 = Var(\gamma_0 + \gamma_1 t) = (Var(\gamma_0) + t^2 Var(\gamma_1) + 2tCov(\gamma_0, \gamma_1) = [SE(\gamma_0)]^2 + t^2[SE(\gamma_1)]^2 + 2tCov(\gamma_0, \gamma_1)$.

The jump is positive and significant during week $t = \tau_1$ (i.e., the first observation of the crisis period) if the null hypothesis is rejected, hence shock contagion would be inferred.

b) A test for "recoupling contagion"

"Recoupling contagion" is present if there is an initial significant fall in the co-movement ($\beta_2(\tau_1) < 0$) and β_t is higher at some point during the crisis compared to what it would have been if the pre-crisis process had continued unchanged. Hence, a suitable test is to find that

$\beta_2(\tau_1) < 0$ and $\beta_2(\tau_2) > 0$ (where τ_1 and τ_2 stand for the first and the last observation of the crisis period, respectively). Figures 3.5A, 3.5B, and 3.5C represent possible scenarios for recoupling contagion. To test for recoupling contagion formally, therefore, requires two tests. The initial step being a one-tailed test with:

$$H_0: \beta_2(\tau_1) \geq 0, \qquad H_A: \beta_2(\tau_1) < 0,$$

and, providing the null hypothesis is rejected, the second step, again one-tailed:

$$H_0: \beta_2(\tau_2) \leq 0, \qquad H_A: \beta_2(\tau_2) > 0.$$

Only if both null hypotheses are rejected can we confirm the existence of recoupling contagion.

c) *A test for "kink contagion"*

"Kink contagion" is referred to as a situation where there is no sudden change in co-movement during the first week of the crisis (i.e., $\beta_2(\tau_1) = 0$), but there is an increase in slope of β_t ($\gamma_1 > 0$) during the crisis period and, consequently, β_t is higher during the crisis than what it would be if the slope of the integration process was the same as in the pre-crisis period. Therefore, firstly a two-sided *t*-test is conducted in order to test whether $\beta_2(\tau_1) = 0$, as there would be evidence of contagion provided that firstly the null of no change in β_t is not rejected and, secondly, the slope of the integration process is significantly higher during the crisis period ($\gamma_1 > 0$) than what it would be if the pre-crisis integration process continued unchanged into the crisis period.[3]

Figure 3.6A, 3.6B, and 3.6C show possible situations where kink contagion would be identified. Unlike in other situations, there is no abrupt change in the co-movement between the world market and the individual country's stock market at the start of the crisis period (point A). However, as the crisis unfolds, β_t is higher than what it would be if the same globalisation process as in the pre-crisis period was being followed, due to $\gamma_1 > 0$ (and leading to $\beta_2(\tau_2) > 0$). Hence, we would interpret the underlying situation as kink contagion. The appropriate testing procedure is therefore:

$$H_0: \beta_2(\tau_1) = 0, \qquad H_A: \beta_2(\tau_1) \neq 0,$$

and, providing the null hypothesis is not rejected, the second step, one-tailed, involves testing:

$$H_0: \gamma_1 \leq 0, \quad H_A: \gamma_1 > 0.$$

Rejection of the null at this second step, following non-rejection at the first, would imply the presence of kink contagion.

[3] Alternatively, instead of testing for an increase in slope ($\gamma_1 > 0$), one could test whether β_t at the end of the crisis period is significantly higher than what it would be in absence of the crisis, i.e., $\beta_2(\tau_2) > 0$.

3.3. Empirical Methodology

Model (3.2) is estimated within a GARCH framework, as the OLS estimation technique may provide not only inefficient but also potentially inaccurate parameter estimates (Hamilton, 2010). More specifically, the Glosten, Jagannathan, Runkle (1993), or GJR, approach is employed to model the process of conditional volatility in residuals. The GJR-GARCH model also captures asymmetries in volatility resulting in positive versus negative shocks. Model (3.2) constitutes the mean equation, whereas the conditional volatility, h_t, is modelled for each country as a GJR-GARCH (p,q)[4] process:

$$h_{i,t} = \omega_i + \sum_{j=1}^{p}(\alpha_{i,j} + g_{i,j}I_{i,t-j})\varepsilon_{i,t-j}^2 + \sum_{k=1}^{q} b_{i,k}\, h_{i,t-k}^2 \qquad (3.3)$$

where $I_{i,t-j} = 1$ if $\varepsilon_{i,t-j} < 0$ and is equal to zero otherwise, $\varepsilon_{i,t-j}$ represents the error term from equation (3.2), for country i, lagged j periods, and it is assumed this error can be decomposed as $\varepsilon_{i,t} = \sqrt{h_{i,t}}v_{i,t}$ with $v_{i,t} \sim iid(0,1)$. This model allows for the impact of past shocks on conditional volatility to be different depending on whether they are positive $(\sum_{j=1}^{p}\alpha_{i,j})$ or negative $(\sum_{j=1}^{p}(\alpha_{i,j} + g_{i,j}))$. Typically for stock market data, one expects $g_{i,j} > 0$, i.e., for a negative shock at lag j to exert a larger impact on conditional volatility of stock returns than a positive shock of the same magnitude, a phenomenon known as the leverage effect (Black, 1976). The GJR-GARCH nests both the GARCH model, which imposes no asymmetries $g_{i,j} = 0$ and the more restrictive ARCH model, $(g_{i,j} = b_{i,k} = 0)$

The combined model (3.2)-(3.3) is subject to a battery of specification tests.

3.3.1. Unit Root test

Firstly, the (log) indices $(P_{i,t})$ and returns $(R_{i,t} \equiv ln(P_{i,t}) - ln(P_{i,t-1}))$ are tested for stationarity using both the Augmented Dickey-Fuller (Dickey, Fuller, 1979) and the Phillips, Perron (1988) tests using the Enders (2010) sequential procedure to select the most appropriate model (with or without deterministic components), to make sure that only stationary variables are used in Eq. (3.2) to avoid potential spurious regression problems.

[4] GJR GARCH model has been selected as it was chosen based on the best Information Criteria (i.e. AIC and BIC). While estimating Eq. 3.2 for each country in the sample a GARCH, E-GARCH, and GJR GARCH have been employed, and based on the AIC and BIC results, GJR GARCH was chosen.

(a) Augmented Dickey-Fuller test

The Augmented Dickey Fuller (ADF) test is used as it is more suited to complicated dynamic structure. This test consists of estimating the following regression:

$$\Delta Y_t = \rho_1 + \rho_{1t} + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t \tag{3.4}$$

Where ε_t is a pure white noise error term and where $\Delta Y_{t-1} = (Y_{t-1} - Y_{t-2})$, $\Delta Y_{t-2}(Y_{t-2} - Y_{t-3})$, etc. In the ADF test, it is tested whether $\delta = 0$. The ADF test whether a variable contains a unit root. The null hypothesis is that it contains a unit root, and the alternative is that the variable was generated by a stationary process. The decision rule is as follows:

- If the estimated (τ)Tau statistic of the regression coefficient > ADF critical value, do not reject null hypothesis, i.e. unit root exists (Not Stationary)
- If the estimated (τ)Tau statistic of the regression coefficient < ADF critical value, reject null hypothesis, i.e. unit root does not exist

3.3.2. Co-integration Test

Second, I test for cointegration between each national and the world (log) index, as existence of cointegration would necessitate an inclusion of an error correction term into Eq. (3.2) to circumvent the omitted variable bias; this is accomplished by employing the Johansen (1991) cointegration test.

A version of Johansen test is employed, where an estimator that minimizes an information criterion is defined. The approach suggested by Gonzalo and Pitarakis (1998) and Aznar and Salvador (2002) is used, where the lag length in an autoregressive model is selected. This approach can be applied to determine the number of co-integrating equations in a VECM. A consistent estimator of the number of co-integrating equations can is provided by choosing the number of co-integrating equations that minimizes the Schwarz Bayesian Information Criterion (SBIC). In case of co-integrated series, the the two-step Error Correction Model (ECM) proposed Engle and Granger (1987), which corrects for disequilibrium in the short run.

3.3.3. Heteroscedasticity

One of the key assumptions of regression is that the variance of errors is constant across observations, i.e. homoscedastic errors. Eq. 3.2 is estimated using OLS and tested for homoscedasticity of residuals.

The White's (1980) test will be used which is a test of the null hypothesis of no heteroscedasticity against heteroscedasticity of unknown, general form. Heteroscedasticity has serious consequences for the OLS estimator and the estimated standard errors is wrong. Hence the confidence intervals and hypotheses test cannot be relied upon.

If the p-value of less than the chosen alpha level, then the null hypothesis is rejected, showing evidence of heteroscedasticity.

3.3.4. ARCH LM tests

Equation (3.2) is firstly estimated by OLS and the residuals are tested for conditional heteroscedasticity using the Engle ARCH LM test. Existence of conditional heteroscedasticity provides further rationale for modelling the error terms within a GARCH framework.

The ARCH LM test which is a Lagrange multiplier (LM) test is used for autoregressive conditional heteroscedasticity (ARCH) in residuals. This particular heteroscedasticity specification was motivated by the observation that in many financial time series, the magnitude of residuals appeared to be related to the magnitude of recent residuals. Ignoring ARCH effects may result in loss of efficiency. The ARCH LM test statistic is computed from an auxiliary test regression, and to test the null hypothesis that there is no ARCH up to order q in the residuals, the following regression is run.

$$\varepsilon_{i,t}^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s \, e_{t-s}^2 \right) + v_t \tag{3.5}$$

Thus, the squared residuals are regressed on a constant and lagged squared residuals up to order q. The squared standardizes residuals can be obtained as follows:

$\hat{s}_t^2 = \varepsilon_{i,t}^2 / \hat{h}_t,$

Where $\widehat{\varepsilon_{i,t}^2}$ is the estimated residuals, and $\hat{h}$ is the variance, are obtained from The Globalisation model.

In order to determine whether there are any ARCH effects in the residuals, the p-value is observed. If the p-value of less than the chosen alpha level (5 % significance level, in this case), then the null hypothesis of No ARCH effect is rejected, and if the p-value is greater than the chosen alpha level, then the null hypothesis cannot be rejected.

3.3.5. Normality Test

The GJR-GARCH model is fitted assuming normal distribution of error terms at first, and the resulting residuals are tested for normality using the Shapiro-Wilk test.

The error term in Eq. (3.2) are assumed to be normally distributed. However, the residuals might not be normally distributed. Hence, the Shapiro-Wilk test is used to test the normality of the residuals. The hypothesis is as follows:

H_0: Residuals are normally distributed

H_1: Residuals are not normally distributed

If the p-value of less than the chosen alpha level (5 % significance level, in this case), then the null hypothesis is rejected, and there is evidence that the residuals tested are not from a normally distributed population.

Where non-normality is found, equation (3.2)-(3.3) is re-estimated under the assumption that residuals follow t-distribution or GED (generalised error) distribution. Subsequently, the final distribution decision (normal, t, or GED) is made based on the information criteria (AIC and BIC), and equation (3.2)-(3.3) is re-estimated.

3.3.6. Autocorrelation

Ljung-Box Q statistics are employed to test whether there remains autocorrelation in residuals. If the standardized residuals display serial correlation, it means that the model of the mean has not been properly specified. The standardized residuals can be expressed as follows:

$\hat{s}_t = \varepsilon_{i,t}^2 / \hat{h}_t^{0.5}$,

Where $\varepsilon_{i,t}^2$ represents the residuals from Eq. (3.2), and $\hat{h}_t^{0.5}$ is the conditional standard deviation. And in order to test for the model of the mean, we propose to perform a Ljung-box Q Statistics for the s_t sequence.

The Ljung-Box test statistic is given by:

$$\mathrm{Q(m)} = \mathrm{N(N+2)} \sum_{\mathrm{h=1}}^{\mathrm{m}} \frac{\hat{\mathrm{p}}_{\mathrm{h}}^2}{\mathrm{N-h}} \tag{3.6}$$

The null hypothesis for this test is that the first m autocorrelations are jointly zero,

H_0 = p1=p2=…=pm=0

and the null hypothesis of the evidence of serial correlation cannot be not rejected if the various Q statistics are equal to zero.

Where evidence of autocorrelation is identified, the residuals are these are modelled as an ARMA process of an appropriate order established empirically. In addition to this, the Engle's LM ARCH test (mention in sub-section 3.3.3) is applied to the standardised residuals to test whether using a GJR-GARCH specification fully captures the ARCH effects in residuals.

A general-to-specific approach in estimation of equation (3.2)-(3.3) is employed. Initially, the full model allowing for linear trends in coefficients β_t in each subperiod is estimated. Next, those trend coefficients found insignificant are dropped from the regression and the reduced model (3.2.2) is estimated. This ensures that the precision of parameter estimates is not negatively affected by the presence of insignificant variables.

3.4. Data

Following Baur (2012), for the main stock index in each of 25 major world economies[5], daily closing prices in local currency are obtained from DataStream for the period 27th October 1979 to 27th March 2012. Mink (2015) demonstrates that returns converted into a common currency also reflect fluctuations in exchange rates, which biases inference about contagion. The sample does not contain more recent observations as otherwise the post-crisis period would be too heterogeneous, especially given economic and political turbulences which took place during that time, hence the differentiation between crisis and post-crisis periods would be more difficult and less precise.

The indices estimated by DataStream are used rather than those provided by other providers, for example, the national stock exchanges, as the former are based on a common methodology and, hence, more comparable across countries than the latter. I calculate weekly Tuesday-close-to-Tuesday-close returns, resulting in 1,693 weeks in the sample, as using weekly data helps to mitigate issues resulting from day-of-the week effects and nonsynchronous trading due to time-zone differences, an issue which plagues daily return observations. Tuesdays are chosen because this minimises the number of non-trading days, hence maximises the sample size, while also reducing the influence of day-of-the-week effects on prices. The specific countries (together with their mnemonics on DataStream) included are: Australia (TOTMKAU), Brazil (TOTMKBR), Canada (TOTMKCN), Chile (TOTMKCL), China (TOTMKCH), France (TOTMKFR), Germany (TOTMKBD), Hong Kong (TOTMKHK), Indonesia (TOTMKID), India (TOTMKIN), Italy (TOTMKIT), Japan (TOTMKJP), Mexico (TOTMKMX), New Zealand (TOTMKNZ), Norway (TOTMKNW), Russia (TOTMKRS), South Africa (TOTMKSA), South Korea (TOTMKKO), Spain (TOTMKES), Sweden (TOTMKSD), Switzerland (TOTMKSW), Taiwan (TOTMKTA), Thailand (TOTMKTH), U.K. (TOTMKUK), and U.S (TOTMKNA). This sample of 32 years and 5 months contains 1450, 86 and 157 weekly observations in the pre-crisis, crisis and post-crisis period, respectively.

To determine the precise date of the beginning and the end of the crisis period, the dates as in Baur (2012) is used. This firstly involves considering both major financial and economic events

[5] The indices for the 25 countries and world stock market are constructed by DataStream. A divisor driven methodology is used by Thomson Reuters Global Equity indices (2015). In other words, the value of the Index of a country is equal to the aggregate market value of all index securities divided by the divisor of the Index. This divisor is an arbitrary number (100, in this case) which is chosen at the beginning of the index to fix the starting value. Moreover, if there is any corporate action which affects the market value of the index, the divisor is then adjusted to offset the change in the market value of the index so that the index value does not jump up or down drastically.

from the timelines provided by the Bank for International Settlements (Filardo et al., 2009). The second step uses estimates of conditional volatility in the financial sector returns (as this is where the initial shock originated), estimated using a GJR-GARCH (1,1) model with a constant in the mean equation, and identifies the crisis as a period where this volatility exceeds a given threshold. Results from these two steps are combined and the resulting crisis period employed in this study spans from 7 August 2007 to 24 March 2009. Dungey and Gajurel (2015) review the literature on dating of the 2007-9 crisis and estimate the start and end point of a crisis using a smooth transition GARCH model. Their estimated centre of transition into (out of) the crisis period is 3 July 2007 (15 May 2009), which implies that the financial markets were fully in the crisis regime after (before) those dates. This corresponds well with the dates employed here.

To obtain the best proxy of the global stock market, *W*, with return $R_{W,t}$ in model (3.2), two candidates are considered: the world stock market index constructed by DataStream, as it captures movements in most of the national stock markets world-wide, and the DataStream's US stock market index, as the global financial crisis of 2007-9 is widely believed to have originated in that country. We estimate model (3.2)-(3.3) for each country *i* with each of those global market proxies at a time, and, based on AIC and BIC information criteria, the world stock market index is found to provide a better model fit across the board. Hence, the world stock market index is employed as a proxy of the global market in model (3.2) in the subsequent analysis.

Descriptive statistics of weekly returns are presented in Table 3.1 below. On average, the crisis period is characterised by lower returns and higher return volatility, but also less negative skewness and lower kurtosis as compared to pre-crisis figures. These results indicate that return distribution during the crisis period was more spread-out and shifted to the left but also less asymmetrical and with less heavy tails than its pre-crisis counterpart. This is maybe because the pre-crisis covers a longer time period containing a number of heterogeneous economic and political events affecting stock returns, which would have generated extreme positive and, more likely, negative returns so contributing to the distribution's asymmetry and its heavy tails. The post-crisis returns are, on average, higher and less volatile than the pre-crisis ones, but also less asymmetrical and heavy-tailed than the pre-crisis returns. Overall, returns characteristics appear to differ across sub-periods, which provides an additional rationale for modelling pre-, during, and post-crisis periods as distinctive regimes.

Table 3.1: Descriptive Statistics

Country	Mean			Standard Deviation			Skewness			Kurtosis		
	Pre-Crisis	**Crisis**	**Post Crisis**	**Pre-Crisis**	**Crisis**	**Post Crisis**	**Pre-Crisis**	**Crisis**	**Post Crisis**	**Pre-Crisis**	**Crisis**	**Post Crisis**
Australia	0.00191	-0.00652	0.00123	0.02549	0.04015	0.02394	-2.10724	-0.38642	-0.21755	30.9189	4.71685	4.63141
Brazil	0.00360	-0.00384	0.00227	0.03846	0.04915	0.02613	-0.27925	-0.21771	-0.25701	6.44343	6.12240	4.43692
Canada	0.00177	-0.00521	0.00218	0.02078	0.38382	0.02166	-1.25210	-0.87762	-0.20278	16.3499	6.49096	3.28318
Chile	0.00355	-0.00286	0.00312	0.02636	0.03105	0.02092	0.13894	-0.59838	-0.62672	4.65206	4.75396	4.79918
China	0.00239	-0.00491	0.00201	0.04989	0.07490	0.04115	-0.19460	-0.49372	-0.29615	7.94312	3.53570	5.26636
France	0.00201	-0.00847	0.00171	0.02663	0.03855	0.03034	-0.85868	0.53744	-0.36013	8.17328	5.82418	3.86073
Germany	0.00153	-0.00758	0.00255	0.02485	0.03496	0.03011	-1.01138	-0.44368	-0.72969	8.70641	3.87844	4.88579
Hong Kong	0.00245	-0.00706	0.00306	0.03999	0.05397	0.03314	-1.24124	-0.23712	-0.14693	12.8475	3.43370	6.22510
Indonesia	0.00125	-0.00569	0.00635	0.04217	0.06573	0.03090	0.14661	-0.62547	-0.70142	7.38568	7.58736	6.05421
India	0.00324	-0.00555	0.00337	0.04410	0.06464	0.03138	-0.34061	-0.76598	0.78500	13.2442	4.40349	6.50855
Italy	0.00238	-0.01062	0.00066	0.03290	0.04269	0.03469	-0.36876	0.93212	-0.28174	7.04928	8.80447	3.46451
Japan	0.00104	-0.00876	0.00052	0.02564	0.04595	0.03018	-0.32883	-0.29314	-1.61279	6.41827	6.03788	15.8027
Mexico	0.00538	-0.00472	0.00443	0.03849	0.03799	0.02009	0.80986	-0.30664	0.06447	11.2984	5.46240	3.98993
New Zealand	0.00112	-0.00596	0.00067	0.02415	0.02318	0.01325	0.25477	-0.38919	-0.42660	11.1097	3.84211	7.39565
Norway	0.00217	-0.00864	0.00292	0.03328	0.05844	0.03561	-1.12240	0.25264	-0.66167	14.4147	6.34500	4.41639
Russia[6]	0.00719	-0.00790	0.00356	0.06610	0.07898	0.04269	-0.27926	-0.48961	-0.49900	10.0495	7.58611	5.46151
South Africa	0.00323	-0.00364	0.00293	0.03139	0.04286	0.02281	-0.85337	-0.18334	-0.52971	8.57973	4.84190	3.79301
South Korea	0.00153	-0.00508	0.00344	0.04343	0.04753	0.02914	0.13487	-0.19350	-1.17768	4.90338	4.08660	8.67198
Spain	0.00179	-0.00821	0.00008	0.02668	0.04092	0.03347	-0.85658	0.18293	0.08794	7.44859	9.04347	3.50523
Sweden	0.00262	-0.00836	0.00355	0.03196	0.04767	0.03071	-0.50988	0.80649	-0.20240	6.13398	7.05835	3.59010
Switzerland	0.00183	-0.00703	0.00161	0.02165	0.03498	0.02238	-1.47246	0.45919	-0.87236	13.7148	5.48303	6.25258
Taiwan	0.00104	-0.00663	0.00235	0.04709	0.04681	0.02926	-0.41153	0.04231	-0.05440	5.22967	3.07305	8.00898
Thailand	0.00192	-0.00803	0.00658	0.04581	0.04748	0.03238	0.16577	-0.24338	-0.43014	7.36816	5.89286	4.58888
U.K.	0.00187	-0.00615	0.00276	0.02150	0.03855	0.02735	-1.53066	0.77247	-0.46278	17.8027	6.43824	4.74983
U.S.	0.00193	-0.00705	0.00362	0.02236	0.03843	0.02517	-1.37652	-0.95022	-0.33767	19.3951	6.13009	3.46606

Note: Descriptive statistics of weekly aggregate stock market returns for each of the 25 countries in the sample for the pre-crisis (Oct 1979 – Jul 2007), crisis (Aug 2007 –Mar 2009) and post crisis (Apr 2009 – Mar 2012) period, with 1450, 86 and 157 observations, respectively.

[6] One of the reasons for a high mean in Russia is because of the shorter data sample (i.e. from 27th January 1998) during the pre-crisis period for Russia, which was obtained from DataStream.

3.5. Empirical Results

3.5.1. Data Features and Model Specifications

This section gives a brief overview of results of data diagnostics and for model adequacy and specifications.

(a) Stationarity test

Firstly, both unit root tests (ADF and PP) show log indices to be nonstationary but returns in each country to be stationary. Table 3.2 below shows the findings pertaining to ADF test. Non-Stationarity is tested both at log-levels and Stock Returns. The lag length is selected using the Schwartz or Bayesian Information (SIC). The "t-statistics" for all Stock Prices is greater than the critical values at 1% level whereas for Stock Returns of the time series, the "τ (Tau)" is less than the critical value at 1% level. As a result, it can be concluded that for stock prices, the null hypothesis is not rejected, indicating that they are non-stationary. On the other hand, the null hypothesis is rejected for stock returns, showing that they are stationary. Henceforth, it can be concluded that all variables appear to be non-stationary at log-levels and stationary in log returns.

Table 3.2: Augmented Dickey Fuller Test

ADF Test	**Stock Prices**				**Stock Returns**			
(Full Sample)	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Australia	-2.616				-17.746			
Brazil	-2.246				-14.472			
Canada	-2.714				-17.755			
Chile	-3.271				-16.028			
China	-2.197				-13.143			
France	-1.362				-17.300			
Germany	-1.972				-17.583			
Hong Kong	-2.778				-17.761			
Indonesia	-2.766				-13.377			
India	-3.205				-13.928			
Italy	-2.328				-17.491			
Japan	-1.976				-17.339			
Mexico	-3.003				-16.512			
New Zealand	-2.497				-19.684			
Norway	-2.447				-16.829			
Russia	-1.329				-12.447			
South Africa	-2.980				-17.011			
South Korea	-2.895				-15.120			
Spain	-1.672				-15.731			
Sweden	-2.435				-16.061			
Switzerland	-1.103				-16.955			
Taiwan	-3.253				-15.904			
Thailand	-2.573				-16.229			
U.K.	-1.799				-28.748			
U.S.	-1.558				-18.993			

ADF test is conducted for the weekly log indices and aggregate stock market returns for each of the 25 countries for the full sample (Oct 1979 – Mar 2012). The lag length is selected using SIC, and the t-statistics and critical values are compared in order to test the null hypothesis of non-stationarity

(b) Co-integration

To identify the correct model specification, the Johansen Test is used to log-prices series to explore possible effects of co-integration. The test uses the Schwaz Bayesian Information Criterion (SBIC). Table 3.3 shows that for all pairs of Stock Prices, the SBIC indicates that there are no co-integrating vectors.

Table 3.3: Johansen Test for Co-integration (IC based)

	SBIC	HQIC	AIC
Australia			
Max Rank: 0	-9.606217*	-9.638618	-9.657673
1	-9.602833	-9.64131*	-9.663938
2	-9.600832	-9.640578	-9.665152
Brazil			
Max Rank: 0	-8.79683*	-8.845398*	-8.875167
1	-8.782711	-8.840385	-8.875736
2	-8.77914	-8.839849	-8.877061
Canada			
Max Rank: 0	-10.40912*	-10.3968	-10.42196
1	-10.39986	-10.41401	-10.42234
2	-10.3968	-10.41298	-10.42249
Chile			
Max Rank: 0	-9.334703*	-9.375537	-9.400126
1	-9.329911	-9.378401*	-9.4076
2	-9.329669	-9.380712	-9.411448
China			
Max Rank: 0	-8.052061*	-8.098883*	-8.127475
1	-8.039381	-8.094982	-8.128935
2	-8.03625	-8.094777	-8.130517
France			
Max Rank: 0	-9.644958*	-9.677359*	-9.696415
1	-9.637088	-9.675565	-9.698193
2	-9.634486	-9.674988	-9.698807
Germany			
Max Rank: 0	-9.756629*	-9.78903*	-9.808086
1	-9.747921	-9.786397	-9.809026
2	-9.74555	-9.786051	-9.809871
Hong Kong			
Max Rank: 0	-8.632158*	-8.664559*	-8.683614
1	-8.350358	-8.663024	-8.685653
2	-8.348715	-8.662499	-8.686318
Indonesia			
Max Rank: 0	-8.359007*	-8.40064*	-8.425759
1	-8.356302	-8.399796	-8.429626
2	-8.350588	-8.400755	-8.432154
India			
Max Rank: 0	-8.244488*	-8.275439*	-8.294096
1	-8.233951	-8.272639	-8.295961
2	-8.231813	-8.273081	-8.297958
Italy			

Max Rank: 0	-8.951536*	-8.983937*	-9.002993
1	-8.944395	-8.982871	-9.0055
2	-8.942147	-9.006468	-9.006468
Japan			
Max Rank: 0	-9.729791*	-9.762192*	-9.781248
1	-9.720921	-9.759397	-9.782026
2	-9.718661	-9.759162	-9.782982
Mexico			
Max Rank: 0	-8.87955*	-8.909464	-8.926037
1	-8.872852	-8.910219*	-8.93096
2	-8.871237	-8.910001	-8.93322
New Zealand			
Max Rank: 0	-9.658554*	-9.69734*	-9.720574
1	-9.648353	-9.722002	-9.722002
2	-9.647796	-9.696279	-9.725321
Norway			
Max Rank: 0	-9.034615*	-9.065997	-9.084393
1	-9.031648	-9.068914*	-9.090759
2	-9.030583	-9.06981	-9.092806
Russia			
Max Rank: 0	-7.516765*	-7.573553*	-7.60892
1	-7.498793	-7.566228	-7.608226
2	-7.491719	-7.562705	-7.606913
South Africa			
Max Rank: 0	-9.076229*	-9.10863	-9.127685
1	-9.073408	-9.111885*	-9.134513
2	-9.07102	-9.111522	-9.135341
South Korea			
Max Rank: 0	-8.414154*	-8.44301*	-8.460281
1	-8.40565	-8.44172	-8.463308
2	-8.402778	-8.441253	-8.46428
Spain			
Max Rank: 0	-9.451827*	-9.494872*	-9.514646
1	-9.443834	-9.489307	-9.513318
2	-9.440461	-9.487549	-9.512973
Sweden			
Max Rank: 0	-9.242322*	-9.275245*	-9.294639
1	-9.232775	-9.271871	-9.294901
2	-9.231391	-9.272545	-9.296788
Switzerland			
Max Rank: 0	-10.05343*	-10.08583*	-10.10489
1	-10.04447	-10.10558	-10.10558
2	-10.04104	-10.08154	-10.10536
Taiwan			
Max Rank: 0	-8.25405*	-8.29248	-8.315478
1	-8.252445	-8.298081*	-8.325392
2	-8.252193	-8.300231	-8.328979
Thailand			
Max Rank: 0	-8.254796*	-8.292451	-8.314939
1	-8.252039	-8.296755*	-8.323459
2	-8.249723	-8.296792	-8.324901
so.			
Max Rank: 0	-10.21828*	-10.22636*	-10.23112
1	-10.20979	-10.22395	-10.23227
2	-10.20707	-10.22325	-10.23276
U.S.			
Max Rank: 0	-10.69365*	-10.72605*	-10.7451
1	-10.68259	-10.72107	-10.74369
2	-10.6793	-10.7198	-10.74362

Johansen test is conducted for the for all pairs of each 25 countries' weekly log indices with the World stock market portfolio log indices for the period from (Oct 1979 – Mar 2012). The test uses SBIC to indicate whether the pairs are co-integrated or not.

(c) Heteroscedasticity

Having established the form of equation (3.2), I estimate it using OLS and test for homoscedasticity of residuals. To test for heteroscedasticity, the White General Heteroscedasticity Test is used. From Table 3.4, it can be concluded that the null hypothesis is rejected for 12 countries (Australia, Canada, Chile, France, Germany, India, Japan, South Africa, Spain, Switzerland, U.K., and U.S.) at 1% level which means that there is a substantial amount of heteroscedasticity from an OLS (Ordinary Least Square) model.

Table 3.4: Testing for Heteroscedasticity in Eq 3.2 from an OLS model

	Chi(2)	**P Value**
Australia	290.34	0.0000
Brazil	1.06	0.3023
Canada	91.20	0.0000
Chile	2.58	0.1080
China	14.98	0.0001
France	9.27	0.0023
Germany	100.83	0.0000
Hong Kong	4.36	0.0368
Indonesia	2.34	0.1263
India	16.23	0.0001
Italy	1.42	0.2338
Japan	17.65	0.0000
Mexico	0.11	0.7450
New Zealand	3.31	0.0688
Norway	1.06	0.3023
Russia	1.32	0.2510
South Africa	26.06	0.0000
South Korea	0.05	0.8242
Spain	32.17	0.0000
Sweden	1.41	0.2348
Switzerland	188.72	0.0000
Taiwan	0.66	0.4161
Thailand	1.24	0.2655
U.K.	104.27	0.0000
U.S.	103.31	0.0000

The White's (1980) test is used to test the null hypothesis of homoscedasticity against heteroscedasticity. The null hypothesis is rejected for 12 countries at 1% level which means that there is a substantial amount of heteroscedasticity from an OLS model.

(d) ARCH Effects after OLS regression

Engle's ARCH test is a Lagrange multiplier test to assess any autoregressive conditional heteroscedastic (ARCH) effects after estimating model (3.2) with an Ordinary Least Square (OLS) model. The results can be observed in Table 3.5 and the p-values are smaller than the chosen alpha (at a 5% significance level), except for Spain. Hence, the residuals do show evidence of ARCH effects, and a more appropriate technique (e.g. GARCH models) should be employed to estimate model (3.2) in order to ensure that there is no remaining ARCH effects.

Table 3.5: ARCH LM test in Eq 3.2 using an OLS model

	Lags	Chi2	Df	Prob>chi2
Australia	1	151.400	1	0.000
Brazil	1	127.781	1	0.000
Canada	1	52.670	1	0.000
Chile	1	77.377	1	0.000
China	1	46.311	1	0.000
France	1	38.268	1	0.000
Germany	1	124.055	1	0.000
Hong Kong	1	59.739	1	0.000
Indonesia	1	47.727	1	0.000
India	1	18.974	1	0.000
Italy	1	41.180	1	0.000
Japan	1	110.861	1	0.000
Mexico	1	62.758	1	0.000
New Zealand	1	39.427	1	0.000
Norway	1	87.11	1	0.000
Russia	1	21.412	1	0.000
South Africa	1	42.393	1	0.000
South Korea	1	68.168	1	0.000
Spain	1	3.012	1	0.0826
Sweden	1	61.933	1	0.000
Switzerland	1	259.767	1	0.000
Taiwan	1	101.852	1	0.000
Thailand	1	13.794	1	0.000
U.K.	1	69.322	1	0.000
U.S.	1	46.666	1	0.000

Engle's ARCH LM test is conducted after modelling equation (3.2) using an OLS method for ARCH effects. It can be observed that there are ARCH effects in all, except, Spain, since the p-values are lower compared to the alphas at 5% significance level

(e) Normality Tests

Next, equation (3.2)-(3.3) allowing for conditional heteroscedasticity is estimated the assumption of error normality is then investigated using the Shapiro Wilk test. Following the test, the p-values of the residuals are less than 5% significance level, which means that the null hypothesis of normality should be rejected. The results are displayed in Table 3.6. Given the non-normality, equation (3.2)-(3.3) is re-estimated assuming a student-*t* distribution and a GED distribution. The results indicate that both the AIC and BIC favour student-*t* distribution for residuals in (3.2).

Table 3.6: Normality test

	W	**V**	**Z**	**Prob>z**
Australia	0.95136	49.541	9.866	0.000
Brazil	0.91278	55.312	9.940	0.000
Canada	0.98087	19.480	7.507	0.000
Chile	0.97264	21.285	7.643	0.000
China	0.94211	38.355	9.050	0.000
France	0.93880	62.330	10.447	0.000
Germany	0.94709	53.887	10.079	0.000
Hong Kong	0.91087	90.776	11.397	0.000
Indonesia	0.93545	46.087	9.722	0.000
India	0.91700	63.729	10.378	0.000
Italy	0.94786	53.106	10.042	0.000
Japan	0.96416	36.507	9.095	0.000
Mexico	0.88295	96.717	11.456	0.000
New Zealand	0.85240	156.876	12.803	0.000
Norway	0.94466	58.485	10.803	0.000
Russia	0.89113	57.317	9.944	0.000
South Africa	0.95918	41.578	9.423	0.000
South Korea	0.96671	28.204	8.371	0.000
Spain	0.96377	30.830	8.602	0.000
Sweden	0.96782	32.177	8.769	0.000
Switzerland	0.94902	51.925	9.985	0.000
Taiwan	0.95262	40.523	9.240	0.000
Thailand	0.95262	40.523	9.290	0.000
U.K.	0.97472	25.753	8.212	0.000
US..	0.96486	35.790	9.044	0.000

Shapiro Wilk test is conducted after modelling equation (3.2)-(3.3) to test for the normality of the error terms. Given the p-values are compared to the 5% significance level in order to determine whether the hypothesis of normality should be rejected or not.

(f) Autocorrelation

Having re-estimated the model assuming that the error term follows a *t*-distribution the residuals are tested for autocorrelation, and in cases where it is found, the errors are modelled as an ARMA process of an appropriate order. The Ljung-Box test is used, the null hypothesis of serial correlation cannot be rejected for Australia, Brazil, Chile, Germany, Indonesia, India, Italy, Norway, South Korea, Switzerland and U.S at 5% significance level.

(g) ARCH Effects after GARCH regression

Lastly, Engle's LM ARCH test shows no remaining ARCH effects in residuals after estimating model (3.2)-(3.3). The results are in Table 3.7. The p-value observed are greater than the chosen alpha (at 5% significance level, in this case), suggesting that the models are correctly specified.

Table 3.7: ARCH LM Test after GJR GARCH using Eq. 3.2

	Lags	Chi2	Df	Prob>chi2
Australia	1	0.030	1	0.8625
Brazil	1	0.094	1	0.7593
Canada	1	0.044	1	0.8330
Chile	1	0.242	1	0.6228
China	1	2.558	1	0.1097
France	1	0.314	1	0.5753
Germany	1	0.010	1	0.9198
Hong Kong	1	0.001	1	0.9769
Indonesia	1	0.007	1	0.9313
India	1	0.032	1	0.8589
Italy	1	0.012	1	0.9141
Japan	1	0.000	1	0.9909
Mexico	1	0.360	1	0.5496
New Zealand	1	0.004	1	0.9491
Norway	1	0.053	1	0.8176
Russia	1	0.043	1	0.8353
South Africa	1	0.008	1	0.9309
South Korea	1	0.001	1	0.9710
Spain	1	0.035	1	0.8509
Sweden	1	0.053	1	0.8185
Switzerland	1	0.009	1	0.9247
Taiwan	1	0.016	1	0.8991
Thailand	1	0.002	1	0.9634
U.K.	1	0.011	1	0.9149
U.S.	1	0.029	1	0.8649

Engle's ARCH LM test is conducted after modelling equation (3.2)-(3.3) for ARCH effects. Given the p-values are greater compared to the alphas (5% significance level), it means there is no remaining ARCH effects in the residuals after estimating Model 3.2 with a GJR GARCH framework

3.5.2. *Model Estimation*

Table 3.8 presents estimation results for equation (3.2). Firstly, it is observed that in 9 out of 25 countries, the intercept varies significantly across sub-periods (α_1 or α_2 significant), supporting the earlier suggestion that imposing a time-constant intercept is a source of misspecification when describing the behaviour of returns over time. Secondly, in most of cases, the coefficient β_t capturing the interdependence between the local and the global financial markets is time-varying before the crisis, as indicated by significance of δ_1[7]. In all but one case, the positive sign on $\hat{\delta}_1$ indicates that financial integration was increasing over time in the pre-crisis period. Hence, if these positive trends had continued unchanged into the crisis period ($\gamma_0 = \gamma_1 = 0$) but were not accounted for (as in model (3.1)), one would be at risk of falsely inferring that there was contagion during the 2007-9 crisis period, even if there was none. However, these trends in globalisation appear to change significantly in the crisis and post-crisis periods in most countries, as indicated by the significance of coefficients γ and θ. These changes could give rise to one of the contagion phenomena as described above, and I investigate them in detail below.

Table 3.9 provide estimation results necessary to assess the existence of all forms of contagion. Firstly, it can be observed that for six countries (Brazil, Canada, Russia, South Africa, Spain, and Switzerland), there was no change in the intertemporal process governing β_t, including at crisis' onset, as $\hat{\gamma}_0$ and $\hat{\gamma}_1$ are not significantly different from zero (at the 10% significance level). This means that the pre-crisis process of integration continued unchanged into the crisis period, hence there is no evidence of any type of contagion. Secondly, for another four countries (France, Germany, Mexico, and Sweden), there was a significant negative change in the level ($\hat{\gamma}_0$<0) but no change in the slope ($\hat{\gamma}_1$=0) of the integration process β_t, i.e., values of β_t during the crisis are all significantly lower, not higher, than what they would have been if the crisis had not struck. Hence, there is no evidence of contagion for these countries, either. Rather, capital markets of these four countries seem to have decoupled and been integrated less, not more, with the world during the crisis period, as compared to their pre-crisis expected integration levels. Bekaert et al. (2011), also found segmentation increased towards the end of 2008 and then falls back to near pre-crisis in 2009. The level of decoupling might depend on financial and trade openness or it might be just that international investors decide to avoid markets having weak corporate governance (for instance, Mexico) or different legal systems. Moreover, according to Dervis (2012), decoupling might be due to differences between business cycles and the varied reactions to global shocks.

[7] Missing values for δ_1 are due to its insignificance in the first pass of the estimation, hence were dropped and the model was re-estimated to increase efficiency of remaining estimates.

Table 3.8: Estimation Results for Model (3.2)

Country				Pre-Crisis		Crisis		Post Crisis	
	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_2$	$\hat{\delta}_0$	$\hat{\delta}_1$	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\theta}_0$	$\hat{\theta}_1$
Australia	0.0012***	-0.0016	-0.0024**	0.7489***	-0.0002***	9.4904***	-0.0060 ***	0.3016***	-
Brazil	0.0031***	0.0018	-0.0037**	1.0132***	-	-0.0176	-	-0.2115***	-
Canada	0.0007*	0.0004	-0.0007	0.7119 ***	-	0.0604	-	-0.0527	-
Chile	0.0021***	-0.0009	0.0009	-0.0387	0.0003***	15.1696 ***	-0.0100 ***	-0.1050	-
China	0.0010*	0.0044	-0.0028	0.6956***	-	28.5010***	-0.0184***	0.4394***	-
France	0.0008	-0.0037**	-0.0025**	0.4475***	0.0004 ***	-0.1464**	-	-0.0022	-
Germany	0.0007	-0.0019	-0.0014	0.2617***	0.0006***	-0.3233 ***	-	-3.6438**	0.0021**
Hong Kong	0.0022***	-0.0013	-0.0022	0.6019***	0.0002**	20.2149***	-0.0132***	-0.0011	-
Indonesia	0.0016	0.0040	0.0029	-0.3847**	0.0009***	19.51***	-0.0129***	-0.4890***	-
India	0.0035***	0.0023	-0.0031	-0.7744***	0.0011***	17.8411***	-0.0118***	5.6710*	-0.0038**
Italy	0.0004	-0.0044***	-0.0034**	0.2928***	0.0004***	-5.4261*	0.0036*	0.1759**	-
Japan	-0.0003	-0.0012	0.00001	0.6580***	0.0003***	16.41***	-0.0110 ***	-0.5609 ***	-
Mexico	0.0033***	-0.0022	-0.0016	0.4680***	0.0003**	-0.1347**	-	5.831***	-0.0039***
New Zealand	0.0012***	-0.0046***	-0.0015	0.3271***	-	0.0728*	-	-0.0678*	-
Norway	0.0017***	-0.0010	-0.0022	0.4195***	0.0003**	0.3194***	-	0.2546***	-
Russia	0.0048***	-0.0031	-0.0042*	1.020***	-	0.0637	-	9.024***	- 0.0055***
South Africa	0.0027***	0.0007	-0.0010	0.2894***	0.0003***	0.1180	-	-0.1565 ***	-
South Korea	0.0002	0.0003	0.0011	-0.2701	0.0010***	11.33 **	-0.0078 **	-0.6987 ***	-
Spain	0.0009*	-0.0044 **	-0.0035**	0.4121 ***	0.0003***	-0.0862	-	-0.0169	-
Sweden	0.0015**	-0.0049**	-0.0014	0.2512***	0.0006***	-0.2956***	-	-0.3612***	-
Switzerland	0.0014***	-0.0039**	-0.0016	0.2247***	0.0004 ***	-0.0556	-	-0.2398***	-
Taiwan	-0.0001	-0.0009	0.0006	0.2185	0.0005***	12.7843***	-0.0086 ***	-0.3326***	-
Thailand	0.0016	-0.0032	0.0030	0.6341 ***	-	0.1914**	-	0.0937	-
U.K.	0.0006	-0.0013	-0.0007	0.5232***	0.0002***	0.09323*	-	0.1417**	-
U.S.	-0.00004	0.0003	0.0012	0.9435 ***	-	-5.7349***	0.0038***	-0.0856 **	-

Note: Parameters stem from model (3.2): $R_{i,t} = \alpha_0 + \alpha_1 D_{t\ CRISIS} + \alpha_2 D_{t\ POST-CRISIS} + +\beta_{1t} R_{W,t} + \beta_{2t} R_{w,t} D_{t\ CRISIS} + \beta_{3t} R_{W,t} D_{t\ POST-CRISIS} + \varepsilon_{i,t}$, where $\beta_{1t} = \delta_0 + \delta_1 t$, $\beta_{2t} = \gamma_0 + \gamma_1 t$, $\beta_{3t} = \theta_0 + \theta_1 t$, where $R_{i,t}$ denotes stock returns in country *i* at time *t*, $D_{t\ CRISIS}$ ($D_{t\ POST-CRISIS}$) is a dummy variable equal to one during the crisis (post-crisis) period and zero otherwise, and $R_{W,t}$ is the return of the world stock index. Error terms are modelled as a GJR-GARCH (1,1) process, corrected for autocorrelation in residuals where required. ***, **, * indicate significance at 1%, 5%, and 10% level, respectively. Insignificant trend terms ($\delta_1, \gamma_1, \theta_1$) are excluded and model (2) is re-estimated where relevant.

Table 3.9: Types of Contagion

Country			First week of the crisis (t=τ_1)		Last week of the crisis (t=τ_2)		Decision	Model (1) results	Constant betas model results
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	t- stats	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	t- stats			
Australia	9.4904***	-0.006 ***	0.7189	7.7736	0.2051	2.2871	Shock Contagion (Permanent)	C	C
Brazil	-0.0176	-	-0.0176	-	-0.0176	-	No Contagion		
Canada	0.0604	-	0.0604	-	0.0604	-	No Contagion	C	C
Chile	15.169 ***	-0.010 ***	0.6314	4.0146	-0.2202	-1.9948	Shock Contagion (Reversal)	C	C
China	28.5010***	-0.0184***	1.7630	6.4243	0.1967	1.0422	Shock Contagion (Transitory)	C	C
France	-0.1464**	-	-0.1464	-	-0.1464	-	No Contagion (Decoupling)	C	C
Germany	-0.3233 ***	-	-0.3233	-	-0.3233	-	No Contagion (Decoupling)		
Hong Kong	20.2149***	-0.0132***	0.9877	5.5096	-0.1386	-1.0507	Shock Contagion (Transitory)	C	C
Indonesia	19.51***	-0.0129***	0.6824	3.0203	-0.4202	-2.4878	Shock Contagion (Reversal)	C	C
India	17.8411***	-0.0118***	0.7513	3.1990	-0.2497	-1.3916	Shock Contagion (Transitory)	C	C
Italy	-5.4261*	0.0036*	-0.1770	-1.7627	0.1305	1.6313	Recoupling Contagion	C	C
Japan	16.41***	-0.0110***	0.3983	2.8124	-0.5399	-5.6790	Shock Contagion (Reversal)	C	
Mexico	-0.1347**	-	-0.1347	-	-0.1347	-	No Contagion (Decoupling)	C	
New Zealand	0.0728*	-	0.0728	-	0.0728	-	Shock Contagion (Level Shift)	C	C
Norway	0.3194***	-	0.3194	-	0.3194	-	Shock Contagion (Level Shift)	C	C
Russia	0.0637	-	0.0637	-	0.0637	-	No Contagion		
South Africa	0.1180	-	0.1180	-	0.1180	-	No Contagion	C	C
South Korea	11.33 **	-0.0078 **	0.0582	0.3192	-0.6028	-3.7450	No Contagion (Decoupling)	C	C
Spain	-0.0862	-	-0.0862	-	-0.0862	-	No Contagion		
Sweden	-0.2956***	-	-0.2956	-	-0.2956	-	No Contagion (Decoupling)		
Switzerland	-0.0556	-	-0.0556	-	-0.0556	-	No Contagion	C	C
Taiwan	12.7843***	-0.009 ***	0.3714	1.8488	-0.3557	-2.2609	Shock Contagion (Reversal)		
Thailand	0.1914**	-	0.1914	-	0.1914	-	Shock Contagion (Level Shift)	C	C
U.K.	0.0932*	-	0.0932	-	0.0932	-	Shock Contagion (Level Shift)	C	C
U.S.	-5.7349***	0.0038***	-0.2733	-3.5387	0.0466	1.0092	No Contagion (Decoupling)		

Note: Parameters stem from model (2): $R_{i,t} = \alpha_0 + \alpha_1 D_{t\,CRISIS} + \alpha_2 D_{t\,POST-CRISIS} + +\beta_{1t} R_{W,t} + \beta_{2t} R_{w,t} D_{t\,CRISIS} + \beta_{3t} R_{W,t} D_{t\,POST-CRISIS} + \varepsilon_{i,t}$, where $\beta_{1t} = \delta_0 + \delta_1 t$, $\beta_{2t} = \gamma_0 + \gamma_1 t$, $\beta_{3t} = \theta_0 + \theta_1 t$, where $R_{i,t}$ denotes stock returns in country *i* at time *t*, $D_{t\,CRISIS}$ ($D_{t\,POST-CRISIS}$) is a dummy variable equal to one during the crisis (post-crisis) period and zero otherwise, and $R_{W,t}$ is the return of the world stock index. Model (1) is: $R_{i,t} = \alpha_0 + \beta_1 R_{W,t} + \beta_2 R_{w,t} D_{t\,CRISIS} + \varepsilon_{i,t}$. ***, **, * indicate significance at 1%, 5%, and 10% level, respectively. 'Constant betas model' is identical to model (2) but with time-invariant β_1, β_2, and β_3. Insignificant trend terms ($\delta_1, \gamma_1, \theta_1$) are excluded and model (2) is re-estimated where relevant. Error terms are modelled as a GJR-GARCH (1,1) process, corrected for autocorrelation in residuals where required. The hypotheses for shock contagion are: $H_0: \beta_2(\tau_1) \leq 0$, $H_1: \beta_2(\tau_1) > 0$, for recoupling contagion: $H_0: \beta_2(\tau_1) \geq 0$, $H_1: \beta_2(\tau_1) < 0$ and $H_0: \beta_2(\tau_2) \leq 0$, $H_1: \beta_2(\tau_2) > 0$, and for kink contagion: $H_0: \beta_2(\tau_1) = 0$, $H_1: \beta_2(\tau_1) \neq 0$ and $H_0: \gamma_1 \leq 0, H_A: \gamma_1 >$

a) Shock Contagion

From Table 3.9, it can be observed that there is an increase in stock returns co-movement ($\beta_2(\tau_1) > 0$) during the first week (i.e. Week 1451) of the financial crisis for Australia, Chile, China, Hong Kong, Indonesia, India, Japan, New Zealand, Norway, South Korea, Taiwan, Thailand and U.K with the world stock market portfolio. Moreover, a t-test shows that $\beta_{2t}(\tau_1)$ is significant 1% for the countries mentioned above, except for South Korea and Taiwan. Hence, it can be concluded that there is evidence of shock contagion for those stock markets with the World Stock Market Portfolio. However, as mentioned in the previous section, there might be different scenarios under which shock contagion might arise.

New Zealand, Norway, Thailand, and U.K experienced shock contagion as their stock markets experienced a significant upwards shift ($\hat{\gamma}_0$>0) in β_t over and above of what one would expect by extrapolating pre-crisis trends in financial integration, where present. This situation can be depicted in Appendix A.1(i) until A.1(iv). These countries did not record any significant changes in the pace of integration ($\hat{\gamma}_1$=0), which implies that their β_t values increased at crisis' onset and remained elevated, as compared to pre-crisis trends, throughout the entire crisis period. Hence, it was the level but not the pace of their financial integration with the world (not the slope of β_t) which was affected by the crisis.

Another frequent type of shock contagion is observed for countries where, β_t experiences a positive and significant shock at crisis' start (t=τ_1), but its slope decreases significantly as compared to the pre-crisis one ($\hat{\gamma}_1$<0). Countries which fall into this category are Australia, Chile, China, Hong Kong, Indonesia, India, Japan, and Taiwan

These initial positive shocks in β_t are statistically significant, i.e., $\hat{\beta}_2(\tau_1) > 0$ as indicated by values of the *t*-statistics in Table 3.9, which constitutes evidence in favour of shock contagion. In addition, model (3.2) allows inference about the persistence of those initial contagious shocks. Firstly, they might have faded away quickly and the financial integration process during the remaining part of the crisis period might have been weaker, not stronger, than what would have been expected if pre-crisis trends prevailed. Alternatively, the initial shocks might have been more persistent and have prevailed, at least partially, throughout the entire crisis period. To differentiate between these two scenarios (temporary vs. persistent contagion shocks), another t-test is conducted in order to find out whether β_{t} in the last week of the crisis (t=τ_2) is significantly different from its value which would have been expected at crisis' end if the crisis have had no impact on the process of financial integration. Should the estimated $\beta_2(\tau_2)$ be significantly positive (negative) at crisis' end, this would imply that the initial positive shock in β_{t} has not completely faded away (has reversed and led to lower-than-expected integration level), indicating at least partially persistent (temporary) contagious shocks.

The results in Table 3.9 and appendix A.1(v) show that the initial contagious shock was significantly permanent only for Australia, as its $\beta_2(\tau_2)$ estimate is positive and significant. For the rest of the relevant countries, the remainder of the initial positive shock at crisis' end. $\hat{\beta}_2(\tau_2)$, is negative and significant for Chile, Indonesia, Japan, and Taiwan, suggesting that initial contagious shocks tend to fade away and the level of integration during the later phases of the crisis was lower, not higher, than what should have been expected given pre-crisis trends in the integration process. This is shown in appendix A.1(vi) to A.1(ix). For China, Hong Kong, and India, the initial shock appears to have completely vanished by the end of the crisis period ($\hat{\beta}_2(\tau_2)$ insignificant), with financial integration process β_{t} returning to the path it would be on if no crisis had occurred. This is displayed in appendix A.1(x), A.1(xi), A.1(xii).

b) Recoupling Contagion

Contagion effects might also arise if there is a fall in β_t following the outbreak of the crisis (i.e., $\beta_2(\tau_1) < 0$), accompanied by a steady rise in the level of β_t as the crisis unfolds, leading to a higher level of β_t at a certain point during this turmoil period. In case of recoupling contagion, this will result in co-movements being stronger by the end of the crisis period (i.e. t=τ_2) than what they would have been if the pre-crisis globalisation process was followed, i.e., $\beta_2(\tau_2)$> 0.

The results in Table 3.9 show for both Italy and the U.S. that the level of β_t was lower on the first week of the crisis period (i.e. $\hat{\beta}_2(\tau_1)$ <0), as compared with what would have been expected pre-crisis. However, there is an increase in the level of β_t as the crisis continues, so that by the end of the turmoil period β_t is higher than what it would have been if the same integration processes as in the pre-crisis period were being followed ($\hat{\beta}_2(\tau_2) > 0$).
However, in order to determine the significance of the fall in co-movement of Italy and the U.S. with the world during the first week of the crisis, and whether $\beta_2(\tau_2)$ was indeed significantly higher at the end of the crisis period, as compared to what it would have been if the crisis did not occur, two t-tests are conducted. The first t-test conducted for week $t = \tau_1$, which is the first week of the crisis, suggests that the null hypothesis of $\beta_2(\tau_2) \geq 0$ can be rejected at 5% and 1% level for Italy and the U.S., respectively. In other words, there has indeed been a significant fall in the co-movement with the world for the abovementioned countries. The second t-test is to ascertain whether the level of β_t was significantly higher for the stock returns

of Italy and the U.S. on the last week of the crisis period (t=τ_2), compared to what it would have been if the crisis did not occur. The results show that the null hypothesis of $\beta_2(\tau_2) \leq 0$ is rejected for Italy at 5% level, but cannot be rejected for the U.S. Hence, we conclude that there is evidence of recoupling contagion only for the Italian stock market, as its integration with the world market at crisis' end was higher than it would have been in absence of the crisis (Figure 3.7(l)). In contrast, the U.S. market appears to have experienced a negative integration shock at crisis onset, from which it has fully recovered (as $\hat{\beta}_2(\tau_2)$ is not significantly different from zero), but no evidence of contagion, i.e., excessive co-movements, can be found for the U.S. market.

c) *Kink Contagion*

"Kink" contagion is referred to as a situation where there is no sudden change in co-movements during the first week of the crisis (i.e., $\beta_2(\tau_1) = 0$), but contagion can still be identified provided there is an increase in integration pace ($\gamma_1 > 0$) during the crisis period and, consequently, β_t is higher during the crisis than what it would have been if the pace of the integration process was the same as in the pre-crisis period. In our sample, none of the countries appears to have experienced this type of contagion (Table 3.9). For South Korea, the *t*-test suggests that the null hypothesis of $\beta_2(\tau_1)$ = 0 cannot be rejected, but the change in the integration speed is negative, not positive. Hence, South Korean market's integration with the world was progressively weaker as the crisis unfolded, relatively to its pre-crisis pace, and it can be concluded that there is no evidence of kink contagion in our sample.

Contagion in this chapter is defined as a significant increase in β_t during the crisis period, over and above of what it would have been if the linkages between the individual country and world stock market portfolio was following the same process and in the pre-crisis period. And therefore the "beta" estimates which would be expected during the "crisis period" if there had been no impact of the crisis in the integration processes between the world market portfolio and individual economies, are extrapolated over the crisis period. It can be seen from Appendix A.1 that for all countries there would have been an increasing and positive integration process had the crisis not happen.

And as far as the limitations of the integration process amongst countries are concerned, unless the asset returns of two economies are not perfectly explained by the same set of global factors, these countries cannot be perfectly integrated, Pukthuanthong and Roll (2009). Moreover, Chambet and Gibson (2008) find that the degree of integration depends on a country's trade diversification, i.e. less diversified economies are more financially integrated."

3.5.3. Discussion

Out of 25 countries in our sample, there is evidence of contagion in 13 countries when using a model which allows for the existence of a post-crisis subperiod as well as for changes in the level of financial integration over time (model 3.2). When applying a specification such as model (3.1), i.e., with no separate post-crisis period and subperiod-specific time-invariant parameters, the results reported in Table 3.9, second-to-last column, indicate the existence of contagion in 18 out of 25 countries.[8] Both models (3.1) and (3.2) find no contagion effects for Brazil, Germany, Russia, Spain, Sweden, and the U.S. However, the globalisation model (3.2) additionally indicates that there is no evidence of contagion for Canada, France, Mexico, South Africa, South Korea and Switzerland. Hence, a model with time-invariant parameters appears to overestimate the occurrence of contagion, as argued in section 3.2 of this chapter.

An additional benefit of using the globalisation model (3.2) is that it allows for a more detailed description of contagious and non-contagious episodes. Firstly, not all contagions are equal: 12 countries experience a positive shock to their co-movements with the world at crisis onset, i.e., "shock" contagion, whereas for Italy there is evidence of a negative initial shock followed by a speedy catching-up process, i.e., "recoupling" contagion.

Secondly, not all shock contagions are equal. For instance, for some countries (e.g., Norway), the initial shock remains fully present across the entire crisis period, i.e., a level shift in the strength of the globalisation process β_t is observed. In other countries, the initial shock dies out over time, but with different end-effects. For instance, in Australia the initial shock appears to be at least partially permanent, as the level of integration remains significantly above what would be expected pre-crisis for the end of crisis period. By contrast, in other countries (e.g., India), at crisis' end the initial shock is no longer observable, which implies its transitory nature. In yet another set of countries (e.g., in Chile), the initial positive shock appears to have not only completely disappeared but reversed and became negative, i.e., the level of financial integration at crisis' end is significantly lower, not higher, than what would have been expected based on pre-crisis trends in globalisation. This heterogeneity of markets' responses to contagious shocks can only be revealed when implementing the globalisation model (3.2) with time-varying betas.

Thirdly, there is also heterogeneity in responses to crisis outbreak among those countries which did not experience contagion. For instance, countries such as Brazil do not record any

[8] The results from model (3.1) differ slightly from the those in Baur (2012), where a shorter sample period was used: our data shows evidence of contagion in Russia but none in Mexico.

significant impact of the crisis period on their intertemporal process of financial integration (insignificant $\hat{\gamma}_0$ and $\hat{\gamma}_1$), and their pre-crisis process of co-movements with the world ($\hat{\delta}_1 > 0$) continues unchanged throughout the turbulent period. Furthermore, another group of countries has not experienced any contagion but has nevertheless been affected by the crisis' outbreak: their co-movements with the world became significantly weaker at crisis' onset, and either remained so throughout the turbulent regime (e.g., France), or just caught up with their pre-crisis globalisation trend at crisis' end (the U.S.). South Korea did not respond to the crisis initially but subsequently slowly drifted away from the world stock market as the crisis unfolded. Again, this heterogeneity in non-contagion cases can only be revealed when implementing the globalisation model (3.2). The results show that out of 14 developed and 11 developing economies, 6 of each show evidence contagion. And there does not seem to be any pattern regarding contagion effects based on the geographical proximity. For instance, it can be observed from Table 3.9 that countries (e.g. Brazil and Mexico) near U.S (crisis originating country) did not show evidence of contagion whereas Australia, the furthest country from U.S experienced contagion.

Moreover, it worth noting that the globalisation model (3.2) generates results which differ substantially from those obtained using model (3.1) not only because it separates the post- from the pre-crisis period, but also because it allows integration parameters to be time-varying within each sub-period. This is demonstrated by estimating a model with a separate post-crisis period, but which still imposes constancy of integration parameters in each sub-period (i.e., model (3.2) with β_1, β_2, and β_3 not being time-varying). It can be observed that the integration process between Australia and the world stock market has been negative during the pre-crisis, compared to other countries. This might be because Australia had a heavily regulated financial system until late 1970s. Bekaert et al (2011), found that heavily regulated industries, for instance banking and insurance sectors, were among the least integrated with the world economy. Other reasons for a negative integration with the world stock market include, different industrial composition of an economy the legal environment and political stability of an economy (La Porta et al. 2007).

The estimation results of that model regarding the presence of contagion are indicated in the last column of Table 3.3. It generates an almost identical set of results as model (3.1) except for two cases: it does not find evidence of contagion in Mexico, which is in line with model's (3.2) findings, but it also fails to find contagion for Japan, even though model (3.2) indicates that the Japanese market experienced shock contagion. Hence, the differences in results between model

(3.1) and (3.2) are due to the fact that the latter allows for time variations in financial integration within each sub-period. This confirms the importance of allowing the process of integration to be time varying, as in our model (3.2).

Additionally, as a robustness test[9], I vary the timing of the crisis episode in two following ways. Firstly, the dates of 03/07/07 and 15/05/09 for the beginning and end of the crisis episode is adopted, based on findings in Dungey et al. (2015); this results in a crisis period starting earlier and finishing later than the original dataset, as adopted from Baur (2012). In addition to this, I also use a shorter crisis period as in Tong and Wei (2011), ranging between 31/07/07 and 31/12/08. The results reported in appendix A.2 indicate that extending the crisis episode as in Dungey et al. (2015) changes little to the main conclusions about occurrence and types of contagion: out of 25 countries investigated, contagion result is different in only three cases (contagion not being detected), and in other three the exact type of market reaction to crisis is different (e.g., no reaction rather than decoupling shift). In the vast majority of cases, however, a longer crisis definition yields identical results as the initial crisis period definition. Results for the Tong and Wei (2011) crisis definition are somewhat less similar, which should come as no surprise as those authors rather radically terminate the crisis episode by the end of year 2008. More specifically, with that short crisis episode, different results in six cases (either non-existing contagion detected or existing contagion not detected) are observed, and further seven cases disagree on the exact for (but not existence) of contagion. These results indicate that it is important to employ a reasonable definition of the crisis episode under investigation, but also that our method is rather robust to small, reasonable variations in this definition. In addition, if one employed a more conservative significance level (e.g., 1% rather than 5%), the differences in results for our various crisis definitions would be even less pronounced.

[9] I have also performed a "counterfactual analysis" by assuming the crisis started and ended at a much earlier date (i.e. from 9 January 2007 to 29 July 2008). The findings are very different from the main contagion results as there were fewer cases of contagion and they were mostly recoupling contagion. For instance, Australia, Hong Kong and India showed evidence of recoupling contagion, which shows that these countries were not affected at the beginning of the sample period but were rather experiencing contagion at later stage.

3.6. Conclusion

The findings of this chapter provide clear evidence that the financial crisis of 2007-09 has led to change in the dynamics of contagion between most of the stock markets of 25 leading world economies, by employing a new model for testing and differentiating among different types of financial contagion.

One of the uniqueness of this paper is that it accounts for pre-crisis trends in financial integration, making mis-diagnosis of contagion less likely. It also allows to describe different patterns of markets' reactions to an outbreak of a crisis, both cross-sectionally and over the duration of the crisis period. Hence, different types of contagion: "shock", "recoupling", and "kink" contagion can be identified. And as a result, a novel meaning of contagion is adopted, described a significant increase in equity markets co-movement during a turmoil period relative to what the co-movement would have been if the crisis did not occur (i.e. the sample intertemporal integration process as the pre-crisis period had prevailed). Moreover, for the purpose of this chapter, I have used easily obtainable stock price data and does not require identification and use of proxies for economic fundamentals. Instead of depending on any structural or latent variables, the market exposures in this paper is time-varying. Previous research studies, for instance, Bakeart and Harvey (1997); Ng (2000); have made the global (regional) market exposures, or betas, time varying by making them conditional on some structural information variables, or on a latent regime variable (for example, Baele, 2005), as discussed in earlier sections. The disadvantage of the first approach is that although it allows betas to change with structural changes in the economic and financial environment, it cannot accommodate cyclical variation in the betas. Additionally, despite the fact that the second approach allows the betas to vary over the cycle, it is less suited for permanent changes in market betas. Baele et al. (2010) combine both approaches, in the sense that the market betas are conditional on three structural variables, reflecting time-varying integration and market development, and a latent regime variable which accounts for temporary economic fluctuations.

When employed to test for contagion during the 2007-9 crisis episode on stock markets of 25 leading world economies, model (3.2) identifies many fewer instances of contagion than a popular alternative approach, which assumes sub-period specific time-invariant world market exposures (e.g., Baur, 2012, Fry-McKibbin et al., 2014, Kenourgios, Dimitriou, 2015, Dungey and Gajurel, 2014, 2015 and Dungey et al., 2015). Hence, financial crises might not be as contagious as commonly believed, in line with previous findings by Forbes, Rigobon (2002), Brière et al. (2012), Beirne and Gieck (2014), etc. In addition, the heterogeneity of markets' reactions to world market shocks is unveiled, with some suffering from contagion in the early phases whereas others in the late phases of the crisis, with initial contagion being permanent or transitory, with the pace of globalisation during crisis being affected positively, or negatively, or not at all, etc. The findings of contagion in this chapter being confined into specific phases of the crisis period correspond well with, e.g., Dungey and Gajurel (2014), Kenourgios and Dimitriou (2015) and Dungey et al. (2015), but in my approach they emerge endogenously from model estimation.

For portfolio investors, it is important to know whether the linkages between asset markets are time-varying, and how these potentially abrupt changes could be predicted, or their impact minimized, in order to devise safer investment strategies to benefit their clients. Policy makers aiming at stabilising domestic financial markets during crises would also benefit from the knowledge that the increased transmission of shocks originating abroad is likely to be due to fundamental, rational causes, and not to irrational contagion, and when it is contagious, it may materialise in one of several different forms, in different phases of the crisis. Moreover, time-varying co-movements have significant impact on international portfolio diversification. The conventional wisdom is that benefits from diversification have been diminishing over time, due to progressing globalisation, and are especially weak in crises, as correlations between stock returns tend to be higher in bear markets. However, finding of contagion in this paper being less prevalent than expected strengthens the rationale for international diversification even in crises, as demonstrated empirically by, e.g., Vermeulen (2013).

Further research could explore how allowing for non-linearity in the market integration process could help to increase the precision of the contagion type identification method proposed here. In addition, it would be an interesting avenue to explore the determinants of the cross-country heterogeneity in responses to crisis outbreaks which the method proposed here allows to uncover.

APPENDIX A: Financial Contagion: A new approach robust to trends in globalisation and interdependence

A.1: Betas during Crisis period compared to what the linkages would have been if the crisis did not prevail

Figure A.1(i) to A.1 (xii) show the time-varying integration process during the crisis (i.e. β_{2t}) between each country's stock market and the world stock market portfolio evolves during the crisis period (depicted by the blue line) as compared to how it would evolve if the same integration process as the pre-crisis was being followed (shown by the red line)

Figure (i): New Zealand

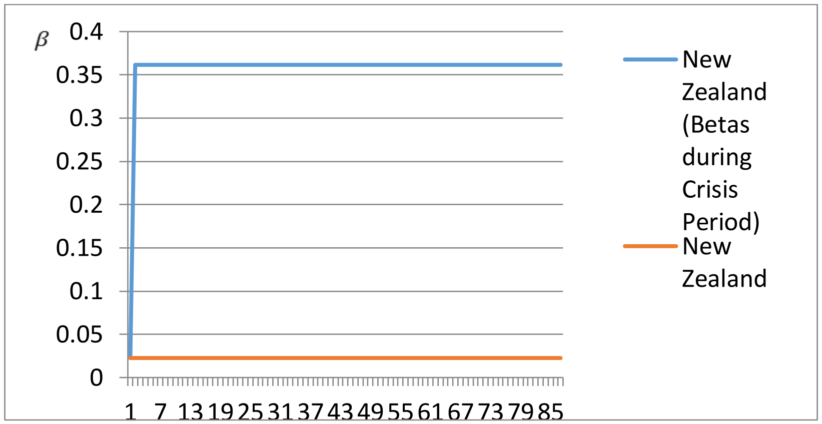

Figure (ii): Norway

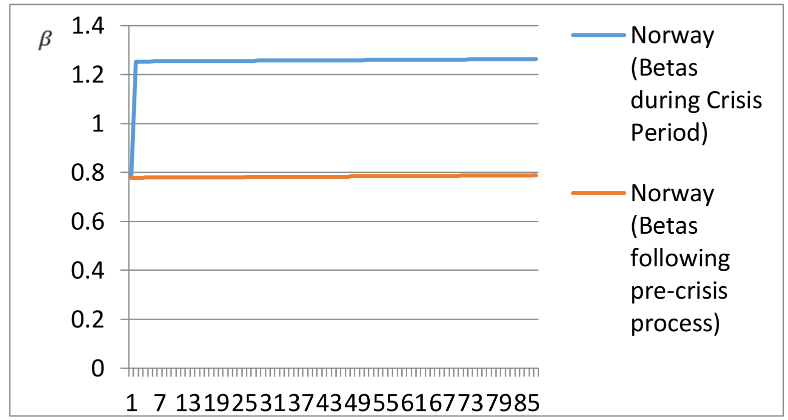

Figure (iii): Thailand

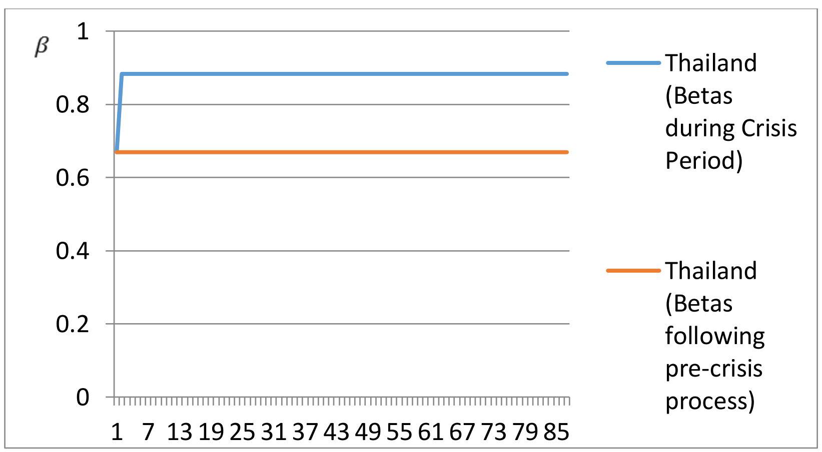

Figure (iv): U.K

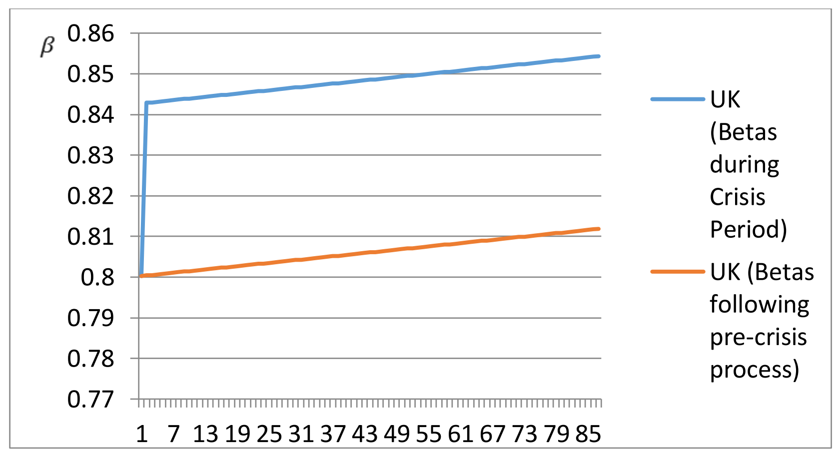

Figure (v): Australia

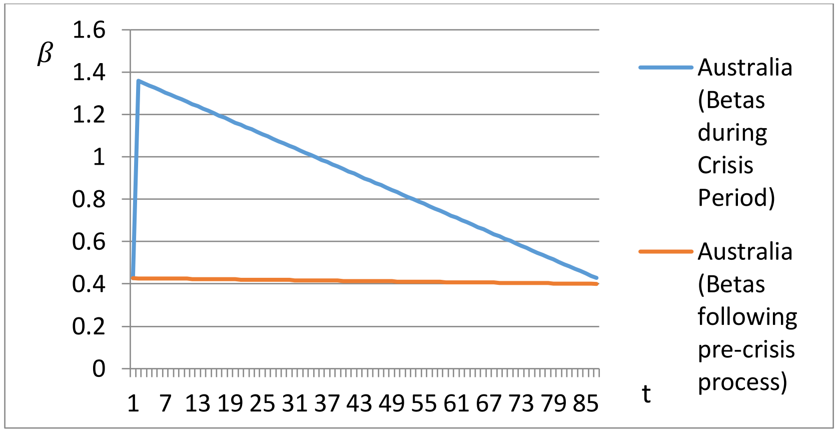

Figure (vi): Chile

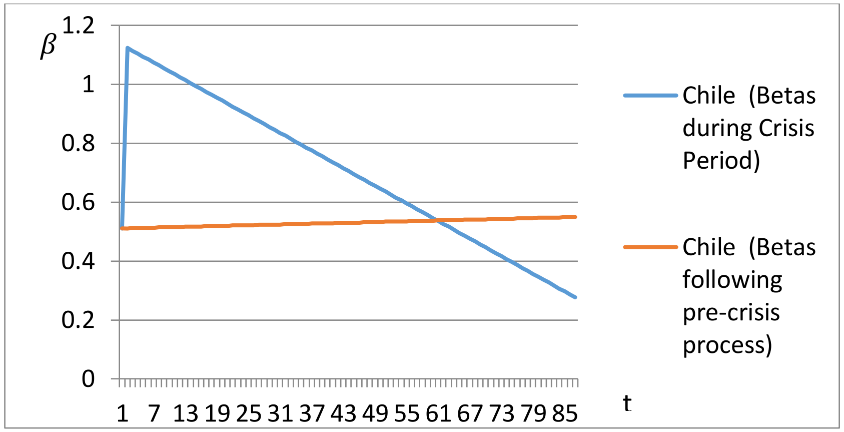

Figure (vii) Indonesia

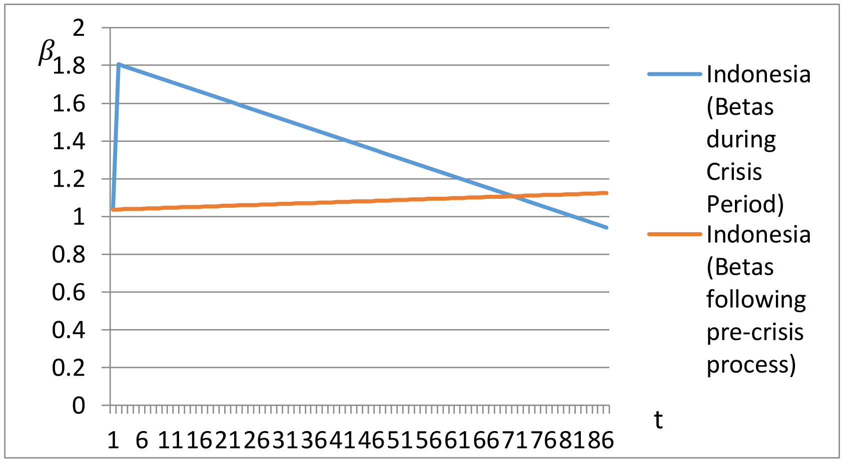

Figure (viii): Japan

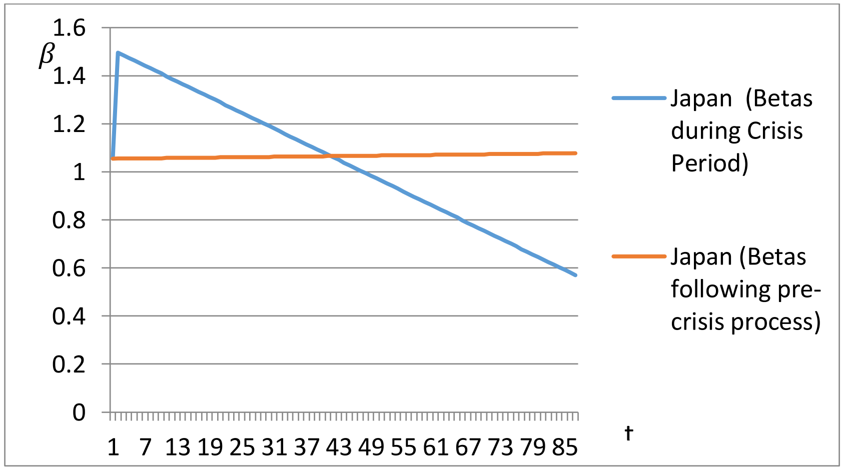

Figure (ix): China

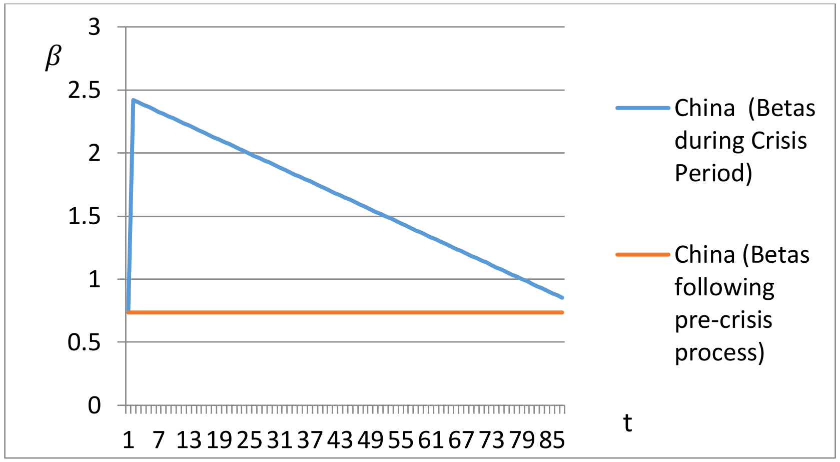

Figure (x) Hong Kong

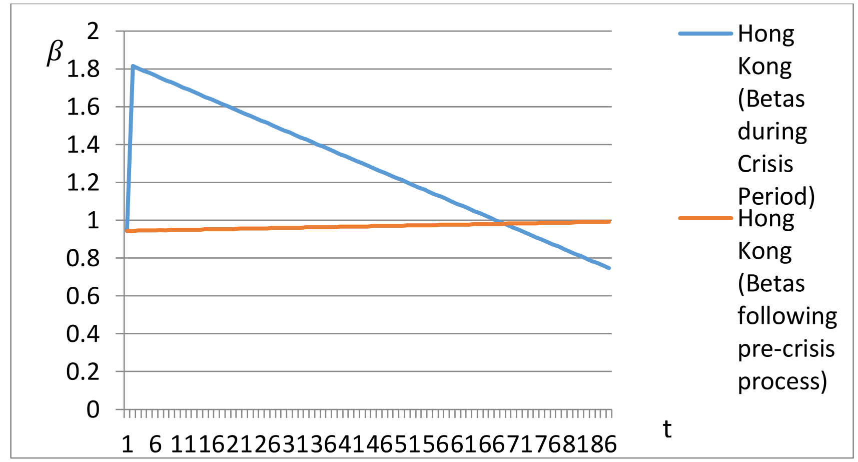

Figure (xi): India

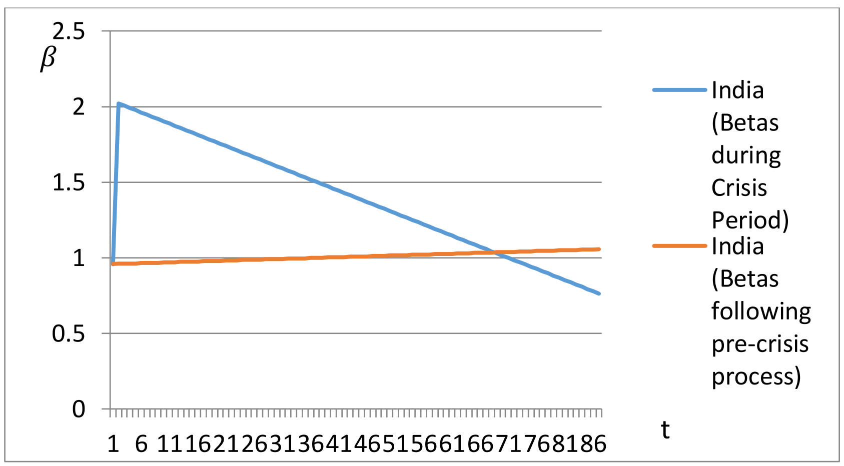

Figure (xii): Italy

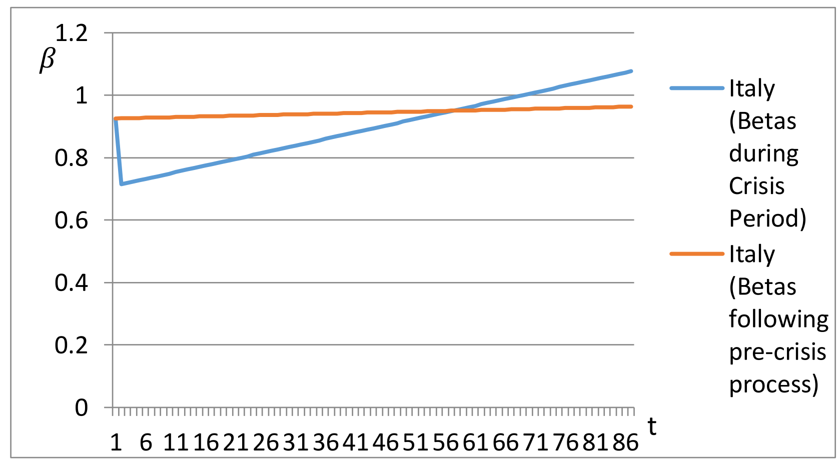

Table A.2: Sensitivity Analysis (Different crisis dates)

	Baur's Crisis Dates (7/08/07 - 24/03/09)			Dungey Crisis Dates (3/07/07-15/05/09)			Tong and Wei Crisis Dates (31/07/07-31/12/08)		
	$\hat{\gamma}_0$	$\hat{\gamma}_1$		$\hat{\gamma}_0$	$\hat{\gamma}_1$		$\hat{\gamma}_0$	$\hat{\gamma}_1$	
Australia	9.4904***	-0.0060 ***	Shock Contagion (Permanent)	9.5203***	-.0061***	Shock Contagion (Permanent)	7.168**	-.00445**	Shock Contagion (Transitory)
Brazil	-0.0176	-	No Contagion	-.2342**	-	No Contagion (Decoupling Shift)	-.1695	-	No Contagion
Canada	0.0604	-	No Contagion	.0630	-	No Contagion	-5.9583**	.0040**	Kink Contagion
Chile	15.1696 ***	-.0100 ***	Shock Contagion (Reversal)	12.12123***	-.0080***	Shock Contagion (Reversal)	15.6877***	-.0104***	Shock Contagion (Reversal)
China	28.5010***	-0.0184***	Shock Contagion (Transitory)	19.8554***	-.0129***	Shock Contagion (Transitory)	30.846***	-.0202***	Shock Contagion (Transitory)
France	-0.1464**	-	No Contagion (Decoupling Shift)	-.1631***	-	No Contagion (Decoupling Shift)	-.1333**	-	No Contagion (Decoupling Shift)
Germany	-0.3233 ***	-	No Contagion (Decoupling Shift)	-.4377***	-	No Contagion (Decoupling Shift)	10.88491***	-.0076***	No Contagion (Decoupling)
Hong Kong	20.2149***	-0.0132***	Shock Contagion (Transitory)	11.3419***	-.0074***	Shock Contagion (Transitory)	24.26847***	-.0159***	Shock Contagion (Transitory)
Indonesia	19.51***	-0.0129***	Shock Contagion (Reversal)	13.5764***	-.0091***	Shock Contagion (Reversal)	.1784231	-	No Contagion
India	17.8411***	-0.0118***	Shock Contagion (Transitory)	8.5299*	-.0056*	Shock Contagion (Transitory)	11.4794**	-.0076*	Shock Contagion (Transitory)
Italy	-5.4261*	0.0036*	Recoupling Contagion	-4.8029**	.0034**	Recoupling Contagion	-5.9050**	.0039**	No Contagion
Japan	16.41***	-0.0110 ***	Shock Contagion (Reversal)	12.0709***	-.0080***	Shock Contagion (Reversal)	13.7231***	-.0093***	Shock Contagion (Reversal)
Mexico	-.1347**	-	No Contagion (Decoupling Shift)	-.1278	-	No Contagion	-.1585**	-	No Contagion (Decoupling Shift)

New Zealand	0.0728*	-	Shock Contagion (Level Shift)	.0646	-	No Contagion	5.0094*	-.00313*	Shock Contagion (Permanent)
Norway	.3194***	-	Shock Contagion (Level Shift)	.3186***	-	Shock Contagion (Level Shift)	-13.5838***	.0094***	Kink
Russia	0.0637	-	No Contagion	.07496	-	No Contagion	-24.7964***	.01683***	Recoupling
South Africa	0.1180	-	No Contagion	.04981	-	No Contagion	.1457948*	-	Shock Contagion(Shift)
South Korea	11.33 **	-0.0078 **	No Contagion (Decoupling)	7.7180*	-.0054*	No Contagion (Decoupling)	8.9027*	-.006175*	No Contagion (Decoupling)
Spain	-0.0862	-	No Contagion	-.1355**	-	No Contagion (Decoupling Shift)	-.1422*	-	No Contagion (Decoupling Shift)
Sweden	-.2956***	-	No Contagion (Decoupling Shift)	-.3047***	-	No Contagion (Decoupling Shift)	-.2623***	-	No Contagion (Decoupling Shift)
Switzerland	-0.0556	-	No Contagion	-.1366**	-	No Contagion (Decoupling Shift)	-.0486	-	No Contagion
Taiwan	12.7843***	-0.0086 ***	Shock Contagion (Reversal)	6.481591*	-.0043*	No Contagion (Decoupling)	10.6461*	-.0071*	Shock Contagion (Transitory)
Thailand	0.1914**	-	Shock Contagion (Level Shift)	.2136***	-	Shock Contagion (Level Shift)	-.01488	-	No Contagion
U.K.	0.0932*	-	Shock Contagion (Level Shift)	.0461	-	No Contagion	.0688	-	No Contagion
U.S.	-5.7349***	0.0038***	No Contagion (Decoupling)	-.0921***	-	No Contagion (Decoupling)	-.1187***	-	No Contagion (Decoupling)

Note: The table displays contagion results for different crisis dates. Parameters stem from model (3.2): $R_{i,t} = \alpha_0 + \alpha_1 D_{t\ CRISIS} + \alpha_2 D_{t\ POST-CRISIS} + +\beta_{1t} R_{W,t} + \beta_{2t} R_{w,t} D_{t\ CRISIS} + \beta_{3t} R_{W,t} D_{t\ POST-CRISIS} + \varepsilon_{i,t}$, where $\beta_{1t} = \delta_0 + \delta_1 t$, $\beta_{2t} = \gamma_0 + \gamma_1 t$, $\beta_{3t} = \theta_0 + \theta_1 t$, where $R_{i,t}$ denotes stock returns in country *i* at time *t*, $D_{t\ CRISIS}$ ($D_{t\ POST-CRISIS}$) is a dummy variable equal to one during the crisis (post-crisis) period and zero otherwise, and $R_{W,t}$ is the return of the world stock index. Error terms are modelled as a GJR-GARCH (1,1) process, corrected for autocorrelation in residuals where required. ***, **, * indicate significance at 1%, 5%, and 10% level, respectively. Insignificant trend terms $(\delta_1, \gamma_1, \theta_1)$ are excluded and model (2) is re-estimated where relevant.

Chapter 4. Financial Contagion: A sectoral perspective

4.1. Introduction

The Financial crisis of 2007-2009 depicts a situation in which acute distress in the subprime mortgage market rapidly spread across both advanced and emerging economies worldwide and has affected both financial activities and macroeconomic conditions across the globe. In many countries, the financial sector is one of the main funding sources for industrial and service firms with little internal funds. Therefore, it is inevitable that non-financial sectors (i.e. the real economy) should be affected by the vagaries of the financial sector, following the outbreak of the crisis, as access to external financing was narrowed, hence restricting the volume of lending.

The importance of the financial section in transmitting financial shocks across both developed and developing economies around the well is well recognised in the literature (Kaufman, 1994; Kalemli-Ozcan et al. (2013). For instance, Tong and Wei (2011) state "that international capital flows rose considerable from 2002, peaking in 2007. However, since 2008, world capital inflows declined sharply by 44% in absolute dollar amount relative to the peak in 2007". This reversal of capital flows could bring disastrous economic results. For instance, the liquidity supply available to firms could be disrupted, which lead to a loss of market confidence in other financial firms and induce investors to withdraw money and eventually forcing those firms to liquidate assets at a price below their intrinsic value. Moreover, the transmission of financial shocks can be intensified by their linkages both within and across countries.

There is a prevailing notion the financial sector is the most vulnerable sector towards financial contagion in both the home country and across the world. However, in this chapter, it is hypothesised that as non-financial firms are also directly interconnected to their foreign counterparts through international trade, non-financial sectors may also be affected by contagion. A business cycle synchronization arises from trade linkages and as a result increases co-movement at a sectoral level (Giovanni and Levchenko, 2010). This interdependence in real economy activities has been considerably reinforced by the liberalization of international trade and rapid rise of multinational corporations over years. And it will be interesting to investigate how this interdependence with the world changes once the crisis has struck.

Another reason why studying contagion in the real economy is important is due to the fact that co-movement at market level may mask the heterogeneous impact on various sectors, as real economy contagion may be asymmetric, i.e. that some sectors are more vulnerable to external shocks compared to others. Furthermore, from a portfolio management perspective, this sectoral heterogeneity of contagion means that there are prospects for achieving the benefit of international diversification during crises, despite the evidence of contagion effects at the market level. Diversification opportunities will arise if there are low correlations between the some of the domestic sectors and the world stock financial sector.

Due to the above arguments and the fact that there has been little attention attributed to contagion effects at the sectoral level (particularly non-financial sectors) compared to research studies on contagion effects at a market level, this chapter investigates contagion effects in financial and non-financial sectors arising from the World Financial sector and domestic financial sectors. In this chapter, I assume that non-financial sectors are directly affected by the global system (i.e. they borrow and lend globally), and as a result the GFC has direct impact on them. Further, GJR-GARCH model is employed and contagion effects is explored in 25 countries (developed and developing), across 10 sectors (financial and non-financial). Moreover, in this study, contagion effects stemming from the World Financial sector, is labelled as "global contagion" which implies an increase in co-movement of either financial or non-financial sectors, or both. Alternatively, contagion arising within a country, from the financial sectors to the real economy, is referred to as "domestic contagion".

As mentioned in Chapter 2 and 3, most research studies (e.g. Bekaert et al. 2005; Boyer et al. 2006; Forbes and Rigobon, 2002) have adopted a strict definition of contagion, and explain it as "a significant increase in correlation between stock returns in different markets/regions." Unlike previous literatures, I define contagion as an increase in co-movement between two equity markets during a crisis period, as compared to what it would have been, had the crisis not occurred[10]. One of the advantages using this description is that, a time-trend model is used to model the natural interdependence between markets, and according to this definition, contagion occurs when there is an excess co-movement during a turbulent period over and above the existing growing natural interdependence. This framework, which has been explained in detail in the previous chapter is also used to disentangle amongst the different situations in which contagion might arise, namely, 'shock', 'recoupling' and 'kink' contagion.

The contribution of Chapter 4, relative the previous one is that it explores contagion at a sectoral level, and not at a country level. As mentioned previously, there have been numerous studies conducted on contagion at a market level, but very few at a sectoral level. Chapter 3 shows which countries displays evidence of contagion during the recent financial crisis and how the integration processes between individual stock market and the world stock market changes during periods. Moreover, it shows the different types of contagion which might arise, namely,

[10] This novel definition has been adopted from Chapter 3 of this thesis.

Shock, Recoupling and Kink contagion. However, it does not mean those countries that did not show signs of contagion were not affected by the crisis. Also contagion can be observed on a market level, but it might be driven by one or a few industries only and not all. And on the other hand, contagion might not be observed at a market level, but it exists in some sectors. Hence it is important for investors and policy makers to be aware of this in order to mitigate risk.

As a result, Chapter 4, examines contagion in a comprehensive manner, i.e. contagion at a sectoral level in the 25 countries which examined in Chapter 3 and shows the integration processes of the real economy of a country and which sector has been most or least affected by the recent financial crisis. Moreover, recent research studies (e.g. Cho et al., 2007) have shown that industries have become more integrated globally over time, and are as a result more prone to facilitate global shocks to spread across countries. For instance, during the recent financial crisis, the turmoil that started in the subprime loan sector propagated to the banking sector and then across the whole world.

The findings of this chapter show that during the 2007-2009 financial crisis all countries experienced "global contagion" through at least one of their sectors, and it had a more pronounced impact on developed relative to developing countries. Additionally, there is less occurrence of "domestic contagion" as compared to exposures from the World financial sector. But, most importantly, the findings show that a high degree of heterogeneity in contagion is experienced across all the sectors, with Basic materials, Financial, and Utilities sector showing the highest incidences of "global contagion". There are numerous potential reasons for sectoral contagion, for e.g. dependence on external financing, the surge in multinational corporations, trade channels, information asymmetry, amongst others. As far as the types of contagion is concerned, it is observed that sectors have been experiencing 'Shock' contagion more than any other type of contagion implying that these sectors were affected immediately after the outbreak of the financial crisis.

This study differs from the above-mentioned research studies and contributes to the literature firstly in terms of our novel definition of contagion, proposed in Chapter 3, in order to overcome the ambiguity surrounding the meaning of contagion and explain this phenomenon as an excess co-movement in asset return during a period of turmoil, in comparison to what the co-movement would have been if the crisis did not occur. Moreover, similar to the previous chapter, a time trend is allowed in this contagion framework, in order to account for long-term processes such as globalisation, and hence allowing to empirically distinguish between genuine contagion and changes in linkages in the financial markets which would have prevailed in normal conditions.

Given the above, the results of this chapter also show how the integration process between the real economy and the global/domestic financial sector has been evolving before, during and after the crisis. This also enables one to look at whether countries that were more integrated with the financial sectors (world) were more prone to contagion compared to those that did not show any positive integration during the pre-crisis period. Another contribution of this research is that since there is an emphasis on the different types of contagion which might arise during a crisis, this enables me to examine whether sectors across 25 countries experienced contagion effect at the beginning of the crisis, or they were affected during the last phase of the crisis period.

The rest of this chapter is organised as follows. In Section 4.2, the literature of contagion effects at a sectoral level are presented. Section 4.3 describes the methodological framework to differentiate among different types of and test for financial contagion. Methodology and data are presented in Sections 4.4 and, respectively, whereas Section 4.5 describes the results and Section 4.6 summarises the findings and concludes.

4.2. Prior Literature on Contagion at a sectoral level

In the literature of equity markets contagion, there seems to be a dominance of country effects as compared to industry effects, which explains the lack of research on a sectoral level. Traditionally, researchers (for e.g. Griffin and Karolyi, 1998, and Serra, 2000) stated that "country effects are important in determining the stock returns and a nation's unique economic environment is the reason why markets do not move closely together, resulting in low correlations and subsequently risk reduction benefits for international diversification." However more recent research studies (e.g. Campa and Fernandes, 2006; Carrieri et al., 2012) show there has been an increase in the importance of industry effects. This is mainly because an economy consists of a mixture of different industries, and their stock prices might not be perfectly correlated with each other. For example, if two countries concentrate in two different sectors, then holding the two country portfolios is similar to holding portfolios of these two sectors. Hence, the two sectors do not have a perfect correlation, the two countries will also have low correlation. The analysis of sectoral spillovers thus provides a complimentary and more granular perspective on equity market spillovers.

4.2.1. *Equity Market Contagion– A sectoral perspective*

The focus of this chapter is to investigate contagion effects in real economy during the recent global financial crisis. As established in the previous chapters of this thesis, there has been an on-going debate in the finance literature about the definition of contagion in international stock markets and returns, since the Forbes and Rigobon (2002) was published, leading to numerous methods and conflicting contagion results during crisis periods. Contagion analysis has evolved from simply examining correlation coefficients to more sophisticated methods, capable of addressing the shortcomings in the probability models, correlation breakdown approach, such as heteroscedasticity, omitted variables and endogeneity. For instance, dynamic copulas have been extensively used in contagion literature (see Patton, 2006; Okimoto, 2008; Aloui et al. 2011). Dynamic conditional correlation (DCC) GARCH models have also been used (Chiang et al. 2007; Dimitriou et al. 2013). And as far as analysing contagion at a sectoral level, several approaches have been used. Amongst them, there is the factor model based on the capital asset pricing approach (e.g. Phylaktis and Xia, 2009, Cho et al. 2015, Dungey and Gajurel, 2014, Bekaert et al. 2014) and multivariate GARCH models (e.g. Chiu et al, 2014, Kenourgios and Dimitriou, 2015).

The objectives of the above-mentioned research studies were however not limited to generate a yes/no answer to the question of whether there was any evidence of contagion. For instance, Dungey and Gajurel (2015) examines the impact of unexpected international transmission of banking crises from 2007 until 2009 for 54 countries and find that these transmissions are beyond any fundamentals that would occur during 'normal' times. Subsequently, they categorise contagion into 3 types, namely systematic contagion, idiosyncratic contagion and structural shift and found that most of the banking sectors in their sample experienced systematic (transmission of common shocks that hit the global market) and idiosyncratic (unanticipated impact of shocks affecting U.S banking sector and transmitted to other banking sectors) contagion during the crisis period.

Bekaert et al. (2014) develops a three-factor model to set a benchmark for what global equity market co-movements should be, based on existing fundamentals (such as capital injections in financial and non-financial firms, trade and financial openness, information asymmetries, etc.). The model distinguishes between a U.S specific factor, a global financial sector and a domestic factor for the pricing of 415 country-sector equity portfolio, across 55 countries. They define contagion as the co-movement in excess of that implied model. They also show that contagion was more dominant from global equity markets to individual domestic equity portfolios as compared to contagion from U.S markets. Moreover, they found that the strongest effect of contagion was experienced in Basic Materials, Industrials, Utilities, and Energy across all regions in their sample.

Additionally, Baur (2012) and Kenourgious and Dimitriou (2015) investigate contagion in the real economy during the recent financial crisis and concluded that the sectors that were affected the most during the recent financial crisis are Energy, Utilities, and Basic Materials whereas the least affected are Telecommunications, Consumer Goods, Industrials and Healthcare. Both research studies look at the impact of external (global or U.S) and regional shocks on the real economies. Cho et al. (2015) detect contagion in Oil & Gas, foods and automobiles industry.

4.2.2. Integration at a sectoral level

"Theoretically, more open and integrated markets should lead to a lower cost of capital, increased savings and eventually, enhanced economic growth through international risk sharing" (Bekaert and Harvey, 2003; Carrieri, Errunza, and Hogan, 2007). Despite the fact that integration has its benefits, it can also make countries more vulnerable to external shocks. The benefits of globalisation have been extensively questioned during the global financial crisis, as there was a general belief that interconnected markets help propagate the crisis across the global markets. However, there are a few research studies that have examined the relationship between stock market integration and financial crisis, and amongst them is Bekaert et al. (2011) who use a three-factor model, to investigate the impact of the subprime crisis on both advance and emerging economies and Pukthaunthong and Roll (2009) who use a multi-factor model based on its explanatory power to investigate recent trends in global integration. These two papers found contrasting findings regarding integration dynamics during the crisis period. The former find than decoupling prevails during crisis periods, while the later find the opposite. Moreover, Bekaert et al. (2014) report that most integrated countries were not the ones that were mostly affected during the global financial crisis. And on the other hand, Lehkonen (2014) who examines the dynamics of stock market integration process by using a multifactor integration measure, on both developed and emerging economies show that higher level of market integration helped to propagate the crisis in several countries at the start of the financial crisis.

Kaltenhauser, (2002), (2003) and Phylaktis and Xia (2009) were amongst these very few research studies that examined integration at a sectoral level in equity markets. Phylaktis and Xia (2009) use a rolling estimation method to examine time variant correlation, explored the integration of 10 sectors for 29 countries at a regional and global (U.S) level. They find that the pattern of the sectors integration changed over time, especially during turmoil periods. For instance, during the period from 1990 to 2009, sectors in Europe and Latin America showed a stronger integration at a regional level, whereas sectors in Asia were more integrated with the global market during the same period of time.

Hence while identifying contagion from the financial sector, this chapter also explores the integration process of the world financial sector and domestic financial sector before the crisis and during the

4.2.3. Reasons for sectoral contagion

There a few research studies conducted on the channels of contagion which tried to explain the varied contagion results. For instance, Kenourgios and Dimitriou (2015) argue that a crisis can quickly spread across sectors as a result of the rapid process of ***financialization*** (for instance, increasing derivatives trading, growth in hedge funds and commodity index funds), which has made the real economy sectors more vulnerable to financial shocks. They also add that ***multinational corporations*** are more susceptible to to contagion, as a shock in the host country is easily diffused to the home country of the multinational corporation. Further, According to Cravino and Levchenko (2015) stated that, "multinational corporations accounted for about one-third of gross output in many developed countries. There are numerous interrelated channels through which multinational corporations affect the co-movement of economic activities across countries. Firstly, multinational corporations play an important role in increasing vertical production linkages across countries, which as a result magnifies the impact of bilateral trade on output co-movement. Secondly, investment rates and returns of foreign affiliates are strongly correlated with those of their parent companies. And lastly, the sales growth of the headquarter is strongly associated with sales growth of affiliates. Hence, the role of multinationals (together with the move towards free trade) in recent decades, has facilitated the transmission of demand and supply shocks across countries though non-financial firms."

Different industry characteristics (such as industry's debt financing, valuation and investment) can also increase the vulnerability to crises (Chiu et al, 2015). Hence if most industries in a sector are dependent on ***external financing***, the likelihood of that sector being affected is higher when a crisis hits, as industries that are dependent on external debt sometimes encounter difficulties to raise funds from the financial sector. And, the probability of finding funds through sales of assets or external funding is better in normal times. However, when the financial sector is in crisis (or foreign financial sectors, in the event that the sector is dependent on external financing from banks outside the country), credit constraints may prevail and, in these situations, industrial sectors may be adversely affected. Rajan and Zingales (1998) also emphasis that those industries that are more dependent on external financing are more severely affected by crises and are more likely to experience larger contractions in investment, output and value-added growth, as a fall in finance have a larger negative impact on industries where external finance is more important. And as far as ***the industries' valuation and investment*** are concerned, the higher the industrial sectors' valuation and investments are, the less likely are they going to be dependent on the financial sector, which minimise the impact of contagion from a crisis in the domestic financial sector. Chiu et al (2015) also added that ***competitive industries*** might be more to suffer from a crisis in the financial sector as compared to concentrated industries.

Another factor that increases the vulnerability of the individual sectors is the ***financial and economic integration*** with the rest of the world (See Briere et al., 2012; Mendoza and Quandrini (2010)). Forbes (2004) stated that the ***trade channel*** has often been associated with international spillovers and contagion. "Changes in relative trade structure ratio has been significantly associated with the probability of contagion from one country to another", according to Luchtenberg and Vu (2015). They also found that an increase in relative export of country *i* from country *j* before and during the financial crisis of 2008 is positively related to contagion. Moreover, they also find that U.S is more independent than any other markets in their study as U.S spreads the most and receives the least financial shock from other countries. They argue that the reason is because during the financial crisis, U.S reduced its imports from other nations. Bekaert et al. (2014) adds that trade and financial channels can indirectly contribute to domestic contagion, if these channels break down during the crisis period. Their observation is that, "if international factor exposures are increasing in external integration, and domestic factor exposures decreasing. This can lead to a partial segmentation model where international firms are priced differently as compared to domestic ones, and the later are still an important part of the domestic market portfolio. And if during a crisis, trade and financial flows collapse, this could cause a pattern whereby firms are now more correlated with the domestic factor and less with international factors."

Information asymmetry is another source of contagion, whereby investors rely on easily available public information which as a result may lead to increasing co-movements. For instance, in the event of imperfect information, investors may believe that other countries undergo similar problems and situations during a financial crisis and as a result sell asset in other countries (especially those with similar conditions as in where the crisis started). Dumas et al (2011) states that "domestic and foreign investors may have difference of opinion on public signals, whereby local investors are better equipped to interpret (local) public news compared to foreign investors. And as a result, returns and international capital flows co-move positively (as foreign investors erroneously view increases in stock market as a signal of future increases)." The wake-up call hypothesis has also been investigated by Bekaert et al. (2014), whereby "a crisis is initially restricted to one market segment or country, and new information provided may prompt investors to reassess their vulnerability of other market segments or countries. Under the wake-up call hypothesis, countries without trade or banking linkages with the country in which the crisis started may experience contagion, but the extent of their exposure depends on the strength of their local fundamentals and institutional factors."

Investors' behaviour may be determined not only by their information (or lack thereof) on countries in their portfolio as mentioned above, but also by information on the action of other investors. Investors may find it less costly and therefore more advantageous to follow the investment pattern of other informed investors, thereby generating additional effects from information asymmetries. Bikhchandani and Sharma (2001) define ***herding*** as an excessive and irrational tendency of traders to ignore fundamental information and flock together which might lead to destabilisation of markets and generate excess volatility. ***Risk aversion*** and liquidity are also factors that might contribute to contagion. As per Baker, Wurgler, and Yuan (2012), international asset prices are quite sensitive to risk aversion and liquidity constraints, which are two factors that might contribute to contagion. During a crisis period, risk aversion tends to increase substantially, and in such circumstances, they might flee to safer assets (e.g. government bonds in their country or other advanced economies) and shun the risky assets. Additionally, Brunnermeier and Perdesen (2008) and Adrian and Shin (2010) stresses the role of illiquity in exacerbating the crisis. For instance, the freezing of credit and interbank markets and a liquidity in U.S made it difficult for financial and nonfinancial institutions to obtain capital.

Due to international exposure, one would expect tradable goods (e.g. manufacturing) denominated sectors to be more prone to contagion as compared to non-tradable goods (e.g. healthcare) denominated sectors. However, a non-tradable denominated sector might not be immune to the financial crisis as well if the sector is dependent upon the domestic financial sector for funding, whereby access to credit has become more difficult following the outbreak of the crisis.

4.2.4. Summary of the Literature Review

This chapter differs from the research studies mentioned above, in the way the exposures ('betas'), while testing for contagion and integration between sectoral returns and financial sectors are modelled. Previous research studies (such as Bekaert et al. 2004; Dungey and Gajurel, 2015) have made global (regional) market exposures, or betas, time-varying by making them on some structural information on a latent regime variable. However, as established earlier, one of the challenges of this method is that while it allows betas to change with structural changes in the economic and financial environment, it cannot account for cyclical variation. Moreover, it is not clear which variables exactly should be included in such a model to fully capture the impact of fundamentals on interdependencies among markets, which might lead to possible model misspecifications due to omitted variable bias and potential incorrect inference about existence of contagion. And, lastly, as many empirical proxies of fundamentals are only available at low frequencies, a researcher is left with either too few observations in the crisis period (when fitting the model to low frequency data), or high persistence and low volatility of explanatory variables (when regressing high frequency stock returns on low frequency economic variables), especially if the crisis period under investigation was short. For instance, Bekaert et al. (2011) and Lekonen (2015) used an annual and monthly frequency of data respectively, which prevents them from capturing higher frequency dynamics. Our method not only allow the co-movement between weekly stock returns to move over time, as it has been widely accepted that market integration process is time-varying (Bekaert and Harvey, 2003; Pukthaunthong and Roll (2009), amongst others), but also distinguishes between the start and the remainder of the crisis. We also treat the pre-crisis and post-crisis period differently, as compared to Baur (2012) and Kenourgios and Dimitriou (2015), for instance, whereby these sub-periods are treated similarly, hence leading to potential overestimation or underestimation of contagion results.

However, it is still challenging to attribute a specific reason for heterogeneity in contagion results in the real economy as it depends on multiple factors (e.g. rapid financilization process, multinational corporations, reliance on external financing, industries' valuation and investment, competitive industries, financial and economic integration, trade channel, information asymmetry, herding, risk aversion, amongst others). Moreover, despite the well scrutinized research on contagion effects in equity market, controversy remains regarding the definition of contagion and the best approach to empirically test of it. Loosely speaking, financial contagion is referred to as the diffusion of financial distress from one market to another and most of the previous literatures as it is in the aforementioned research studies define contagion as being "a significant increase in linkages between stock returns in different markets during a crisis episode, beyond linkages in fundamentals." The disagreement on whether contagion is observed or not is due the lack of agreement on a definition of contagion, and hence also on an appropriate testing technique. Understanding the concept of contagion, and its origin is important for policy makers and fund managers, who aim to diversity risk.

4.3. Empirical Methodology

The methodological framework is based on Chapter 3. In this chapter, the impact of the world (and domestic) financial market on the real economy is being examined. Hence, the key difference between the equations of the third and fourth chapter is that in the latter, instead of looking at the world stock market portfolio as the exogenous variable, world financial market is used instead. Moreover, the endogenous variables will no longer be the equity returns across countries but will be the equity returns at a sectoral level across the 25 countries investigated in this chapter.

4.3.1. The Sub-period Specific Constant Spillovers Model

For the first part of this study, a standard contagion model, based on Eq. 3.1 is used:

$$R_{S,i,t} = \alpha_0 + \beta_1 R_{fin,w,t} + \beta_2 R_{fin,w,t} D_{t\ CRISIS} + \omega_1 R_{fin,i,t} + \omega_2 R_{fin,i,t} D_{t\ CRISIS} + \varepsilon_{S,i,t} \quad (4.1)$$

Where $R_{S,i,t}$ denotes sector returns in country i, $D_{t\ CRISIS}$ is a dummy variable equal one in crisis period and zero otherwise. The coefficients β_i measures the impact the world financial sector portfolio ($R_{fin,w,t}$) on sector (S) during non-crisis (β_1) and crisis ($\beta_1 + \beta_2$). And on the other hand, ω_i measures the impact the domestic financial sector ($R_{fin,i,t}$) on sector (S) during non-crisis (ω_1) and crisis ($\omega_1 + \omega_2$). Using the above model (i.e. Eq. 4.1), the presence of contagion effects from the world and domestic financial sector on each sectors of country i is examined. There is the evidence of contagion determined if $\beta_2(\omega_2)$ is positive and significant.

This test assumes that the global financial system has direct impact on non-financial firms, i.e. firms lend and borrow globally and hence are directly affected by the GFC. And in order to control for an impact of the domestic financial sectors, while testing contagion effects from the world financial portfolio to the real economy, I include the domestic financial sector in both normal ($R_{fin,i,t}$) and crisis ($R_{fin,i,t} D_{t\ CRISIS}$) periods in the above equation. Moreover, as compared to Baur (2012), the sample period is longer, i.e. from October 1979 until March 2012, which allows for an extended post crisis period, as I wish to look at the short term changes in the integration processes between sectoral returns and the world (domestic) financial sector after the turbulent period.

The assumptions of Eq. (4.1) have been extensively discussed in Chapter 3, and due to its shortcomings and potential biasedness regarding contagion results that may arise from (4.1), Eq. (4.2) below is employed to investigate contagion effects and integration processes, more precisely.

4.3.2. Globalisation Model

$$R_{S,i,t} = \alpha_0 + \alpha_1 D_{t\,CRISIS} + \alpha_2 D_{t\,POST-CRISIS} + \beta_{1t} R_{fin,w,t} + \beta_{2t} R_{fin,w,t} D_{t\,CRISIS} + \beta_{3t} R_{fin,w,t} D_{t\,POST-CRISIS} + \omega_{1t} R_{fin,i,t} + \omega_{2t} R_{fin,i,t} D_{t\,CRISIS} + \omega_{3t} R_{fin,i,t} D_{t\,POST-CRISIS} + \varepsilon_{S,i,t} \qquad (4.2)$$

where $\beta_{1t} = \delta_0 + \delta_1 t$, $\beta_{2t} = \gamma_0 + \gamma_1 t$, and $\beta_{3t} = \theta_0 + \theta_1 t$.

And where $\omega_{1t} = \mu_0 + \mu_1 t$, $\omega_{2t} = \rho_0 + \rho_1 t$ and $\omega_{3t} = \varphi_0 + \varphi_1 t$

The Globalisation model[11] aims to capture the time-varying nature of sector-level integration and allows the betas to change over time. Eq. (4.2) shows the integration process of the real economy with the world financial sector and domestic financial sector in 3 sub-samples, measured by β and ω respectively. $\delta_1(\mu_1)$ shows the pace of globalisation during the pre-crisis period, as measured by the sensibility of sectors "s" returns to returns on world (domestic) financial sector portfolio. $\delta_1 + \gamma_1(\mu_1 + \rho_1)$ and $\delta_1 + \theta_1(\mu_1 + \varphi_1)$ are defined as the pace of globalisation during crisis, and post crisis period respectively for the world and domestic financial sector with the real economy. Moreover, (4.2) treats the pre-crisis and post crisis differently, by assigning a dummy variable (i.e. $D_{t\,POST-CRISIS}$) to the latter and the intercept is also varied across time, i.e. a dummy is assigned for the constant term during the crisis and the non-crisis period.

And similar to Eq. (4.1), I control for an increased co-movement of the financial sector with the domestic financial sector and include the latter in normal ($\omega_{1t} R_{fin,i,t}$), crisis ($\omega_{2t} R_{fin,i,t} D_{t\,CRISIS}$), and post crisis ($\omega_{3t} R_{fin,i,t} D_{t\,POST-CRISIS}$) periods in the above equation.

It should be noted that (4.2) nests (4.1). If, $\delta_1, \gamma_1, \mu_1, \rho_1, \alpha_1, \alpha_2$, ω_{3t} and β_{3t}= 0, Eq. (3.1) is obtained, i.e. the Baur (2012) model. Hence, the second model is more flexible than the previous one as it treats pre-crisis and post-crisis period differently and employs allows for time-varying intercepts. But most importantly the coefficients β_t which measure the co-movement between

[11] The use of categorical variables can result in a multicollinearity problem. This predominantly occurs when the combinations of all dummy variables included in the regression as explanatory variables, are the same length as the full sample dependent variable. This is often referred to as the dummy variable trap. Eq. 4.2 does not fall in the dummy variable trap and therefore there is no multicollinearity problem of this type. Multicollinearity has also been tested with investigated where interaction variables are in use. Correlation can be reduced by "centering the variables" through an exercise of subtracting the mean (constant) from the interaction dummy. However, this suggested solution has been shown to have minimal overall benefit to the efficiency of the regression (Wißmann and Toutenburg, 2007).

the world financial sector portfolio on country i in pre-crisis (β_{1t}), crisis ($\beta_{1t} + \beta_{2t}$), and post crisis ($\beta_{1t} + \beta_{3t}$) period, respectively, and are allowed to change over time within each sub period, to allow for globalisation.

This model is motivated by Eq. 3.2. It attempts to avoid the misidentification of contagion, and restrictive specification regarding the post-crisis period having the same characteristics (in terms of the coefficients) as the pre-crisis period, as in financial contagion literature (e.g. Baur, 2012; Kenourgios and Dimitriou, 2015).

The details on how evidence of contagion is captured by this model are briefly explained below (as it has been comprehensively discussed in Chapter 3).

a) Shock Contagion

The term "shock" contagion in this chapter refers to a positive jump in the co-movement (β_{2t}) between the sectors returns of each 25 countries and the world financial sector, following the outbreak of the crisis. In other words, it means that $\beta_{2t} > 0$ at the starting point of the crisis period ($t = \tau_1$). As far as shock contagion from the local financial sectors to the real economy is concerned, it is going to be denoted by a positive jump in the co-movement (ω_{2t}) between the sectors returns of the individual countries in our study and their local financial sectors, following the outbreak of the crisis, i.e. $\omega_{2t} > 0$ at $t = \tau_1$)

Following this initial rise in the co-movements of sectors returns with the world financial sector (β_{2t}) or domestic financial sector (ω_{2t}) , there are different scenarios which may occur during the crisis period, i.e. contagion might be permanent, transitory, or reversed.

b) Recoupling Contagion

Recoupling contagion, here, is a situation where there is an initial fall in the co-movement ($\beta_2(\tau_1) < 0$) between the individual sectors returns and the world financial sector, but subsequently the β_t increases above the level which would have prevailed with no change due to the crisis. This situation can be defined as contagion only if there is an increase in the slope (γ_1> 0) during the crisis period, and if β_t is higher at a certain point during the crisis than what it would have been if the slope of integration process would have been the same as the pre-crisis period. In other words, it means that the β_t should be higher at the end of the crisis period than what it would have been if the same integration process as the pre-crisis period was being continued.

In the case of Recoupling contagion from the domestic financial sector to the other sectors of the economy, it is going to be represented by a as an initial fall in the co-movement between the individual stock market and the world stock market ($\omega_2(\tau_1) < 0$), followed by a subsequent rise in ρ_t above the level which would have prevailed with no change due to the crisis.

c) Kink Contagion

"Kink" contagion is whereby there is no abrupt change in co-movement (i.e. $\beta_2(\tau_1)$=0) between the sectors returns of individual countries and the world financial sector during the first week of the crisis. In these instances, contagion is identified provided there is an increase in the slope ($\gamma_1 > 0$) during the crisis period and consequently β_t is higher during the crisis than what it would have been if the slope of integration process would have been the same as the pre-crisis period.

And for Kink Contagion to occur from the local financial sector to the real economy, $\omega_2(\tau_1)$=0, provided there is an increase in the slope ($\rho_1 > 0$) during the crisis period, and consequently ρ_t is higher during the crisis as compared to what if it would have been if the integration process would be the same as the pre-crisis period.

4.3.3. Tests for Contagion Definitions

As mentioned in the previous section, the occurrence of contagion can be categorised into three scenarios. And in order to determine the type of contagion, a *t*-test is performed later in order to test for the significance of β_t and ω_t at a specific point of time (more precisely, for the first and last week of the crisis period).

The level of β_t and ω_t at each point in time across the crisis period is calculated from the estimated model (4.2), both the crisis-specific β_t and ω_t values as well as those values which would be observed if the pre-crisis process in continued unchanged into the crisis period:

$$\boldsymbol{\hat{\beta}}\ (\textbf{during the crisis period}) = \boldsymbol{\hat{\delta}_0} + \boldsymbol{\hat{\gamma}_0} + \left(\boldsymbol{\hat{\delta}_1} + \boldsymbol{\hat{\gamma}_1}\right) \boldsymbol{t}$$

$$\boldsymbol{\hat{\omega}}\ (\textbf{during the crisis period}) = \boldsymbol{\hat{\mu}_0} + \boldsymbol{\hat{\rho}_0} + (\boldsymbol{\hat{\mu}_1} + \boldsymbol{\hat{\rho}_1})\ \boldsymbol{t}$$

Where *t* is $1451 \leq \boldsymbol{t} \geq 1536$

Given the estimates of model (3.2) parameters as well as their variance-covariance matrix, a *t*-test can be performed in order to test for the significance of the difference in $\beta_t(\omega_t)$ between the crisis $\beta_t(\omega_t$) values and those which would have been observed if crisis outbreak had had no effect on the intertemporal movement in $\beta_t(\omega_t)$, at any point in time. The particular form of the *t*-test (i.e. a one tailed- or two-tailed test) will depend upon the type of contagion which is being tested for.

4.4. Empirical Methodology

Equation (4.2) is estimated within a GARCH framework, as the OLS estimation technique may provide not only inefficient but also potentially inaccurate parameter estimates (Hamilton, 2010). More specifically, following Chapter 3 of this thesis, the Glosten et al. (1993) or GJR, approach is employed to model the process of conditional volatility in residuals. The GJR-GARCH model also allows to capture asymmetries in volatility's responses to positive and negative shocks. Model (4.2) constitutes the mean equation, whereas the conditional volatility, $h_{S,i,t}$, is modelled as a GJR-GARCH (p,q) process:

$$h_{S,i,t} = \omega_{S,i} + \sum_{j=1}^{p}(\alpha_{S,i,j} + g_{S,i,j} I_{S,i,t-j})\varepsilon^2_{S,i,t-j} + \sum_{k=1}^{q} b_{S,i,k}\, h^2_{S,i,t-k} \tag{4.3}$$

where $I_{S,i,t-j} = 1$ if $\varepsilon_{S,i,t-j} < 0$ and is equal to zero otherwise, $\varepsilon_{S,i,t-j}$ represents the error term from equation (4.2), for sector *S* in country *i*, lagged *j* periods, and it is assumed this error can be decomposed as $\varepsilon_{S,i,t} = \sqrt{h_{S,i,t}} v_{S,i,t}$ with $v_{S,i,t} \sim iid(0,1)$. This model allows for the impact of past shocks on conditional volatility to be different depending on whether they are positive ($\sum_{j=1}^{p} \alpha_{S,i,j}$) or negative ($\sum_{j=1}^{p}(\alpha_{S,i,j} + g_{i,j})$). Typically for stock market data, one expects $g_{i,j} > 0$, i.e., for a negative shock at lag *j* to exert a larger impact on conditional volatility of stock returns than a positive shock of the same magnitude, a phenomenon known as the leverage effect (Black, 1976). The GJR-GARCH nests both the GARCH model, which imposes no asymmetries $g_{S,i,j} = 0$ and the more restrictive ARCH model, ($g_{S,i,j} = b_{i,k} = 0$)

Similar to Chapter 3, the combined model (4.2) and (4.3) is subject to a battery of specification tests. Firstly, the (log) indices and returns are tested for stationarity using both the Augmented Dickey-Fuller (Dickey and Fuller, 1979) and the Phillips and Perron (1988) tests using the Enders (2010) sequential procedure to select the most appropriate model (with or without the constant and the deterministic trend), to make sure that only stationary variables are used in equation (4.2) to avoid potential spurious regression problems. Second, we test for cointegration between each national and the world (log) index, as existence of cointegration would necessitate an inclusion of an error correction term into equation (4.2) to circumvent the omitted variable bias; this is accomplished by employing both the Engle and Granger (1987) test using Mackinnon (1996) critical values, and the Johansen (1991) cointegration test. For the latter, in addition to the trace and eigenvalue statistics, we also employ an alternative approach suggested by Gonzalo and Pitarakis (1998) and Anzar and Salvador (2002) to determine the number of co-integrating equations in a VECM: a consistent estimator of the number of co-integrating equations is provided by choosing the number of co-integrating equations that minimizes the Schwarz Bayesian Information Criterion (SBIC).

The resulting mean equation (4.2) is firstly estimated by OLS and the residuals are tested for heteroscedasticity using the White (1980) test. Existence of heteroscedasticity provides further rationale for modelling the error terms within a GARCH framework. The GJR-GARCH model is fitted assuming normal distribution of error terms at first, and the resulting residuals are tested for normality using the Shapiro-Wilk test. Where non-normality is found, model (4.2)-(4.4) is re-estimated under the assumption that residuals follow t-distribution or GED (generalised error) distribution. Subsequently, the final distribution decision (normal, t, or GED) is made based on the information criteria (AIC and BIC), and model (4.2)-(4.3) is re-estimated. Next, Ljung-Box Q statistics are employed to test whether there remains autocorrelation in residuals, and where required, these are modelled as an ARMA process. Lastly, we test whether using a GJR-GARCH specification fully captures the ARCH effects in residuals, by applying Engle's Lagrange multiplier test to standardised residuals.

A general-to-specific approach in estimation of model (4.2)-(4.3) is employed. Initially, the full model allowing for linear trends in coefficients β_t in each subperiod is estimated. Next, those trend coefficients found insignificant are dropped from the regression and the reduced model (4.2) is estimated. This ensure that the precision of parameter estimates is not negatively affected by the presence of insignificant variables.

4.5. Data

The data comprises of weekly prices (Tuesday to Tuesday closing prices) from October 1979 to March 2012 of 10 sector stock equity indices[12] for 25 countries. The sectors under study are as following: Basic Materials, Oil and Gas, Consumer Goods, Consumer Services, Healthcare, Telecommunications, Financials, Industrials, Technology and Utilities. The data has been obtained from DataStream and are classified by industry and sector type, for example financials is a sector within which several industries are included, such as banks, life insurance and real estate. Each sector contains a representative sample of major stocks within that classification. The components of each sectors are found in Table 4.1 below. The classification structure is based on the Industry Classification Benchmark (ICB) jointly created by FTSE and Dow Jones.

Table 4.1: Sectors classification based on Industry Classification Benchmark (ICB)[13]

Sector	Industries Included
Oil & Gas	Oil & Gas Producers Oil Equipment & Services Alternative Energy
Basic Materials	Chemicals Industrial Metals & Mining Specialty Chemicals Forestry & Paper Mining

[12] For some countries (e.g. Mexico and Russia), and some equity indices are not available for the whole period on DataStream, i.e. from October 1979 to March 2012. This is because some sectors (such as Consumer goods and Healthcare in Mexico, and Healthcare and Consumer services in Russia) did not exist in these two countries during the first few years of the sample period, and hence some sectoral indices are non-existent during that period. This, however does not affect the contagion result, as the dataset still covers the crisis and post crisis period.

[13] *Source: DataStream Global Indices, User Guide (5), Thomson Reuters*

Industrials	Construction & Materials Industrial Goods & Services Aerospace & Defence General Industrials Electronic & Electric Equipment Industrial Engineering Industrial Transportation Support Services
Consumer Goods	Automobiles & Parts Food & Beverage Household Goods & Home Construction Leisure Goods Personal Goods Tobacco
Healthcare	Healthcare Equipment & Services Pharmaceuticals & Biotechnology
Consumer Services	Food & Drug Retailers General Retailers Media Travel & Leisure
Telecommunications	Fixed Line Telecommunications Mobile Telecommunications
Utilities	Electricity Gas, Water & Multi utilities
Financials	Banks Nonlife insurance Life Insurance Real Estate investment & Services

	Real Estate Investment Trusts Financial Services Equity Investment Instruments Non-equity Investment Instruments
Technology	Software & Computer Services Technology Hardware & Equipment

The table above gives a breakdown of the Datastream Global Equity Index hierarchy based on ICB.

All national stock-price indices are used in local currency terms and are based on weekly Tuesday closing prices for each market. The advantage of using the local stock indices is that it only captures the changes in indices, as compared to if the sector prices would be converted in the same currency, where there would exchange rate differences as well. Hence, the issue of exchange rate dynamics influencing our analysis is avoided. The sector equity indices are transformed into weekly rates of returns taking the first difference of the natural log of each equity-price index. Moreover, the World aggregate financial sector index (constructed by DataStream) is used as a proxy for the global market, assuming that the crisis caused shifts in investors' global appetite for risk, as international investors might react to a given shock by re-balancing their portfolios globally in assets

To determine the precise date of the beginning and the end of the crisis period, the approach of Baur (2012) is used. This firstly involves considering both major financial and economic events from the timelines provided by the Bank for International Settlements (Filardo et al., 2009). The second step uses estimates of conditional volatility in the financial sector returns (as this is where the initial shock originated), estimated using a GJR-GARCH(1,1) model with a constant in the mean equation, and identifies the crisis as a period where this volatility exceeds a given threshold. Baur (2012) combines the results from these two steps and the resulting crisis period spans from 7 August 2007 to 24 March 2009.

4.6. Empirical Results

4.6.1. Estimation Results (Eq. 4.1)

Using Equation 4.1 (assuming that $R_{fin,i,t} = 0$), the presence of contagion effects between the individual financial sectors in each country and the world financial sector portfolio is being tested, as an example, in order to compare how contagion results, differ or might be biased in a basic contagion model (i.e. Eq. 4.1) relative to the globalisation model (Eq. 4.2). The results are displayed in Table 4.2 below and there is evidence of contagion of 19 financial sectors during the recent financial crisis, as β_2 is positive and significant.

Table 4.2: Contagion to domestic Financial Sector (From the World Financial Sector portfolio)

	α	β_1	β_2	Contagion
Australia	.0012083 **	.3972421***	.3065287***	C
Brazil	.0020346**	.6809292***	.1636065***	C
Canada	.0011045***	.4749424***	.2145499***	C
Chile	.0017454 ***	.2691906***	.0860059**	C
China	.0000629	.6802793***	.2067327	C
France	.0004519	.678415***	.4340321***	C
Germany	.0007054	.68362***	.1402096***	C
Hong Kong	.0014135**	.0014135***	.1063249***	C
Indonesia	.0010109	.5441784***	.1901294**	C
India	.0032275***	.4895776***	.5802807***	C
Italy	.0002194	.0002194***	.0083542	C
Japan	-.0008767	.884915***	.0460306	-
Mexico	.0014992**	.5244779***	.3351242***	C
New Zealand	-.0001199	.2017622***	-.0050248	-
Norway	. .001111	.6094749***	.3904166**	C
Russia	.0050206***	.8901564***	.0356846	-
South Africa	.0029723***	.3659149***	.1890433***	C
South Korea	-.0011189	.7122791 ***	-.0608928	-
Spain	.0004861	.7208038***	.1592954***	C
Sweden	.0009786	.8151634***	.031285	-
Switzerland	.0006622	.5545509 ***	.5545509***	C
Taiwan	-.0006856	. 6250277***	..200964***	C
Thailand	.001415	.5103346***	.0257338	-
U.K.	.0001381	.5020889***	.071512	C
U.S.	.0004538	.803150***	.2144841***	C

Using Baur (2012) model (23rd October 1979 until 27th March 2012) as shown by Eq. 4.1

As established before, the linkages between countries/sectors equity indices tend to follow an upward trend due to the process of globalisation, and hence is time-variant. Therefore if Eq. 4.1

(assuming $R_{fin,i,t} = 0$) is used to estimate financial contagion, this might lead to the inference of biased contagion results. Hence model (4.2), which accounts for a time-varying integration process between sectors and the world financial sector/local financial sectors; equity returns and whereby the pre-crisis and post crisis period are treated differently. Another benefit of employing the globalisation model is that it is more informative as compared to the former one, in terms of depicting any integration or segmentation process of the real economy with the financial sector while also showing at point of time during the crisis, each sector was affected.

4.6.2. Estimation Results (Eq. 4.2)

In this section, for financial contagion for a set of 10 sectors across 25 countries is examined by estimating Eq. (4.2)-(4.3). Table 4.2 shows the findings from Eq. 4.1 only for Financial Sector Contagion, as an example. A summary of the results (estimated from Eq. 4.1) for contagion to the financial and non-financial sectors from the world financial sector portfolio and contagion to real economy from the domestic financial sector is reported in B.5 and B.6 respectively. Using the ADF test to test for unit root, it is observed that log indices are non-stationary and returns in each sector is stationary (Appendix B.1). Eq. (4.2)-(4.4) allows the conditional volatility to be expressed using a GJR-GARCH model, with both student-*t* distributed errors and ARMA disturbances. This specification is chosen in order to account for non-normality and autocorrelation that have been detected using a Shapiro-Wilk and Ljung Box-Q test respectively. Additionally, an Engle ARCH LM test (Engle, 1982), suggests that there are no remaining ARCH effects (Appendix B.2) present in the squared residuals, while using a GJR-GARCH model, hence supporting the use of this particular specification.

a) Global Contagion

Table 4.3 shows a summary of the results pertaining to the type of contagion that prevailed during the crisis period across 10 different sectors in 25 countries. Appendix B.3, on the other hand, presents the estimated results from Eq. 4.2 and displays the intercepts ($\delta_0, \gamma_0, \theta_0$) and slopes ($\delta_1, \gamma_1, \theta_1$) of integration process arising from the world financial sector to the real economy during the pre-crisis, crisis and post crisis period. Appendix B.4 displays further details for contagion (e.g. point estimates at the beginning and end of the crisis period and their t-statistics) from the global financial sector portfolio to the real economies and financial sector of the 25 countries.

It can be observed, from Table 4.3 that there are 60 instances of contagion from the world financial sector. France followed by Norway have the highest number with seven, and five (out of ten) sectors respectively. The most affected sectors during the crisis period, across the 25 countries in our sample are Basic Materials (13), followed by Financial sector and Utilities sector with 10 and 9 contagion cases respectively. On the other hand, Technology (2), Healthcare (3) and Oil (3) are the least affected sectors across all countries.

a) Domestic Contagion

Table 4.3 illustrates a summary of evidence of contagion from Financial Sectors to non-financial sectors across 25 countries. The estimates from Model (4.2) are shown in detail in Appendix B.3 section. The intercepts and slopes of integration process arising from the local financial sector to the real economy during the pre-crisis, crisis and post crisis period are represented by $(\mu_0, \rho_0, \varphi_0)$ and $(\mu_1, \rho_1, \varphi_1)$ respectively. Appendix B.5 shows further details for contagion (e.g. point estimates at the beginning and end of the crisis period and their t-statistics) from the domestic financial sector to the real economies of the 25 countries. There are 68 cases, as shown by Table 4.4, depicting evidence of "domestic contagion", and most cases of contagion from the local financial sector can be observed in the Oil (10), Utilities (10) and Basic Material (9) sectors, whereas Technology and Consumer Goods are the least affected ones with 4 and 5 cases of contagion respectively. The non-financial sectors in Hong Kong (8), followed by Brazil (7) and New Zealand (7) experienced the most cases of contagion from their domestic financial sector. France, Italy, Mexico, South Africa, Switzerland and U.K on the other hand did not show any evidence of real economy contagion from their nation's financial sector.

Table 4.3: Global Contagion (From World Financial Sector)

	Oil	Basic Material	Industrial	Consumer Goods	Healthcare	Consumer Services	Telecom	Utilities	Technology	Financial
Australia	SC (Level)	SC (Level)	SC (Level)	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	SC (Level)
Brazil	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	N/A	No Contagion	No Contagion	No Contagion	No Contagion
Canada	No Contagion	SC (Level)	SC (Level)	No Contagion	No Contagion	SC (Reversal)	No Contagion	SC (Level)	No Contagion	No Contagion
Chile	No Contagion	SC (Transit)	SC (Reversal)	SC (Reversal)	No Contagion	No Contagion	No Contagion	N/A	No Contagion	SC (Reversal)
China	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	SC (Level)
France	SC (Level)	SC (Level)	SC (Level)	SC (Level)	No Contagion	SC (Level)	No Contagion	SC (Level)	SC (Level)	No Contagion
Germany	No Contagion	No Contagion	No Contagion	SC (Level)	No Contagion	No Contagion	No Contagion	RC	No Contagion	No Contagion
Hong Kong	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	SC (Transit)
India	SC (Level)	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	SC (Level)	No Contagion	No Contagion	No Contagion
Indonesia	N/A	No Contagion	No Contagion	No Contagion	No Contagion	N/A	No Contagion	No Contagion	N/A	No Contagion
Italy	No Contagion	SC (Level)	No Contagion	SC (Level)	SC (Level)	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion
Japan	No Contagion	SC (Level)	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion
Mexico	N/A	SC (Level)	No Contagion	N/A	N/A	No Contagion	No Contagion	N/A	N/A	No Contagion
Norway	No Contagion	SC (Level)	N/A	SC (Level)	N/A	No Contagion	No Contagion	SC (Transit)	SC (Transit)	RC
New Zealand	No Contagion	No Contagion	SC (Level)	No Contagion	No Contagion	No Contagion	SC (Level)	SC (Level)	No Contagion	SC (Reversal)
Russia	No Contagion	No Contagion	N/A	No Contagion	N/A	No Contagion	No Contagion	No Contagion	N/A	No Contagion

South Africa	No Contagion	SC (Level)	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	KC
South Korea	No Contagion	SC (Transit)	No Contagion	No Contagion	No Contagion	SC (Level)	SC (Transit)	SC (Level)	N/A	No Contagion
Spain	No Contagion	SC (Level)	No Contagion	No Contagion	No Contagion	SC (Level)	No Contagion	No Contagion	No Contagion	No Contagion
Sweden	No Contagion	No Contagion	No Contagion	No Contagion	SC (Level)	No Contagion	No Contagion	N/A	No Contagion	No Contagion
Switzerland	No Contagion	SC (Level)	SC (Level)	No Contagion	No Contagion	No Contagion	No Contagion	SC (Level)	No Contagion	No Contagion
Taiwan	No Contagion	No Contagion	No Contagion	No Contagion	N/A	No Contagion	No Contagion	N/A	No Contagion	SC (Level)
Thailand	No Contagion	SC (Level)	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion
U.K.	No Contagion	SC (Level)	No Contagion	SC (Reversal)	No Contagion	No Contagion	No Contagion	SC (Level)	No Contagion	SC (Level)
U.K.	No Contagion	No Contagion	No Contagion	No Contagion	SC (Level)	No Contagion	SC (Transit)	SC (Level)	No Contagion	No Contagion

Table 4.3 summarises the findings from Eq. 4.2, in terms of the type of contagion. It shows the impact of the world financial sector portfolio on 10 different sectors across 25 countries during the crisis period.

Key:

1. *Shock contagion: SC* 3. *Kink Contagion: KC*
2. *Recoupling Contagion: RC* 4. *Unavailability of data or non-convergence: N/A*

Table 4.4. Domestic Contagion (From Local Financial Sector)

	Oil	Basic Material	Industrial	Consumer Goods	Healthcare	Consumer Services	Telecom	Utilities	Technology
Australia	No Contagion	No Contagion	No Contagion	No Contagion	SC (Reversal)	No Contagion	No Contagion	SC (Reversal)	No Contagion
Brazil	SC (Level)	SC (Level)	SC (Level)	No Contagion	N/A	SC (Transit)	SC (Transit)	SC (Reversal)	SC (Level)
Canada	RC	No Contagion	No Contagion	SC (Level)	No Contagion	No Contagion	No Contagion	No Contagion	SC (Level)
Chile	SC (Level)	No Contagion	SC (Level)	No Contagion	No Contagion	No Contagion	SC (Reversal)	N/A	No Contagion
China	No Contagion	SC (Level)	SC (Level)	No Contagion	No Contagion	No Contagion	SC (Level)	No Contagion	No Contagion
France	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion
Germany	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	KC	No Contagion	SC (Transit)	No Contagion
Hong Kong	SC (Transit)	SC (Transit)	SC (Reversal)	SC (Reversal)	SC (Reversal)	SC (Reversal)	SC (Reversal)	SC (Transit)	No Contagion
India	No Contagion	SC (Transit)	SC (Reversal)	No Contagion	No Contagion	No Contagion	No Contagion	SC (Reversal)	No Contagion
Indonesia	SC (Transit)	N/A	No Contagion	No Contagion	SC (Level)	N/A	No Contagion	KC	N/A
Italy	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion
Japan	No Contagion	No Contagion	No Contagion	No Contagion	KC	No Contagion	No Contagion	SC (Level)	No Contagion
Mexico	N/A	No Contagion	No Contagion	N/A	N/A	No Contagion	No Contagion	N/A	
Norway	No Contagion	No Contagion	SC (Transit)	SC (Reversal)	N/A	N/A	No Contagion	No Contagion	No Contagion
New Zealand	SC (Level)	SC (Level)	SC (Transit)	SC (Level)	SC (Level)	SC (Level)	No Contagion	SC (Level)	No Contagion
Russia	SC (Level)	SC (Level)	No Contagion	No Contagion	N/A	N/A	SC (Level)	SC (Level)	N/A

South Africa	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion
South Korea	SC (Transit)	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	SC (Level)	No Contagion
Spain	SC (Level)	No Contagion	SC (Reversal)	No Contagion	SC (Transit)	SC (Reversal)	No Contagion	No Contagion	No Contagion
Sweden	No Contagion	SC (Level)	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	N/A	SC (Transit)
Switzerland	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion
Taiwan	SC (Level)	SC (Level)	No Contagion	No Contagion	N/A	SC (Level)	SC (Reversal)	N/A	No Contagion
Thailand	SC (Level)	SC (Level)	No Contagion	SC (Level)	SC (Level)	No Contagion	No Contagion	No Contagion	No Contagion
U.K.	No Contagion	No Contagion	No Contagion	No Contagion	SC (Reversal)	SC (Reversal)	No Contagion	No Contagion	SC (Reversal)
U.K.	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion	No Contagion

Table 4.4 summarises the findings from Eq. 4.2, in terms of the type of contagion. It shows the impact of the domestic financial sector on 9 different sectors across 25 countries during the crisis period.

Key:

1. *Shock contagion: SC* 3. *Kink Contagion: KC*
2. *Recoupling Contagion: RC* 4. *Unavailability of data or non-convergence: N/A*

Identifying different types of Contagion

Evidence of contagion from both global and domestic financial sectors can be identified in the following situations:

(a) Shock Contagion

The findings show that most sectors experienced a "shock" contagion, i.e. ($\beta_2(\tau_1)$ >0) as compared to other types of contagion (i.e. Recoupling or Kink Contagion). Similar to "global" contagion, the findings pertaining to "domestic" contagion also show that most sectors experienced a Shock Contagion ($\omega_2(\tau_1)$ >0), as compared other types of contagion (i.e. Recoupling or Kink Contagion). It can be observed from Appendix B.4 that some sectors have experienced contagion across the whole crisis period, despite the fact that there have been no changes in the slope of the integration process during the crisis period, as compared for the pre-crisis, i.e. there was a level shock, whereby $\hat{\gamma}_0$> 0 and $\hat{\gamma}_1$=0. An example of 'level' shock Contagion (whereby there are no changes in the slope, but only changes in the level of co-movement) from the Global Financial Sector can be observed in the Oil Sector (Australia, France and India), whereby $\beta_2(\tau_1)$>0, $\gamma_0 > 0$ and $\gamma_1 = 0$. Moreover, instances of Level Shock Contagion can be observed in Oil, Basic Material, Industrial, and Technology (Brazil) from domestic Financial Sectors, whereby $\omega_2(\tau_1)$>0, $\rho_0 > 0$ and $\rho_1 = 0$

However, contagion is not always persistent across the all the phases of the crisis period. It might occur temporarily. In other words, there might be cases whereby the increasing co-movement fades away or even be lower than what it would have been had the crisis not occurred (i.e. a reversal). And to differentiate whether the contagious effects from the Global Financial Sector or Local Financial sector to the real economy is only temporary or permanent, a t-test is conducted at the end of the crisis period to test whether β_{t} (for global contagion) or ω_t (for domestic contagion) in the last week of the crisis (t=τ_2) is significantly different from its value which would have been expected at crisis' end if the crisis had no impact on the process of financial integration, i.e., if γ_0 = γ_1=0. If the estimated $\beta_2(\tau_2)$ is significantly positive (negative) at crisis' end, this would imply that the initial positive shock in β_{t} has not completely faded away (has reversed and led to lower-than-expected integration level), indicating partially persistent (temporary) contagious shocks. There are 7 and 13 cases of temporary shock contagion from the world and domestic financial sectors respectively. The Financial Sector (Hong Kong), Basic Materials (Japan and Mexico), Consumer Goods, Utilities and Technology in Norway, and Telecommunications (U.S.) only experienced a temporary contagious shock, as $\beta_2(\tau_1)$ >0, accompanied by decreasing slope of integration (i.e. γ_1< 0). Moreover, the Oil Sector (Hong Kong and South Korea), Basic Materials (India and Indonesia), Consumer Goods (Spain), for instance, also experienced a temporary contagious shock, as $\omega_2(\tau_1)$ >0, accompanied by decreasing slope of integration (i.e. ρ_1< 0).

There are also occasions where initial shock seems to have been faded away as the crisis evolved. For some sectors, there was a reversal contagion shock, whereby, at the end of the crisis period, the integration level was at a lower level as compared to what it was supposed to be if the crisis had not occurred. There are 6 cases of reversal shock contagion to the real economy from the world financial sector and 18 from domestic financial sector. Healthcare and Consumer Services (Canada), Industrial, Consumer Goods and Financial Sector (Chile), Financial (New Zealand), and Consumer goods (U.K.) experienced a reversal shock contagion from the world financial sector. And Healthcare and Utilities (Australia), Telecom (Chile), and Consumer goods (Norway) experienced a reversal shock contagion from their local financial sector. The resulting fall in the slope of the linkages ($\gamma_1 < 0$) and ($\rho_1 < 0$) during crisis might be an indication of disintegration and hence contagion is not prevalent during the whole crisis.

(b) Recoupling Contagion

Contagion effects might also arise if there is a fall in β_t following the outbreak of the crisis (i.e. $\beta_2(\tau_1) < 0$ at Week 1451), accompanied by steady rise in the level of the β_t as the crisis unfolds, leading to higher level of β_t at a certain point during this turmoil period, and the co-movement being higher by the end of the crisis period (i.e. before Week 1536) than what it would have been if the same globalisation processes was being followed ($\beta_2(\tau_2)$> 0). Contagion effects from domestic financial sector might also arise if there is a fall in ω_t following the outbreak of the crisis (i.e. $\omega_2(\tau_1) < 0$ at Week 1451), accompanied by steady rise in the level of the ω_t as the crisis unfolds, leading to higher level of β_t at a certain point during this turmoil period, and the co-movement being higher by the end of the crisis period (i.e. before Week 1536) than what it would have been if the same globalisation processes was being followed ($\omega_2(\tau_2)$> 0).

The Utilities sector (Germany) and Financial sector (Norway) experienced recoupling contagion during the crisis period, as $\beta_2(\tau_1) < 0$ and $\beta_2(\tau_2)$> 0. Evidence of Recoupling contagion from Domestic Financial sectors is found in the Oil sector (Canada), where $\omega_2(\tau_1)$<0, $\rho_0 > 0$ and $\omega_2(\tau_2)$>0.

(c) Kink Contagion

"Kink" contagion is referred to a situation whereby there is no sudden change in co-movement during the first week of the crisis (i.e. $\beta_2(\tau_1) = 0$), but contagion can be identified provided there is an increase in integration slope ($\gamma_1 > 0$) during the crisis period and β_t is higher at a certain point during the crisis than what it would have been if the slope of integration process would had been the same as the pre-crisis period. Contagion effects from domestic financial sector might also arise if there is a fall in ω_t following the outbreak of the crisis (i.e. $\omega_2(\tau_1) < 0$ at Week 1451), accompanied by steady rise in the level of the ω_t as the crisis unfolds, leading to higher level of β_t at a certain point during this turmoil period, and the co-movement being higher by the end of the crisis period (i.e. before Week 1536) than what it would have been if the same globalisation processes was being followed ($\omega_2(\tau_2)$> 0).

From the findings, in Appendix B.4 in the Appendix, it can be observed that there is evidence of Kink contagion from the Global Financial Sector to the financial sector in South Africa, as $\beta_2(\tau_1) = 0$ and $\gamma_1 > 0$. Kink contagion from the Domestic Financial Sector can be observed in Japan (Healthcare), Consumer Services (Germany) and Utilities (Indonesia) as $\omega_2(\tau_1)$=0 and $\omega_2(\tau_2)$>0.

It can be observed from Appendix B.3 and B.4 that there are more cases of shock contagion relative to recoupling and kink contagion. More precisely, there is evidence of 'level' shock contagion from both world and domestic financial sector more than any other type of contagion, indicating that these sectors were suffering from financial contagion throughout the whole crisis period.

4.6.3. Integration with the World Financial Sector (Pre-and during Crisis)

In conjunction with examining contagion effects in the real economy, this chapter also investigates for time-varying integration between sectors and world financial sector. I am particularly interested in examining how the integration processes of the asset returns changed the during the crisis and post crisis period, as compared to the pre-crisis. Moreover, I also wish to determine whether increased financial integration with the world made the sectors across 25 countries more vulnerable and prone to contagion effects.

δ_1, $\delta_1 + \gamma_1$, and $\delta_1 + \theta_1$ in Appendix B.3 represent the integration process of the real sectors with the world financial sector during the pre-crisis, crisis and post crisis period respectively. It can be observed that the results are mixed during the pre-crisis, with most of the sectors (65.6%) showing no integration process (δ_1 =0) with the world financial sector, and some sectors (around 32.6%) experiencing a positive slope for the integration (δ_1 >0) process. And as far as the segmentation with the world financial sector is concerned, there are very few cases (e.g. Utilities-Canada; Telecommunication and Financial sector-New Zealand), depicted by a negative integration (δ_1< 0) slope.

The surprising findings from Eq. (4.2) is that most the sectors that had a positive integration with the world financial sector during the pre-crisis, did not suffer from contagion effects during the recent global financial crisis, i.e. $\beta_2 = 0$ during the whole crisis period. On the other hand, there are situations whereby sectors that experienced a negative integration (e.g. Telecommunication and Financial sector in New Zealand) during the crisis period, suffered from contagion effects in the turmoil period.

The reason for sectors not showing evidence of contagion, despite the positive integration process during the pre-crisis period might be because of good policies and institutions, and as well as sound macro-economic fundamentals in the economy and the fact that the global financial linkages had only a minor effect on the crisis transmission. Additionally, it can also be assumed that investors would abandon the markets with poor investment environment and move to more secure markets (Bekaert et al. 2014).

As far as integration process between the sectors and world financial sector during the crisis period is concerned, it mostly remains the same as the pre-crisis period, i.e. $\gamma_1 = 0$, and for the rest, the speed integration process during the crisis period are lower as compared to the crisis period, i.e. $\delta_1 + \gamma_1$ <0. After the crisis, the integration process of most sectors goes to back to be the same as it was during the pre-crisis period (θ_1= 0), despite the fact that there has been changes during the crisis period.

4.6.4. Discussion

a) Developed vs Emerging countries

Appendix B.4 and B.5 in the show the estimation results for contagion from the world financial sector and local financial sector. When the Basic Contagion Model (Eq. 4.1), i.e., with no separate post-crisis period and sub-period specific time-invariant parameters (model 4.1), the results reported in both tables (last column) indicate the existence of contagion in 112 and 111 cases from the world financial sectors and domestic financial market, respectively, as compared to 60 and 68 instances of contagion from model (4.2). Hence, it can be concluded that a model with time-invariant parameters appears to overestimate the occurrence of contagion in many cases. Moreover, model (4.2) shows the type of contagion, which allows to determine at which stage the crisis affected the sectors (i.e. whether at the start or end of the crisis period, or it is prevalent during the whole period).

The results show that no country in our sample was immune to the recent global financial crisis, except for Russia which shows no evidence of contagion from the global financial sector. The results have revealed substantial heterogeneity in contagion across individual country-sector equity portfolios, which might be attributed to external exposures of the real economy to the global financial sector or to country specific factor. There are 14 developed countries and 11 emerging countries in this study and it can be also observed that the occurrence of contagion from the global market is more prevalent in the sectors pertaining to developed countries, with 44 cases showing evidence of contagion as compared to emerging countries with only 16 displaying signs of contagion effect. However, there are 35 and 33 cases of contagion from local financial sector to the real economy in developed and emerging markets respectively, showing that both markets were more or less equally affected. The fact that developed markets have been showing more evidence of contagion from the global financial system can be explained by the fact that the sectors in developed markets are comprised of more multinationals as compared to less mature markets. And, as multinationals have branches worldwide, this makes them more vulnerable to negative shocks due to a crisis. Another possible reason why the sectors of developed nations show are more prone to contagion from the world is the strong financial and economic integration before the occurrence of the crisis period, making them more vulnerable towards external shocks. . In addition to this, there might be limits to foreign investment in certain developing countries (e.g. Russia) or foreign investors might lack local knowledge and hence mistrust the local accounting standards and practices. This might result into less investment in these developing countries and as a result have lower integration with the world stock market. Similar to the findings pertaining to this chapter, Baur (2012) also finds that the lowest number of contagion incidences is found in emerging markets, as compared to developed ones which displayed the highest incidences of contagion across sectors. This indicates that the sectors in developed countries are more globally exposed compared to emerging ones. Bekaert et al. (2014) found that the contagion effects from the global financial sector are small as compared to the impact from the domestic financial market to individual domestic portfolios, which is in line with our results for emerging countries, whereby only 15 sectors suffered from contagious effects from the global financial market and contagion effect from the local financial sector has affected 33 sectors.

b) Financial sector

In addition to showing whether the real economies experienced contagious effects from the global financial market or domestic financial sector, Eq. 4.2 also reveals how the linkages have evolved. It can be also be observed that there has been an positive integration between 13 financial sectors (Canada, France, Germany, India Italy, Japan, Russia, South Korea, Spain, Sweden, Thailand, U.K., and U.S.) and the world financial portfolio during the pre-crisis period, and that the slope of the integration process remained the same during the turmoil period, i.e. $\delta_1 > 0$and $\gamma_1 = 0$. There are also instances where some financial sectors (Brazil, Chile, China, Hong Kong, Indonesia, and New Zealand) showed a slower pace of integration with the global financial market across the crisis period, as compared to the pre-crisis period where an positive slope of integration can be observed, i.e. $\delta_1 > 0$and $\gamma_1 < 0$. For the financial sectors in Chile, China, Hong Kong, Indonesia and New Zealand that experienced Shock Contagion (Reversal or Transitory), and $\gamma_1 < 0$, this shows potential herding behaviour by investors, as the increase in co-movement during the crisis period is short-lived.

Contrary to the popular belief and previous research studies, for instance Baur (2012) and Kenourgious and Dimitriou (2015), it is observed from the findings of this chapter that financial sectors do not show the highest instances of contagion across all countries. Appendix B.4 displays evidence of contagion in only 10 financial sectors across 25 countries. Out of the 10, there were 6 instances of Shock Contagion (Australia, China, Hong Kong, Taiwan and U.K.), and with Norway and South Africa experiencing Recoupling and Kink Contagion respectively. However, this does not mean that the remaining 15 financial sectors in our sample have not been affected by the crisis.

Moreover, it can be observed that there has been no level shift at the start of the crisis of many of the advanced and developing financial sectors. The hypothesis $\beta_2(\tau_1) = 0$ is not rejected for Brazil, Canada, France, India, Japan, Mexico, Russia, Switzerland, and U.S. This may be due to the fact that these countries did not experience an exposure to the global systematic risk factor or an idiosyncratic risk pertaining to a particular financial sector during the financial crisis. This can occur as a result of the nature of the economies in terms of being relatively small and closed (in some cases), or having a sound macroeconomic fundamentals and clear legal framework, or due to the policy decisions taken by the home country. For instance, Ait-Sahalia et al. (2012) notice that financial policies are normally aimed to restore financial stability, while macroeconomic policies help to avoid the vicious feedback between financial sector and the broader economy. However, according to Dungey and Gajurel (2015) it is difficult to distinguish that whether policy actions undertaken were sufficient to offset any potential change with the World Financial Portfolio.

It is also observed that some of the financial sectors that did not experience a shock from the global financial market at the first week of the crisis, i.e. $\beta_2(\tau_1) = 0$, did not spread any contagious effects to the local sectors. For example, the real economies of France, Mexico, Switzerland and U.S. did not experience any return spillovers from their domestic financial market (which did not experience contagion from the world financial sector). On the other hand, despite the fact that $\beta_2(\tau_1) = 0$ for the Brazilian, Canadian, Indian, Japanese, Russian domestic financial sector, there was still contagion effects from the later to the real economies of these above-mentioned countries.

The Financial sectors of some countries, e.g. Germany, Norway, South Korea, Spain, Sweden, Taiwan and Thailand experienced structural break in terms of a fall in co-movement during the first week of the crisis, i.e. $\beta_2(\tau_1) < 0$. However, during the pre-crisis period, it can be observed that these counties were experiencing positive linkages with the World Financial Sector Portfolio, i.e. $\delta_1 > 0$, and there has been no change in the linkages during the crisis period (i.e. $\gamma_1 = 0$), except for Norway and South Korea where there was an increasing slope of integration during the crisis period, i.e. $\gamma_1 > 0$, which eventually led to Recoupling contagion in the case of Norway. The fact Germany, Spain, Sweden, Taiwan and Thailand experienced a positive integration before the outbreak of the crisis and did not experience contagion effect might be explained by the fact that the policy initiatives were effective in suppressing the transmission of the crisis to the financial sector. Financial sector policies include the tools commonly used to resolve systemic banking crises, for instance asset purchase, liability guarantees, and recapitalization.

The findings are quite surprising in the sense that some financial markets (for e.g. Chile, Indonesia and Taiwan) that are considered to be generally small have experienced Shock Contagion, whereas most of the financial sectors of advanced markets in our sample are not showing evidence of contagion. One of the factors might be that the above-mentioned economies are open to foreign financial and trade. However, no contagion does not mean that advance markets have not been affected by the recent financial crisis, as the financial sectors of mature markets have either experienced a significant decrease in co-movement following the outbreak of the crisis, or experienced a disintegration with the World Financial Sector, or both (in some cases).

Moreover, as stated before, there is a general perception that the financial sector of a particular country has to be affected by the crisis in order for the real economy to experience contagion. However, it is observed from the findings that the financial sector of a country does not need to be affected for the real sectors of the economy to show evidence of domestic contagion. This is mainly due to the fact that the global financial crisis has a direct impact in non-financial companies (i.e. they borrow and lend globally) and hence are directly affected by the global financial crisis, and sectors that comprises of industries that trade more or competitive industries are more vulnerable to a crisis compared to domestically centred industries. Even economies that are not interconnected through bank or trade linkages might be affected. This can be explained through the "wake-up call" hypothesis, which has been explained in chapter 2 of this thesis, whereby a default in one country prompts investors to revise their priors, not only for the country in question, but for all countries with similarly bad fundamentals. Investors' behaviour might be another reason as well. For instance, risk aversion during a crisis period, might induce investors to flee into safer assets and shun risky ones.

c) Tradable vs non-tradable sectors

Findings pertaining to the real economy are heterogeneous which makes it difficult to attribute a specific cause which might lead contagion in the non-financial sectors. The highest incidence of contagion from the global financial sector are found in Basic Materials (13), followed by Financial (10) and Utilities (9). The least affected during the crisis period are Oil (3), Healthcare (3) and Technology (2). Baur (2012) and Kenourgious et al. (2015) also finds that Basic Materials depicts the highest number of contagion occurrences during the recent financial crisis as compared to other sectors.

One of the reasons leading to a high occurrence of contagion in the Basic Materials Sector that tradable sectors are more vulnerable to shocks compared to non-tradable sectors. And it can be observed from Table 4.3 and Table 4.4 that overall, tradable sectors (e.g. basic materials, utilities, consumer goods, industrial, and oil) were more likely to experience contagion during the recent financial crisis as compared to non-tradable sectors (consumer services, healthcare, telecom, technology and financial). The vulnerability of the tradable sectors to the crisis might be due to the increasing economic integration over the past decade.

Another potential reason for contagion in tradable sectors is herding behaviour, whereby investors dismiss their private beliefs and follow the market in the asset valuation and trades. According to

Calvo and Mendoza (2000), herding might be rational or as per Scharfstein and Stein (1990) and Bikhchandani and Sharma (2000), it might be due to reputational and conformist preferences. Klein (2013) finds that herding behaviour intensifies during turmoil periods and high volatility by employing a time-varying Markov regime switching model. Gebka and Wohar (2013) shows that there is herding is prevalent in Basic Materials, Consumer Services, and Oil and Gas during the recent financial crisis, which might be due to might be due to overconfidence or excessive flight of quality. Flight of quality occurs when investors sell their assets which they perceive as being risky and purchase safe assets instead, leading to severe disruptions in financial markets. Moreover, according to Shleifer and Summers (1990), individual investors may herd if they decide to follow the same signal (e.g. overreacting on recent news). This might exacerbate the spillovers across international markets. Litimi (2017) also detected herding behaviour in tradeable sectors during both a crisis and non-crisis period. The author postulate that these sectors overall bear a higher risk than others and hence due to prevailing uncertainties, investors might decide to enter a herd. The findings are in conjunction with that of Bekaert et al. (2014) who show that the sectors that depicted evidence of contagion across all regions from their sample are the Industrial, Energy, Basic Materials and Utility sector, whereas Technology was the sector showing the least evidence of contagion during the recent financial crisis.

Whether there is contagion between the individual sectors and World Financial Sector not only depends on the sound macroeconomic fundamentals of the economy, irrationality of investors but also depends on the individual sectors' characteristics. For instance, Chiu et al. (2015) found industrial characteristics such as Net debt issuance, industry valuation and industry investment have an impact on the number of joint extreme negative returns occurrences in an industry.

4.7. Conclusion

Following the severity and global reach of the recent financial crisis, this paper investigates how the real economies across a set of 25 countries experience contagion from the global financial market and domestic financial market. A new approach, as in Chapter 3, is used to determine the different situations whereby financial contagion can arise and the changing linkages across the pre-crisis and crisis also explored. The detailed results are presented in Appendix B.3, B.4 and B.5.

The results show that at least one sector of all countries in our sample were affected during the crisis, either by global or local factors. If this is compared to the findings of Eq. 3.2 in Chapter 3, it can be observed than there are 12 markets (Brazil, Canada, France, Germany, Mexico, Russia, South Africa, South Korea, Spain, Sweden, Switzerland, and U.S) showing no evidence of contagion. However, it can be clearly seen from Appendix B.4 and B.5 that the real economy of these countries depicts evidence of financial contagion.

There is also evidence of more cases of contagion in real sectors of economies of developed markets as compared to emerging markets. Moreover, the findings show that real economies experienced Shock Contagion more often as compared to any other type of contagion, and Basic Material was more vulnerable to exposures from the global financial sector, Oil and Gas Industry showed the highest occurrence of contagious effects from the local financial sector. One of the apparent reasons might be since trade linkage is an important determinant of a country's exposure to crisis arising in other countries. And this is not surprising as Basic Materials (which includes metals and mining) has one of the highest tradability indexes. Other reasons (for Shock Contagion) might be attributed to the "Wake up" call hypothesis or herding behaviour by investors. Moreover, the analysis also shows that there are cases whereby the sectors did not show any evidence of contagion but was still affected in terms of a negative shock following the outbreak of the crisis or changing linkages during the crisis period with the world or domestic financial sector. Hence it can be observed that there is a heterogeneity in the contagion results.

The findings pertaining to this chapter have implications for investment decisions and regulations, since contagion has relevance for optimal asset allocation and risk measurement. The evidence shows that the real economy of developed markets has been more vulnerable to some extent, following the recent financial crisis compared to the developing markets. There are a few sectors, particularly tradable industries that investors need to be careful about when including them in their investment portfolios since they exhibit high contagion occurrence with the world financial sector, in either developed or emerging countries or both. In addition to this, the diversification potential during the crisis seemed to have decreased given the rising integration with the world. During the years after the crisis (3 years, in this case), the intertemporal integration process has reversed to the pre-crisis level for almost all the markets. The results show that sectors involving tradable goods are more prone to contagion, as compared to non-tradable goods.

APPENDIX B

B.1.: Augmented Dickey Fuller Test

ADF Test (Full Sample) **-** Australia	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
World Financial	-1.883				-17.829			
Australia Financial	-2.478				-23.091			
Utilities	-2.579				-31.554			
Telecommunication	-2.376				-23.547			
Technology	-1.981				-29.037			
Oil	-2.587				-42.843			
Industrial	-2.181				-44.597			
Healthcare	-2.458				-43.788			
Con. Services	-1.350				-43.026			
Con. Goods	-1.848				-44.710			
Basic Materials	-2.179				-42.266			

ADF Test (Full Sample) **-** Brazil	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Australia Financial	-1.977				-24.723			
Utilities	-2.689				-18.651			
Telecommunication	-3.569				-34.669			
Technology	-1.316				-23.038			
Oil	0.302				-23.425			
Industrial	-1.706				-14.098			
Healthcare	-2.572				-14.936			
Con. Services	-1.438				-10.967			
Con. Goods	-2.725				-31.697			
Basic Materials	-0.640				-32.985			

ADF Test (Full Sample) **-** Can	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Australia Financial	-2.181				-41.450			
Utilities	-2.483				-42.957			
Telecommunication	-2.412				-43.928			
Technology	-1.892				-19.999			
Oil	-2.770				-43.138			
Industrial	-1.923				-43.928			
Healthcare	-0.967				-31.384			
Con. Services	-2.025				-29.653			
Con. Goods	-1.881				-43.425			
Basic Materials	-3.055				-42.388			

ADF Test (Full Sample) - Chile	**Prices**					**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**		**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120			-3.960	-3.410	-3.120
Chile Financial	-3.062					-17.655			
Utilities	-2.414					-23.153			
Telecommunication	-2.998					-24.754			
Technology	-2.248					-15.405			
Oil	-3.266					-26.321			
Industrial	-2.163					-19.137			
Healthcare	-2.996					-36.712			
Con. Services	-3.245					-23.610			
Con. Goods	-3.842					-23.703			
Basic Materials	-2.361					-18.936			

ADF Test (Full Sample) - China	**Prices**					**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**		**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120			-3.960	-3.410	-3.120
China Financial	-2.799					-33.711			
Utilities	-2.344					-33.906			
Telecommunication	-2.302					-33.029			
Technology	-2.290					-32.139			
Oil	-1.790					-29.520			
Industrial	-2.139					-14.819			
Healthcare	-1.968					-22.204			
Con. Services	-2.924					-23.589			
Con. Goods	-2.988					-16.376			
Basic Materials	-3.201					-15.695			

ADF Test (Full Sample) - France	**Prices**					**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**		**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120			-3.960	-3.410	-3.120
France Financial	-1.748					-43.965			
Utilities	-1.483					-28.740			
Telecommunication	-2.943					-30.704			
Technology	-1.768					-42.286			
Oil	-1.827					-31.882			
Industrial	-2.131					-44.213			
Healthcare	-1.805					-30.955			
Con. Services	-1.876					-41.272			
Con. Goods	-2.029					-43.317			
Basic Materials	-2.733					-31.094			

ADF Test (Full Sample) - Germany	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Germany Financial	-1.972				-19.990			
Utilities	0.035				-30.028			
Telecommunication	-1.597				-44.644			
Technology	-1.796				-37.651			
Oil	-1.789				-15.778			
Industrial	-2.813				-30.314			
Healthcare	-3.222				-42.785			
Con. Services	-1.970				-43.926			
Con. Goods	-2.864				-32.472			
Basic Materials	-2.742				-44.803			

ADF Test (Full Sample) – Hong Kong	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
HK Financial	-2.258				-28.851			
Utilities	-2.603				-44.245			
Telecommunication	-2.337				-27.759			
Technology	-2.494				-35.884			
Oil	-3.034				-19.382			
Industrial	-2.365				-28.616			
Healthcare	-2.373				-29.526			
Con. Services	-2.945				-19.900			
Con. Goods	-4.001				-26.600			
Basic Materials	-2.588				-37.020			

ADF Test (Full Sample) – India	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
India Financial	-3.369				-15.397			
Utilities	-2.174				-36.002			
Telecommunication	-1.995				-33.637			
Technology	-1.837				-20.042			
Oil	-2.705				-16.133			
Industrial	-2.146				-16.319			
Healthcare	-2.940				-36.879			
Con. Services	-2.338				-37.052			
Con. Goods	-1.726				-37.752			
Basic Materials	-2.228				-15.979			

ADF Test (Full Sample) – Indonesia	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Indo Financial	-1.087				-36.272			
Utilities	-1.508				-11.976			
Telecommunication	-2.832				-23.148			
Technology	-2.947				-6.716			
Oil	-1.635				-33.717			

Industrial	-1.696		-25.104
Healthcare	-2.502		-25.911
Con. Services	-2.239		-18.994
Con. Goods	-2.122		-36.920
Basic Materials	-2.289		-13.477

ADF Test (Full Sample) – Italy	**Prices**					**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**		**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120			-3.960	-3.410	-3.120
Italy Financial	-2.942					-20.059			
Utilities	-1.821					-31.081			
Telecommunication	-1.176					-24.444			
Technology	-2.107					-19.072			
Oil	-2.456					-39.628			
Industrial	-3.348					-19.096			
Healthcare	-2.243					-37.743			
Con. Services	-2.795					-28.707			
Con. Goods	-2.128					-19.825			
Basic Materials	-2.693					-17.522			

ADF Test (Full Sample) – Japan	**Prices**					**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**		**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120			-3.960	-3.410	-3.120
Japan Financial	-2.260					-20.587			
Utilities	-1.965					-43.517			
Telecommunication	-2.115					-30.454			
Technology	-1.856					-14.082			
Oil	-2.521					-44.055			
Industrial	-2.877					-20.717			
Healthcare	-2.307					-30.314			
Con. Services	-1.675					-30.299			
Con. Goods	-2.767					-20.655			
Basic Materials	-2.277					-20.228			

ADF Test (Full Sample) – Mexico	**Prices**					**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**		**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120			-3.960	-3.410	-3.120
Mex Financial	-3.514					-16.651			
Utilities	-1.520					-7.443			
Telecommunication	-1.946					-36.445			
Industrial	-3.204					-17.617			
Healthcare	-0.852					-30.432			
Con. Services	-3.412					-20.356			
Con. Goods	-2.392					-18.079			
Basic Materials	-2.042					-17.474			

ADF Test (Full Sample) – Norway	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Norway Financial	-3.158				-19.783			
Utilities	-1.907				-19.817			
Telecommunication	-2.070				-14.697			
Technology	-2.115				-42.379			
Oil	-2.344				-20.710			
Industrial	-1.633				-40.509			
Healthcare	-2.310				-20.966			
Con. Services	-4.599				-18.028			
Con. Goods	-2.042				-24.305			
Basic Materials	-3.766				-19.049			

ADF Test (Full Sample) – New Zealand	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
NZ Financial	-2.784				-17.101			
Utilities	-2.798				-23.254			
Telecommunication	-2.330				-27.238			
Technology	-2.718				-18.445			
Oil	-1.984				-38.948			
Industrial	-1.787				-23.782			
Healthcare	-1.638				-27.894			
Con. Services	-2.212				-19.591			
Con. Goods	-1.584				-36.639			
Basic Materials	-2.659				-24.987			

ADF Test (Full Sample) – Russia	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Russia Financial	-1.699				-18.905			
Utilities	-1.699				-29.045			
Telecommunication	-1.792				-29.371			
Oil	-1.807				-13.462			
Industrial	-2.554				-9.203			
Healthcare	-1.492				-18.146			
Con. Services	-4.076				-19.891			
Con. Goods	-1.586				-24.091			
Basic Materials	-2.547				-27.760			

ADF Test (Full Sample) – South Africa	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
SA Financial	-1.666				-30.525			
Utilities	-2.789				-33.144			
Telecommunication	-2.128				-23.750			
Technology	-1.447				-29.851			
Oil	-3.121				-43.512			
Industrial	-1.759				-44.265			

Healthcare	-1.773				-41.266			
Con. Services	-1.224				-15.121			
Con. Goods	-2.224				-35.355			
Basic Materials	-2.291				-43.125			

ADF Test (Full Sample) – South Korea	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
SK Financial	-2.401				-27.446			
Utilities	-3.445				-38.241			
Telecommunication	-2.305				-24.234			
Technology	-1.427				-32.204			
Oil	-2.302				-38.671			
Industrial	-2.256				-26.273			
Healthcare	-3.436				-28.654			
Con. Services	-2.601				-38.714			
Con. Goods	-2.571				-27.534			
Basic Materials	-1.994				-38.726			

ADF Test (Full Sample) – Spain	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Spain Financial	-1.588				-36.935			
Utilities	-1.580				-39.300			
Telecommunication	-1.214				-26.903			
Technology	-2.874				-30.609			
Oil	-1.908				-38.086			
Industrial	-2.357				-25.648			
Healthcare	-2.599				-20.345			
Con. Services	-2.114				-29.717			
Con. Goods	-2.261				-21.068			
Basic Materials	-2.111				-14.115			

ADF Test (Full Sample) – Sweden	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Sweden Financial	-1.595				-19.899			
Utilities	-0.452				-22.451			
Telecommunication	-2.383				-22.775			
Technology	-2.821				-14.681			
Oil	-1.428				-13.092			
Industrial	-2.707				-19.058			
Healthcare	-0.924				-43.892			
Con. Services	-2.721				-16.861			
Con. Goods	-2.453				-21.331			
Basic Materials	-3.219				-20.677			

ADF Test (Full Sample) – Switzerland	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Switz Financial	-1.595				-19.899			
Utilities	-0.452				-22.451			
Telecommunication	-2.383				-22.775			
Technology	-2.821				-14.681			
Oil	-1.428				-13.092			
Industrial	-2.707				-19.058			
Healthcare	-0.924				-43.892			
Con. Services	-2.721				-16.861			
Con. Goods	-2.453				-21.331			
Basic Materials	-3.219				-20.677			

ADF Test (Full Sample) – Taiwan	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Taiwan Financial	-3.759				-34.929			
Telecommunication	-6.353				-29.388			
Technology	-1.812				-17.535			
Oil	-2.115				-19.209			
Industrial	-2.353				-16.550			
Con. Services	-3.283				-16.775			
Con. Goods	-2.902				-38.304			
Basic Materials	-2.916				-36.322			

ADF Test (Full Sample) – Thailand	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Thailand Financial	-1.915				-25.162			
Utilities	-2.031				-17.464			
Telecommunication	-2.122				-18.786			
Technology	-3.020				-19.136			
Oil	-1.733				-26.728			
Industrial	-3.147				-17.013			
Healthcare	-1.231				-37.679			
Con. Services	-1.757				-38.812			
Con. Goods	-2.645				-15.920			
Basic Materials	-3.178				-16.849			

ADF Test (Full Sample) – Thailand	**Prices**				**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**	**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120		-3.960	-3.410	-3.120
Thailand Financial	-1.915				-25.162			
Utilities	-2.031				-17.464			
Telecommunication	-2.122				-18.786			
Technology	-3.020				-19.136			
Oil	-1.733				-26.728			

Industrial	-3.147		-17.013
Healthcare	-1.231		-37.679
Con. Services	-1.757		-38.812
Con. Goods	-2.645		-15.920
Basic Materials	-3.178		-16.849

ADF Test (Full Sample) – U.K.	**Prices**					**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**		**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120			-3.960	-3.410	-3.120
U.K. Financial	-1.521					-25.162			
Utilities	-2.812					-17.464			
Telecommunication	-2.970					-18.786			
Technology	-1.770					-19.136			
Oil	-2.161					-26.728			
Industrial	-3.539					-17.013			
Healthcare	-2.156					-37.679			
Con. Services	-2.334					-38.812			
Con. Goods	-3.386					-15.920			
Basic Materials	-2.731					-16.849			

ADF Test (Full Sample) – U.S.	**Prices**					**Returns**			
	T Stats	**1% C.V**	**5% C.V**	**10% C.V**		**T Stats**	**1% C.V**	**5% C.V**	**10% C.V**
		-3.960	-3.410	-3.120			-3.960	-3.410	-3.120
US Financial	-1.352					-31.858			
Utilities	-2.653					-44.567			
Telecommunication	-1.387					-32.115			
Technology	-1.649					-31.711			
Oil	-3.344					-46.819			
Industrial	-2.109					-44.728			
Healthcare	-1.645					-31.568			
Con. Services	-2.436					-44.951			
Con. Goods	-2.268					-43.851			
Basic Materials	-3.417					-25.008			

ADF test is conducted for the weekly log indices and aggregate stock market returns for all sectors each of the 25 countries for the full sample (Oct 1979 – Mar 2012). The lag length is selected using SIC, and the t-statistics and critical values are compared in order to test the null hypothesis of non-stationarity.

B.2: ARCH LM EFFECTS AFTER GJR REGRESSIONS

Australia	Lags	Chi2	Df	Prob>chi2
Oil	1	0.025	1	0.8740
Basic Materials	1	0.046	1	0.8308
Industrial	1	0.009	1	0.9264
Consumer Goods	1	0.003	1	0.9577
Healthcare	1	0.000	1	0.9863
Consumer Services	1	0.001	1	0.9695
Telecommunication	1	0.006	1	0.9361
Utilities	1	0.156	1	0.6927
Technology	1	0.126	1	0.7223
Financial	1	0.000	1	0.9924

Brazil	Lags	Chi2	Df	Prob>chi2
Oil	1	0.025	1	0.8739
Basic Materials	1	0.050	1	0.8231
Industrial	1	0.010	1	0.9216
Consumer Goods	1	0.006	1	0.9401
Consumer Services	1	0.004	1	0.9526
Telecommunication	1	3.580	1	0.0585
Utilities	1	0.002	1	0.9610
Technology	1	0.000	1	0.9832
Financial	1	0.010	1	0.9211

Chile	Lags	Chi2	Df	Prob>chi2
Oil	1	0.015	1	0.9037
Basic Materials	1	0.188	1	0.6643
Industrial	1	0.050	1	0.8235
Consumer Goods	1	0.004	1	0.9485
Healthcare	1	0.475	1	0.4905
Consumer Services	1	0.034	1	0.8544
Telecommunication	1	0.022	1	0.8810
Technology	1	0.118	1	0.7309
Financial	1	0.001	1	0.9737

China	Lags	Chi2	Df	Prob>chi2
Oil	1	0.046	1	0.8307
Basic Materials	1	0.008	1	0.9289
Industrial	1	0.014	1	0.9072
Consumer Goods	1	0.053	1	0.8173
Healthcare	1	0.000	1	0.9867
Consumer Services	1	0.003	1	0.9561
Telecommunication	1	0.081	1	0.7764
Utilities	1	0.005	1	0.9442
Technology	1	0.065	1	0.7982
Financial	1	0.011	1	0.9163

France	Lags	Chi2	Df	Prob>chi2
Oil	1	0.000	1	0.9848
Basic Materials	1	0.208	1	0.6482
Industrial	1	0.001	1	0.9734
Consumer Goods	1	0.003	1	0.9536

Healthcare	1	0.525	1	0.4686
Consumer Services	1	0.054	1	0.8165
Telecommunication	1	0.066	1	0.7968
Utilities	1	0.030	1	0.8623
Technology	1	0.002	1	0.9643
Financial	1	0.005	1	0.9455

Germany	Lags	Chi2	Df	Prob>chi2
Oil	1	0.046	1	0.8309
Basic Materials	1	0.080	1	0.7766
Industrial	1	1.270	1	0.2598
Consumer Goods	1	0.001	1	0.9737
Healthcare	1	0.000	1	0.9930
Consumer Services	1	0.039	1	0.8439
Telecommunication	1	0.007	1	0.9312
Utilities	1	0.138	1	0.7106
Technology	1	0.005	1	0.9424
Financial	1	0.002	1	0.9684

HK	Lags	Chi2	Df	Prob>chi2
Oil	1	0.000	1	0.9917
Basic Materials	1	0.215	1	0.6427
Industrial	1	0.148	1	0.7008
Consumer Goods	1	0.002	1	0.9610
Healthcare	1	0.005	1	0.9416
Consumer Services	1	0.030	1	0.8625
Telecommunication	1	0.009	1	0.9249
Utilities	1	0.069	1	0.7923
Technology	1	0.450	1	0.5026
Financial	1	0.001	1	0.9746

India	Lags	Chi2	Df	Prob>chi2
Oil	1	0.001	1	0.9755
Basic Materials	1	0.000	1	0.9981
Industrial	1	0.003	1	0.9576
Consumer Goods	1	0.005	1	0.9429
Healthcare	1	0.008	1	0.9289
Consumer Services	1	0.002	1	0.9625
Telecommunication	1	0.115	1	0.7344
Utilities	1	0.061	1	0.8042
Technology	1	0.003	1	0.9555
Financial	1	0.001	1	0.9763

Indonesia	Lags	Chi2	Df	Prob>chi2
Oil	1		1	
Basic Materials	1		1	
Industrial	1	0.002	1	0.9661
Consumer Goods	1	0.007	1	0.9322
Healthcare	1	0.376	1	0.5399
Consumer Services	1	0.013	1	0.9103
Telecommunication	1	0.003	1	0.9591
Utilities	1	0.020	1	0.8867
Financial	1	0.016	1	0.8991

Italy	Lags	Chi2	Df	Prob>chi2
Oil	1	0.066	1	0.7965
Basic Materials	1	0.000	1	0.9887
Industrial	1	0.007	1	0.9342
Consumer Goods	1	0.004	1	0.9518
Healthcare	1	0.067	1	0.7956
Consumer Services	1	0.012	1	0.9137
Telecommunication	1	0.118	1	0.7309
Utilities	1	0.272	1	0.6021
Technology	1	0.001	1	0.9787
Financial	1	0.022	1	0.8808

Japan	Lags	Chi2	Df	Prob>chi2
Oil	1	0.012	1	0.9113
Basic Materials	1	0.003	1	0.9553
Industrial	1	0.086	1	0.7691
Consumer Goods	1	0.158	1	0.6914
Healthcare	1	0.098	1	0.7548
Consumer Services	1	0.001	1	0.9729
Telecommunication	1	0.005	1	0.9420
Utilities	1	0.002	1	0.9647
Financial	1	0.040	1	0.8406

Mexico	Lags	Chi2	Df	Prob>chi2
Oil	1	144.500	1	0.0000
Basic Materials	1	235.667	1	0.0000
Industrial	1	0.004	1	0.9508
Consumer Goods	1	0.004	1	0.9497
Healthcare	1		1	
Consumer Services	1	0.002	1	0.9650
Telecommunication	1	0.070	1	0.7917
Financial	1	0.238	1	0.6253

Norway	Lags	Chi2	Df	Prob>chi2
Oil	1	0.075	1	0.7836
Basic Materials	1	2.367	1	0.1239
Industrial	1	0.000	1	0.9835
Consumer Goods	1	0.179	1	0.6722
Consumer Services	1	0.001	1	0.9788
Telecommunication	1	0.395	1	0.5295
Utilities	1	0.014	1	0.9048
Technology	1	0.003	1	0.9551
Financial	1	0.075	1	0.7846

NZ	Lags	Chi2	Df	Prob>chi2
Oil	1	0.031	1	0.8600
Basic Materials	1	0.007	1	0.9334
Industrial	1	0.006	1	0.9392
Consumer Goods	1	0.013	1	0.9087
Healthcare	1	2.110	1	0.1463
Consumer Services	1	0.014	1	0.9049
Telecommunication	1	0.264	1	0.6072
Utilities	1	0.007	1	0.9347
Technology	1	0.047	1	0.8287
Financial	1	0.013	1	0.9099

Russia	Lags	Chi2	Df	Prob>chi2
Oil	1	0.029	1	0.8656
Basic Materials	1	0.003	1	0.9540
Consumer Goods	1	0.008	1	0.9303
Consumer Services	1	0.002	1	0.9624
Telecommunication	1	0.010	1	0.9214
Utilities	1	1.257	1	0.2622
Financial	1	1.725	1	0.1891

South Africa	Lags	Chi2	Df	Prob>chi2
Oil	1	0.007	1	0.9355
Basic Materials	1	0.020	1	0.8869
Industrial	1	0.001	1	0.9788
Consumer Goods	1	0.371	1	0.5423
Healthcare	1	0.004	1	0.9504
Consumer Services	1	0.002	1	0.9653
Telecommunication	1	0.057	1	0.8120
Utilities	1	0.082	1	0.7749
Technology	1	0.002	1	0.9690
Financial	1	0.085	1	0.7712

South Korea	Lags	Chi2	Df	Prob>chi2
Oil	1	0.033	1	0.8553
Basic Materials	1	0.773	1	0.3793
Industrial	1	1.260	1	0.2617
Consumer Goods	1	0.820	1	0.3651
Healthcare	1	0.001	1	0.9744
Consumer Services	1	0.513	1	0.4740
Telecommunication	1	0.018	1	0.8939
Utilities	1	0.003	1	0.9553
Technology	1	0.002	1	0.9690
Financial	1	0.000	1	0.9978

Spain	Lags	Chi2	Df	Prob>chi2
Oil	1	13.008	1	0.0003
Basic Materials	1	0.556	1	0.4559
Industrial	1	3.942	1	0.0471
Consumer Goods	1	0.063	1	0.8019
Healthcare	1	0.002	1	0.9666
Consumer Services	1	0.001	1	0.9796
Telecommunication	1	0.855	1	0.3553

Utilities	1	0.102	1	0.7489
Technology	1	0.006	1	0.9396
Financial	1	0.019	1	0.8912

Sweden	Lags	Chi2	Df	Prob>chi2
Oil	1	0.005	1	0.9434
Basic Materials	1	42.669	1	0.0000
Industrial	1	3.088	1	0.0789
Consumer Goods	1	0.044	1	0.8332
Healthcare	1	0.347	1	0.5557
Consumer Services	1	0.244	1	0.6215
Telecommunication	1	0.000	1	0.9997
Technology	1	0.025	1	0.8745
Financial	1	0.098	1	0.7548

Switzerland	Lags	Chi2	Df	Prob>chi2
Oil	1	0.007	1	0.9356
Basic Materials	1	2.828	1	0.0926
Industrial	1	0.029	1	0.8641
Consumer Goods	1	0.007	1	0.9331
Healthcare	1	0.001	1	0.9766
Consumer Services	1	0.032	1	0.8586
Telecommunication	1	0.043	1	0.8352
Utilities	1	0.034	1	0.8545
Financial	1	0.011	1	0.9179

Taiwan	Lags	Chi2	Df	Prob>chi2
Oil	1	0.007	1	0.9317
Basic Materials	1	0.160	1	0.6889
Industrial	1	0.007	1	0.9349
Consumer Goods	1	0.002	1	0.9687
Consumer Services	1	0.002	1	0.9636
Telecommunication	1	0.002	1	0.9636
Technology	1	0.000	1	0.9972
Financial	1	0.002	1	0.9616

Thailand	Lags	Chi2	Df	Prob>chi2
Oil	1	0.085	1	0.7710
Basic Materials	1	0.572	1	0.4494
Industrial	1	1.877	1	0.1707
Healthcare	1	0.296	1	0.5866
Consumer Services	1	0.006	1	0.9373
Telecommunication	1	0.131	1	0.7179
Utilities	1	0.155	1	0.6942
Technology	1	0.045	1	0.8326
Financial	1	0.017	1	0.8954

U.K.	Lags	Chi2	Df	Prob>chi2
Oil	1	0.001	1	0.9760
Basic Materials	1	0.854	1	0.3555
Industrial	1	0.057	1	0.8113
Consumer Goods	1	0.333	1	0.5637

Healthcare	1	6.707	1	0.0096
Consumer Services	1	0.001	1	0.9714
Telecommunication	1	0.010	1	0.9185
Utilities	1	0.050	1	0.8229
Technology	1	0.016	1	0.8990
Financial	1	0.019	1	0.8917

U.S.	Lags	Chi2	Df	Prob>chi2
Oil	1	0.111	1	0.7391
Basic Materials	1	0.013	1	0.9090
Industrial	1	0.024	1	0.8759
Consumer Goods	1	0.408	1	0.5229
Healthcare	1	0.035	1	0.8507
Consumer Services	1	0.039	1	0.8433
Telecommunication	1	0.433	1	0.5107
Utilities	1	0.000	1	0.9858
Technology	1	0.106	1	0.7453
Financial	1	0.023	1	0.8783

Engle's ARCH LM test is conducted after modelling equation (4.2)-(4.3) for ARCH effects. Given the p-values are compared to the alphas (5% significance level) in order to determine whether there are any remaining ARCH effects in the residuals after estimating Model 4.2with a GJR GARCH framework

B.3.: Estimation results for Equation 4.2

World Financial Sector Returns

Australia	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$	$\boldsymbol{\gamma_0}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{\theta_0}$	$\boldsymbol{\theta_1}$
Oil	-.0636464	.0002119**	.2862246**		.1709803	
Basic Mat	.1067239***		.4892814***		.4676907***	
Industrial	.117956***.		.168926***		.0990863	
Cons. Goods	.0944449***	.000125**	6.676481**	-.0045232**	-.0423999	
Healthcare	.1209533***		.000437		-.0483086	
Cons. Ser	.2160029***		-.1141036*		-.0617736	
Tele.	.1448927**		-.0052552		-.1581481	
Utilities	.0439203		.0066816		.0027846	
Tech.	3.600563***	.0030422***	9.923613**	-.0071357**	4.762188*	-.0036206**
Financial	.3669687***		.332405***		.2070348***	

Country Specific Financial Sector Returns

Australia	μ_0(ausfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.7327458***	-.0002643***	-.4004428***		.1200774	
Basic Mat	.9200518***	-.0002753***	-.4264326***		-.0862427	
Industrial	.5927778***		4.136045*	-.0028496*	-.04643	
Cons. Goods	.503238***		-.0937987		-4.161769**	.0024868**
Healthcare	.5749611***		14.21875***	-.0096833***	-.156593*	
Cons. Ser	.8241529***	-.0002582***	.090169		.0468332	
Tele.	.3082775***		-.1116415		-.0075693	
Utilities	.6439895***	-.0001908**	6.708346**	-.0045093**	-3.801317**	.0024834**
Tech.	.3833116***		-.0813837		.0622554	

World Financial Sector Returns

Brazil	δ_0**(wdfin)**	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	.4834158***		-.2927354*		.1675143	
Basic Mat	-.5143023	.0008***	-.5658096***		-.1309337	
Industrial	.3263042***		-.2404242**		-.1630703**	
Cons. Goods	.2951287***		-.1366311		-.2201524***	
Cons. Ser	.673441***		-.8324322***		-.5973466***	
Tele.	.4574854***		-.3962817***		-.3410684***	
Utilities	.3793045***		-.5271235***		-.3967766***	
Tech.	1.505769**		-1.479819 **		-1.431893**	
Financial	-1.199928***	.0016647***	11.7901**	-.0081342**	-.7992782***	

Country Specific Financial Sector Returns

Brazil	μ_0(ausfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.9061115***	-.0003897**	.3890226**		.0289908	
Basic Mat	.3607405***		.4441938***		.0142011	
Industrial	.6714966***	-.0002787**	.3456938***		.2452228**	
Cons. Goods	.3364164***		-.1769288**		.0458332	
Cons. Ser	.3582091***		11.56188***	-.0074692***	.201736**	
Tele.	1.982135 ***	-.0012329***	7.084672**	-.0046038**	.303732 **	
Utilities	1.240995***	-.0004789***	9.361423***	-.0062392***	-.0831504	
Tech.	11.0247***	-.0079085***	1.296307***		-9.315845*	.0071189**

World Financial Sector Returns

Canada	δ_0**(wdfin)**	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	.1838468 ***		.205306		.3537118***	
Basic Mat	-.0259461	.0004285***	.4450694***		-.2163901*	
Industrial	-.042261	.0004666***	.2948048***		-.4333354***	
Cons. Goods	.3538034***		-.2556026***		-.1379128	
Healthcare	.1960639***		9.895044***	-.00668***	-.0788886	
Cons. Ser	.1798068***		7.381037***	-.0048897***	-.0910535***	
Tele.	-.013600	.0001642***	-.094205		-.3340428	
Utilities	.1177999***	-.0000956***	.1410629**		.2135367***	
Tech.	-.136319**	.0005427***	-.8726043***		-.4957629**	
Financial	.2386165***	.0002585***	-.0203873		-.1994019***	

Country Specific Financial Sector Returns

Canada	μ_0(ausfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.5055573***	-.0002848***	-17.83214***	.0118705***	.3193477**	
Basic Mat	.7241774***	-.0004049***	-.8953528***		.1655434	
Industrial	.8738444***	-.0004235***	.1814187		.2490933*	
Cons. Goods	.3150748***		.20367**		.1062294	
Healthcare	.537758***	-.0001416***	.0933701		-.1411083	
Cons. Ser	.458691***		-.2401777***		-3.942504**	.0023347**
Tele.	.0002762***		-.3179988***		-.1569983	
Utilities	.3201853***		-.1005402		-.119026*	
Tech.	.54512***		17.50536**	-.0112848*	.1170136	

World Financial Sector Returns

Chile	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$	$\boldsymbol{\gamma_0}$	$\boldsymbol{\gamma_1}$ **(r3)**	$\boldsymbol{\theta_0}$ **(D4)**	$\boldsymbol{\theta_1}$ **(r5)**
Oil	-.2018645*	.0002021*	-.2385976**		-.037711	
Basic Mat	.1055963***		9.292373***	-.006158***	.0975074	
Industrial	.0729807**		13.94309***	-.0092831***	-7.301987***	.0045607***
Cons. Goods	.1611971***		13.95091***	-.0092926***	-.1256039*	
Healthcare	.0021653		-.1520803**		.0366007	
Cons. Ser	.1478279***		-.1339314**		.2049768***	
Tele.	.3857454***		-.2917657***		-.3254143***	
Tech.	-.1968869		.2661955		.4252287	
Financial	-.4141297***	.000603***	11.6727***	-.0078322***	-.2166693***	

Country Specific Financial Sector Returns

Chile	μ_0(ausfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	-.3731451***	.0006474***	1.142379***		.3492096***	
Basic Mat	-.2391918***	.0006569***	-.0036806		-.1328472	
Industrial	.3592687***		.4222701***		.5082302***	
Cons. Goods	.377268***		.200122		.2108144**	
Healthcare	-.1691797***	.0003141***	-11.59458**	.0080703**	5.119041*	-.0031214*
Cons. Ser	.2865392***		.7715064***			
Tele.	-.0670299	.0005925***	27.84973***	-.0186308***	-.446744***	
Tech.	-69.20355*	.0491613**	.0491613**	-.0620116**	67.04323*	-.0476492**

World Financial Sector Returns

China	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$	$\boldsymbol{\gamma_0}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{\theta_0}$	$\boldsymbol{\theta_1}$
Oil	.0155071		-.172901		.2209088**	
Basic Mat	-.8005567**	.0007072**	-.4886391**		-.2222472	
Industrial	.0008442		-.1798762		.0731283	
Cons. Goods	-.0186201		-.1528284		.158155	
Healthcare	-.0220486		-.0490384		-.0198445	
Cons. Ser	.0265121		-.2332693		-.0125061	
Tele.	.0637843		-.2130643		.0832424	
Utilities	.0222449		-.2490636		-.0147633	
Tech.	.0859597		-.3987751		.0647111	
Financial	-1.013044**	.0012539***	20.70133***	-.0136861***	-.1133527	

Country Specific Financial Sector Returns

China	μ_0(ausfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	-.4367648*	.000588***	.0595361		4.939125***	-.0032448***
Basic Mat	.2235493***		.4073679 ***		9.767629 ***	-.0058711***
Industrial	.2707486***		.190199*		5.223235***	-.0031778***
Cons. Goods	-.0941947	.0003086**	.0007551		6.587198***	-.0041892***
Healthcare	-.2091539	.000399***	-.1858613		-.2699939**	
Cons. Ser	.2374362***		.1737032		6.35025***	-.0038052***
Tele.	.2467256***		.345325***		-.0927365	
Utilities	.2467827***		.1362577		3.813224**	-.0023035**
Tech.	.2395852***		-8.941528*	.0061152**	-.0003405	

World Financial Sector Returns

France	δ_0**(wdfin)**	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	.0766661**		.4932247***		.6866733***	
Basic Mat	.1390502***		.6862201***		.6930013***	
Industrial	.1593966***		.4053669***		.5474579***	
Cons. Goods	.1411097***		.42061***		.6070122***	
Healthcare	.10467		-.1355753		.3333438	
Cons. Ser	.1326454 ***		.4617216***		.482639***	
Tele.	.3200787**		-.2028088		-.0777533	
Utilities	.0739215		.6777524***		.1749278	
Tech.	.1372397***		.4896644***		.5891669***	
Financial	-.0420915	.0008122***	-.0739583		-3.795727**	.0023847**

Country Specific Financial Sector Returns

France	μ_0(ausfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.568567***		-.6657228***		-.497834***	
Basic Mat	.706247***	-.0001208***	-.6878462		-.4410183***	
Industrial	.6492268***		3.587362	-.0027116**	-.4952507***	
Cons. Goods	.678517***		3.497402	-.0027497*	-.6844706***	
Healthcare	.7166696***	-.0001979***	-.1688586		-.3574468***	
Cons. Ser	.5910125 ***	-.0000807**	-.4450351 ***		-.3354401***	
Tele.	.5243661***		-.4986107***		-.2946603**	
Utilities	.6280186***		-.9076931***		-.2131693*	
Tech.	.5156235***	.000317***	-.869716***		-.9124173***	

World Financial Sector Returns

Germany	δ_0(wdfin)	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	2.034141***		-1.63149***		-1.276159***	
Basic Mat	-.0118753	.0001285***	-.107169		.3752335***	
Industrial	-.0907702***	.0002295***	-.0970055		.247394	
Cons. Goods	-.1257109***	.000281***	.2823034**		.2369994**	
Healthcare	.0651875***		-.136101**		.0220929	
Cons. Ser	-.0642645	.0002918***	-.1620355		.0473493	
Tele.	.0506742*		-.2664174*		.0181485	
Utilities	.0531373***		-24.51294***	.0164457***	.0288965	
Tech.	.0897221		-.0755054		.3688801***	
Financial	.2316179***	.0005063***	-.1865879***		-5.941582***	.0035952***

Country Specific Financial Sector Returns

Germany	μ_0(ausfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	-.1314933		.5933332		.3559764	
Basic Mat	.6252184***		.0434341		-.2577802***	
Industrial	.7038287***		.0800787		3.957266**	-.0025861***
Cons. Goods	.6332915***		-.4209429***		-.3388395***	
Healthcare	.6063416***	-.0001834***	-.0577812		-.0867136	
Cons. Ser	.6431514***	-.0000964*	-6.141887**	.0041873**	-.1021693	
Tele.	.7056845***		-.2174042		-.3188615**	
Utilities	.3342288***	-.0002478***	17.91711**	-.0117539**	.693254***	
Tech.	.4066361***	.0003854***	-.3499223**		-.7308257***	

World Financial Sector Returns

Hong Kong	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$	$\boldsymbol{\gamma_0}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{\theta_0}$	$\boldsymbol{\theta_1}$
Oil	.1125938		.1092187		.3867253	
Basic Mat	-.0734657*		-.2326189		.3948726***	
Industrial	.0536226***		-.1045453*		.1268692*	
Cons. Goods	-.4590869	.0006201**	-11.52026**	.0074143**	-.3905627**	
Healthcare	-.0434386		.2491076		.1847112	
Cons. Ser	-.0344261	.0001093**	-10.66151**	.007026**	-.0728329	
Tele.	-.0586728	.0002656*	-.0591815		-.3231216	
Utilities	-.0020202		.0688361		.0604198	
Tech.	-.3793666*	.000559***	-.3259491*		-.2828912	
Financial	.4698451***	.0001753**	10.20342***	-.0067271***	.1259599	

Country Specific Financial Sector Returns

Hong Kong	μ_0	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.652528***		17.09992***	-.0109448***	-1.229224	.0008064**
Basic Mat	1.135819***	-.0003561***	9.74095**	-.0061037**	.256514**	
Industrial	1.043672***	-.0000685**	7.927667***	-.005294***	-.1708046**	
Cons. Goods	-.0936848	.0006076***	30.08185***	-.0201336***	-.2857842**	
Healthcare	-1.271481	.0011489	15.13527**	-.0102225**	8.633625**	-.0053021**
Cons. Ser	.7934579***		19.00454***	-.0126851***	-4.785054***	.0029985***
Tele.	.1098572	.0006687***	13.74816***	-.0094406***	-.7251568***	
Utilities	.9097044***	-.0004758***	8.405808***	-.0055413***	-3.391692***	.0021563***
Tech.	.5723438***	.0004019***	-.2258891		-.5194077***	

World Financial Sector Returns

India	δ_0(wdfin)	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	.1838219***		.1394704***		-.0445135	
Basic Mat	.076048**		.0427408		6.005339***	-.0034251**
Industrial	.165917***		-.1267327		-.0578497	
Cons. Goods	.1658704***		-.0623765***		-.1564743**	
Healthcare	.1028069***		.0015299		.0303922	
Cons. Ser	-.2839022	.0003428*	-.244454		-.1634866	
Tele.	.0883203		.275372**		-.0096075	
Utilities	.0150612		.1192363		.1065933	
Tech.	.2994693***		-.0001253		.0377585	
Financial	-1.140122***	.0014577***	.0132143		5.584263*	-.0037664**

Country Specific Financial Sector Returns

India	μ_0(ausfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	-.220419***	.0006343***	6.805485**	-.0047142**	-.3302781***	
Basic Mat	-.0267701	.0005361***	5.414931*	-.0036108*	-.2621056***	
Industrial	.0408572	.0004799***	6.556578***	-.0044163***	-.1267327**	
Cons. Goods	.0156462	.0004474***	8.834088***	-.0061***	-.4161058***	
Healthcare	.2929428***	.0001208**	-.2361033***		-.3343255***	
Cons. Ser	-.0305105	.0005059***	-.178723**		-.2831646***	
Tele.	-.1888602*	.0007543***	9.183346***	-.0064536***	2.820875	-.002082*
Utilities	.1760618***	.0003626***	12.98202***	-.0087538***	-.1986512***	
Tech.	.1417413***	.000274***	-.3289401***		-.3391582***	

World Financial Sector Returns

Indonesia	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$**(r1)**	$\boldsymbol{\gamma_0}$ **(D2)**	$\boldsymbol{\gamma_1}$ **(r3)**	$\boldsymbol{\theta_0}$ **(D4)**	$\boldsymbol{\theta_1}$ **(r5)**
Oil	Use OLS					
Basic Mat	.1481961***		.0116983		6.006489**	-.00353**
Industrial	-.1017523***		.1533715		.3652875***	
Cons. Goods	-.1427899		-.206911		-.2401987*	
Healthcare	.2271857***		-.2131318**		-.0194926	
Tele.	.4591112***		-.3155408**		-.4032458***	
Utilities	.4780087**		-.3285038		-.2244965	
Financial	-.4302728*	.000921***	16.74174***	-.0112624***	-.4348772**	

Country Specific Financial Sector Returns

Indonesia	μ_0(ausfin)	μ_1(r6)	ρ_0(d5)	ρ_1(r7)	φ_0(d6)	φ_1(r8)
Oil						
Basic Mat	.0050389	.0004149***	13.42532**	-.00883**	-.067882	
Industrial	-2.084885	.0019686***	.0714488		-.4950401***	
Cons. Goods	.0208822	.000437***	.0934365		-.1202608	
Healthcare	.3839423***		.2077905***		.2519832**	
Tele.	.051839	.0003967***	-.0796285		-.3772684***	
Utilities	.5295586***		-15.41157***	.0105609***	-.0796985	

World Financial Sector Returns

Italy	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$	$\boldsymbol{\gamma_0}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{\theta_0}$	$\boldsymbol{\theta_1}$
Oil	-.2199434**	.000422***	-.1141203		-11.30046***	.0070577***
Basic Mat	.0438736	-.0000266	.678437***		1.157604***	
Industrial	-.0080953	.0001447***	.1256384		.361737	
Cons. Goods	.0386524		.4402754***		.827176***	
Healthcare	.015288		.30875***		.3627638***	
Cons. Ser	-.1689421***	.0003162***	8.547773***	-.005772***	.1508089	
Utilities	.0020208		.0694753		.2769931***	
Tech.	.0553729		-.0402521		.2639105**	
Financial	.0700043	.0005729***	-7.645113***	.0050148***	-5.261543**	.0034491**

Country Specific Financial Sector Returns

Italy	μ_0(ausfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.708657***	-.0002762***	-.0482231		7.146579***	-.0044249***
Basic Mat	.8551992***	-.0001591***	-.4869624**		-.6973303***	
Industrial	.7770791***		-.4819567***		-.4892729***	
Cons. Goods	.8950074***		-.6429192***		-.8057655***	
Healthcare	.6562648***		-.5919789***		-.5303361***	
Cons. Ser	.8741705***	-.0003373***	.1180407		-.0184356	
Utilities	.8555343***	-.0002405***	-.1267277		-.1751507***	
Tech.	.871396***		.0627276		2.608132	-.0019536**

World Financial Sector Returns

Japan	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$	$\boldsymbol{\gamma_0}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{\theta_0}$	$\boldsymbol{\theta_1}$
Oil	.1816134***		.1224156		.2810419***	
Basic Mat	.1961606***		8.097122**	-.0052986**	.1384892**	
Industrial	.3170299***		-.0878522		.0180025	
Cons. Goods	.2606244***		-.1042849		-.0877606	
Healthcare	.1780863***		-.1262173		-.1506996***	
Cons. Ser	.1919049***		-.0792386		-.1628576	
Tele.	.0474133	.000326***	-.5013826***		-.5103402***	
Utilities	.1071592***		-.1384267*		-.1699059***	
Financial	.2610779	.0009479***	22.29286***	-.0153157***	-1.316025***	

Country Specific Financial Sector Returns

Japan	μ_0(japfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.1816134***	.0002438***	-.1721466*		.0611892	
Basic Mat	.2603505***	.2603505***	-.1913652***		.0286153	
Industrial	-.0019385	.0004506***	-.1188635**		-.0510869	
Cons. Goods	.092399***	.0002962***	-.0575742		.0976144**	
Healthcare	.450326***	-.0001562***	-4.086262**	.0028089*	.2246638***	
Cons. Ser	.399362***	.0000889***	2.861237*	-.002096**	-.1219323***	
Tele.	.4026538***		-.0769862		-.0505273	
Utilities	.7193729***	-.0005108***	.2376792***		.2489054***	

World Financial Sector Returns

Mexico	δ_0**(wdfin)**	δ_1	γ_0	γ_1	θ_0	θ_1
Basic Mat	-.1839973	.0005754***	14.98944***	-.0099316***	8.34284***	-.0052279***
Industrial	-.1096809	.0004528***	-.0935916		-.2411969**	
Cons. Ser	-.0369207	.000316**	-.2132867**		5.47655***	-.0035685***
Tele.	.5466785***		-.0576317		-.1949114**	
Financial	.4879001***		-.1043562**		-.0840567	

Country Specific Financial Sector Returns

Mexico	μ_0(ausfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Basic Mat	.4308496***		.0645409		.0132029	
Industrial	.321477***	.0001352**	-.0112716		-.1999042**	
Cons. Ser	.1152537**	.0002466***	-.0466371		-.200974**	
Tele.	.1817567**	.000257***	-.2437473*		4.077934	-.0027909*

World Financial Sector Returns

Norway	δ_0**(wdfin)**	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	.1876755***		.1569223		.3821753***	
Basic Mat	.0722094	.0001649**	.5154479***		.3963155***	
Con. gds	.2308226***		12.68166**	-.0083509**	.3070183***	
Cons. Ser	-.1610322*	.0005795***	-.3214672**		-.0120681	
Tele.	.5974229***		-.2201282		11.10201***	-.0069386***
Utilities	-.009803	.0002795***	26.92938***	-.0176702***	-.285959**	
Tech.	-.5933655***	.0011549***	23.69854***	-.0161894***	-.9154268***	
Financial	.0905958	.0003856***	-27.46403***	.0185923***	.3671219***	

Country Specific Financial Sector Returns

Norway	μ_0(norwfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.315644***	.0001028*	9.096573**	-.0061389**	-.1954788*	
Basic Mat	.4394547***		-.2538955**		-.1274933*	
Cons. Goods	.294847***		9.481874**	-.0062433*	-.0737364	
Cons. Ser	.2690698***	.0001188*	17.80147***	-.0117513***	-.0386007	
Tele.	-1.226641	.0011726**	8.074046*	-.0056763*	-.4965454**	
Utilities	.3695675***	-.0001737**	-.158344		.0469359	
Tech.	.1219889	.0001835*	-.1665574		-.1757496	

World Financial Sector Returns

New Zealand	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$	$\boldsymbol{\gamma_0}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{\theta_0}$ **(D4)**	$\boldsymbol{\theta_1}$
Oil	.1311675***		.0401828		-.0067582	
Basic Mat	.195139***		-.0847797		.1222878	
Industrial	.1050415**		.1078578*		.1877074***	
Cons. Goods	.1392005***		-8.827166**	.0058544**	.09834	
Healthcare	.1029463 ***		-.1147449*		.0295227	
Cons. Ser	.163298***		.0366122		.0679714	
Tele.	.5801631***	-.0003797**	.22365*		.2830523**	
Utilities	.0678233**		.1226466**		.0665088	
Tech.	-.8095646		.8747107		.9604491	
Financial	.6572476***	-.0003235***	2.98398*	-.0019726*	1.47496	-.0009278*

Country Specific Financial Sector Returns

New Zealand	μ_0(nzfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.1141211***		.374515*		-12.70039*	.0082445**
Basic Mat	.6445853***	-.0002588***	.5875929***		.2680981	
Industrial	.9611657***	-.0005203**	10.91419*	-.0070157*	.1468694	
Cons. Goods	.3080156***		.4857895***		.0532338	
Healthcare	.2752758***		.5660061***		-.1235104	
Cons. Ser	.1416186***	.0001719***	.3739562***		-.2600349**	
Tele.	.3324804***		-.0200624		-13.86054**	.0087396**
Utilities	.2316205***		.4062832***		-.0074679	
Tech.	-2.173753		2.563729		2.271076	

World Financial Sector Returns

Russia	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$	$\boldsymbol{\gamma_0}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{\theta_0}$	$\boldsymbol{\theta_1}$
Oil	.5317007***		-.4496847***		-.194451*	
Basic Mat	.5962602***		-.2647309*		-.293865**	
Cons. Goods	.0634151		-.0966464		.0584733	
Cons. Ser	.1504818		-.1930932		.2983936*	
Tele.	.3502451***		-.2347094***		-.2452177**	
Utilities	.3061243		-.4884243***		-.2114662	
Financial	-2.125081*	.0022369**	-.3275292		12.64629***	-.0080648***

Country Specific Financial Sector Returns

Russia	μ_0(russfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	1.019715***	-.0004453***	.3997451***		.1962617**	
Basic Mat	.3502096***		.2888739***		.2387487***	
Cons. Goods	-.9933805*	.0008365*	-.0002773***		4.893931***	-.003172***
Cons. Ser	1.075243***	-.0004616***	.1377057		-.1135719	
Tele.	1.322885***	-.0008251***	.2364718***		.2716033***	
Utilities	1.227233***	-.0006669***	.311118***		.4506276***	

World Financial Sector Returns

South Africa	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$	$\boldsymbol{\gamma_0}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{\theta_0}$	$\boldsymbol{\theta_1}$
Oil	.2050746***		-14.08375***	.009605***	.1936501**	
Basic Mat	.2649773***		.3428916**		.2094506**	
Industrial	.1844682***		.0295753		.0309741	
Cons. Goods	.1598255***		-.0557462		.0433314	
Healthcare	.0665939**		.07137		.006782	
Cons. Ser	-.1576467	.0003037***	-.0500749		-.1300702	
Tele.	.2524047***		.1574526		-.2156225*	
Tech.	.059333		-.1073694		.1404568	
Financial	-.0842488	.0005485***	-.1997099***		-.3251416***	

Country Specific Financial Sector Returns

South Africa	μ_0(safin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.3059806***		-.1394578		-7.437455	.0047958*
Basic Mat	.2227072***	.0001691**	-.4374323***		-.05869	
Industrial	.3476115***	.0002298***	-.1827857***		-.1234551	
Cons. Goods	-.2755967***	.0006405***	6.96525**	-.0048561**	-3.874429**	.0021792*
Healthcare	.1738797***	.0002733***	-.1510717*		4.893343**	-.0030874**
Cons. Ser	-.0155007	.0004907***	7.069597**	-.0048803**	-.2238896**	
Tele.	.7505674***		-.3854877***		-.0529897	
Tech.	.0884305*		.0376064		-12.36486***	.007624***

World Financial Sector Returns

South Korea	δ_0(wdfin)	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	-.2464262*	.0004105***	-.0956565		.1510526	
Basic Mat	-.2116911*	.0005253***	15.88821***	-.0105463***	-.3040335**	
Industrial	-.1719682	.000486***	-.3134594**		-.3838783**	
Cons. Goods	-.1014639	.0003171**	-.1263786		-.2729992*	
Healthcare	.1302473**		.0086324		-.0313015	
Cons. Ser	.1641132***		.2116056**		-.229716**	
Tele.	.2447077***		10.79641**	-.0071016**	-.3736692***	
Utilities	.2076539***		.1675703**		-.106146	
Tech.	.3784618***		-.0921164		-.3688679**	
Financial	-.3901014**	.0011339***	-.623032***		-.655339***	

Country Specific Financial Sector Returns

South Korea	μ_0(skfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.4398362***		8.786256*	-.0056734*	-.0688063	
Basic Mat	.5292159***		-.0643663		-.0241498	
Industrial	.5474979***		.1615823		-3.578062*	.0022871*
Cons. Goods	.5330621***		-.1727554***		-.2303987***	
Healthcare	.2918154***		12.12986**	-.0081429**	-.0273265	
Cons. Ser	.6242961***		-.3320715***		-.0795848	
Tele.	.3290339***		-.3889282***		-5.702411***	.0035913***
Utilities	.8622742***	-.0005003***	.1987066**		.4388296***	
Tech.	.634075***		-.1840434**		-7.467241***	.004613***

World Financial Sector Returns

Spain	δ_0(wdfin)	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	.1321021***		-.1394928*		.4106088***	
Basic Mat	.1018576***		.2838545***		.6008944***	
Industrial	.1496933***		.0753426		.3974176***	
Cons. Goods	.0613516		-.0510151		.2155726***	
Healthcare	.0438102		-.0537475		-5.156509***	.0033758***
Cons. Ser	.0902951***		.2231115***		.5082834***	
Tele.	.0282605		-.0795231		.2214862***	
Utilities	.0523055*		.0432102		.1960213**	
Tech.	.2003398*		.0434136		.3196664*	
Financial	-.129507**	.0007929**	-.1859995***		-.1189872	

Country Specific Financial Sector Returns

Spain	μ_0(spainfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.9170856***	-.0004192***	.2616518***		.0616929	
Basic Mat	.6040451***		-.2025386***		-.4283474 ***	
Industrial	.7538812***	-.000241***	17.78176***	-.0117001***	-2.437905**	.0014728**
Cons. Goods	.4096204***		-.1827271**		-2.455225**	.0012994**
Healthcare	1.078008***	-.000643***	20.31967***	-.0132649***	.2035582**	
Cons. Ser	.557807 ***		14.56442***	-.0097204***	-.3596418***	
Tele.	.528531***	.0002698***	-.4190458***		-3.844811***	.0020055**
Utilities	.8703319***	-.0003159***	-.0127926		.0880665	
Tech.	.7584792***		12.78499***	-.0088386***	-.6314016***	

World Financial Sector Returns

Sweden	δ_0(wdfin)	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	-4.600749*	.0035415**	-.0735788		5.57753	-.003838
Basic Mat	-.1248741**	.0003324***	10.7443***	-.0073112***	.1111438	
Industrial	-.2108439***	.0005099***	-.3097138***		-.3614875***	
Cons. Goods	-.0896566	.000332***	-.2936086***		-.4303164***	
Healthcare	.1601115***		.1961506*		-.0185083	
Cons. Ser	-.088525	.0003283***	-.1106239		-.4141832***	
Tele.	.3338137***		-.0653285		-.2719393*	
Tech.	-.0776347	.0006174***	-.6909693***		-.9194633***	
Financial	.084831	.0006795***	-.2732642***		-.1833774**	

Country Specific Financial Sector Returns

Sweden	μ_0(swedenfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.3989224***		.0811296		.2254636	
Basic Mat	.5639545***	-.0001459**	.4219127***		-3.254003**	.002178**
Industrial	.4813649***		10.44252***	-.0067858***	.2607143***	
Cons. Goods	.528898***		-.0030495		.0598258	
Healthcare	.289765***		.015079		.1107374	
Cons. Ser	.1116881***	.0002808***	10.45993***	-.0071501***	-.0429638	
Tele.	.5329701***		-.3406202***		-.119177	
Tech.	.457873***		9.513287**	-.0062859*	.0769116	

World Financial Sector Returns

Switzerland	δ_0(wdfin)	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	.8122427		.2708971		.1438219	
Basic Mat	.0580686***		.3707663***		-5.51964***	.0036132***
Industrial	.0266446	.000194***	.2885768**		.1877571	
Cons. Goods	-.1093472	.0002507*	.0965489		-.0599072	
Healthcare	.0477043**		-.0085931		5.368887**	-.0033105*
Cons. Ser	.0898618***		.0014796		-4.381292***	.0029257***
Tele.	.1756609**		-.158447		-.0081375	
Utilities	.0608414***		.2573081**		.0263379	
Financial	.0333401	.0007199***	-.0471052		-.2714638***	

Country Specific Financial Sector Returns

Switzerland	μ_0(skfin)	μ_1(r6)	ρ_0(d5)	ρ_1(r7)	φ_0(d6)	φ_1(r8)
Oil	.515735		-.362919		.1658291	
Basic Mat	.6098866***	-.0000758**	-.4092727***		-.2043538**	
Industrial	.7434773***	-.000168***	5.966218**	-.0041008**	-.0624398	
Cons. Goods	.9128734***	-.0003258***	-.443446***		-4.5553***	.0026554***
Healthcare	.8901996***	-.000377***	-.1525578**		-10.97039***	.006766***
Cons. Ser	.7540944***	-.0001477***	8.010424***	-.0055177***	-.3153355***	
Tele.	.148492***		.082247		-3.438158**	.0021111**
Utilities	.3717817***	-.0002488***	.0611233		-3.800092***	.0025628***

World Financial Sector Returns

Taiwan	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$**(r1)**	$\boldsymbol{\gamma_0}$ **(D2)**	$\boldsymbol{\gamma_1}$ **(r3)**	$\boldsymbol{\theta_0}$ **(D4)**	$\boldsymbol{\theta_1}$ **(r5)**
Oil	.1914751		-.0452428		.0284179	
Basic Mat	.1469026***		-.1039246		.0972872	
Industrial	-.3423446**	.0006583***	-.5740607***		-.4971633***	
Cons. Goods	.1383793***		-.2603666***		-.0032873	
Cons. Ser	.1875556***		-9.730527***	.0062657***	-.0638424	
Tele.	-1.128143**	.0009061**	-.1769522*		2.818813*	-.0019581**
Tech.	.4341896***		-.1696968		-.180709**	
Financial	.5581804***		.266812***		.2017499***	

Country Specific Financial Sector Returns

Taiwan	μ_0(taiwanfin)	μ_1(r6)	ρ_0(d5)	ρ_1(r7)	φ_0(d6)	φ_1(r8)
Oil	.2361725***		.2124727*		.1313357	
Basic Mat	.6852639***	-.0001737***	.1999758**		.0438711	
Industrial	.7468922***	-.0001583**	.1208452		.0982408	
Cons. Goods	.3387252***	.0003038***	.0418251		3.075459**	-.0020618**
Cons. Ser	.7705137***	-.000246***	.3771787***		.0450095	
Tele.	1.008481***	-.0006102***	9.231421***	-.0061174***	.0849917	
Tech.	.8691045***	-.0002216**	.0183201		-.1015621	

World Financial Sector Returns

Thailand	$\boldsymbol{\delta_0}$**(wdfin)**	$\boldsymbol{\delta_1}$	$\boldsymbol{\gamma_0}$	$\boldsymbol{\gamma_1}$	$\boldsymbol{\theta_0}$	$\boldsymbol{\theta_1}$
Oil	.1317807**		.1359527		.3070304***	
Basic Mat	.043686		.1964009**		.2720924***	
Industrial	.1471874*		-.0488954		.0188111	
Cons. Goods	.1618367***		-.0138583		-.1282086	
Healthcare	.1051627**		-.0123391		-.3030852***	
Cons. Ser	.1192891***		-.105315		-.22209***	
Tele.	.1338356**		-.1129651		-.2295024**	
Utilities	.0416492		.0111941		-.0393278	
Tech.	.2500782***		-.2722906***		-.2320086**	
Financial	-.1430139	.0007154***	-.3730895***		-.4107574***	

Country Specific Financial Sector Returns

Thailand	μ_0(thaifin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.5320113***		.3552337***		.1182149	
Basic Mat	.873322***	-.0001865***	.1975234*		.310645***	
Industrial	.2164671	.0002409*	.0837283		4.0281***	-.0023796***
Cons. Goods	.6324819***		.1731944**		.0830625	
Healthcare	.5884378***	-.0002884***	.2872077***		.3222497***	
Cons. Ser	.2211264***	.0002035***	.0201614		-3.306769**	.0021485**
Tele.	.6763047***		-.2400307**		-.2596727***	
Utilities	.3950872***		-.0249351		-.1738969***	
Tech.	1.090612***	-.0003443***	-.1501325		-.1270965	

World Financial Sector Returns

U.K.	δ_0(wdfin)	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	-.248028***	.0004455***	.1234727		.177419	
Basic Mat	.0554321***		1.52571***		.8941668***	
Industrial	-.2438762***	.0004858***	-.1989267**		-.2673652**	
Cons. Goods	.0263304		5.100295**	-.0033952**	-2.777452**	.0018102**
Healthcare	-.0069249	.0001164**	-.0886259		-.1620235	
Cons. Ser	.0876354***		-21.00349***	.0139506***	.0915632	
Tele.	.0659167**		.1225386		-.0679848	
Utilities	.0557993*		.3700032***		.2000773*	
Tech.	-.0814492	.0003488***	-15.0136**	.009886**	-.262062**	
Financial	.3121897***	.0003776***	.1489306***		.1111702*	

Country Specific Financial Sector Returns

U.K.	μ_0(ukfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.889314***	-.0004529***	-.2405504*		.0006274	
Basic Mat	.9324614***	-.0003284***	-.8850486***		-.0164177	
Industrial	1.024753***	-.0004987***	7.415186***	-.0049195***	.2274482**	
Cons. Goods	.6542199***		-.3849232***		-.4123949***	
Healthcare	.9042951***	-.0004107***	7.747076***	-.0052095***	-5.59414***	.0034713***
Cons. Ser	.8873596***	-.0002718***	28.28175***	-.0187894***	-2.193634**	.0013124**
Tele.	.7186761***		-.6051906***		-.3041336***	
Utilities	.6311002***	-.0002919***	-.3140017***		-.0830962	
Tech.	.0473127	.0004367***	23.74303***	-.0160147***	-.3198009 ***	

World Financial Sector Returns

U.S.	δ_0(wdfin)	δ_1	γ_0	γ_1	θ_0	θ_1
Oil	-.1423477 **	.0004142 ***	-.0396929		-.0284327	
Basic Mat	-.1669508***	.0005454***	.1370463		-.1898869	
Industrial	-.1260013***	.0003255***	-.0498193		-.1380823	
Cons. Goods	.0838971***		.0719895		.110661*	
Healthcare	.0524485***		.1108117*		.1402708*	
Cons. Ser	.0199911		.0315345		.1672625*	
Tele.	-.041912	.0001607***	7.345191***	-.0048477***	-.0263422	
Utilities	.0554634***		.1885169**		.1885192***	
Tech.	-.107498*	.0003006***	-.0451663		-.0520918	
Financial	.5874581***	.0002362***	.0625162		-.1397181**	

Country Specific Financial Sector Returns

U.S.	μ_0(usfin)	μ_1	ρ_0	ρ_1	φ_0	φ_1
Oil	.5467677 ***	-.000294***	-6.616911 **	.0043845**	.2940694**	
Basic Mat	.9806046***	-.0004743***	-.2192346**		.3681043***	
Industrial	.8968847***	-.0002647***	-.2141838***		.1738514*	
Cons. Goods	.8343682***	-.0001268***	-.4885761***		-.3193987***	
Healthcare	.7969756***	-.000215***	-.381935***		-.1100401	
Cons. Ser	.9486662***	-.0001509***	-.2639905***		-.2436295***	
Tele.	.560173***		-.2891341***		-.271386 ***	
Utilities	.4842754***	-.000081**	-4.404169**	.0027059**	-.1587108**	
Tech.	.926354***	-.000163*	-.4407684***		-.2127214	

Note: Parameters stem from model (4.2): $R_{S,i,t} = \alpha_0 + \alpha_1 D_{t\,CRISIS} + \alpha_2 D_{t\,POST-CRISIS} + \beta_{1t} R_{fin,w,t} + \beta_{2t} R_{fin,w,t} D_{t\,CRISIS} + \beta_{3t} R_{fin,w,t} D_{t\,POST-CRISIS} + \omega_{1t} R_{fin,i,t} + \omega_{2t} R_{fin,i,t} D_{t\,CRISIS} + \omega_{3t} R_{fin,i,t} D_{t\,POST-CRISIS} + \varepsilon_{S,i,t}$, where $\beta_{1t} = \delta_0 + \delta_1 t$, $\beta_{2t} = \gamma_0 + \gamma_1 t$, $\beta_{3t} = \theta_0 + \theta_1 t$, and $\omega_{1t} = \mu_0 + \mu_1 t$, $\omega_{2t} = \rho_0 + \rho_1 t$ and $\omega_{3t} = \varphi_0 + \varphi_1 t$. $R_{i,t}$ denotes stock returns in sector i at time t, $D_{t\,CRISIS}$ ($D_{t\,POST-CRISIS}$) is a dummy variable equal to one during the crisis (post-crisis) period and zero otherwise. and $R_{W,t}$ is the return of the world financial index whereas $R_{i,t}$ is the return on domestic financial sector. Error terms are modelled as a GJR-GARCH (1,1) process, corrected for autocorrelation in residuals where required. ***, **, * indicate significance at 1%, 5%, and 10% level, respectively. Insignificant trend terms ($\delta_1, \gamma_1, \theta_1$) and ($\mu_1, \rho_1, \varphi_1$) are excluded and model (4.2) is re-estimated where relevant.

B.4: Estimation for Model (4.2): Contagion from World Financial Market Portfolio

Global Financial Contagion of the Real Economy Sector								
Australia			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	.2862246**		0.2862246**		0.2862246**		Shock Contagion (Level Shock)	C
Basic Material	.4892814***		0.4892814***		0.4892814***		Shock Contagion (Level Shock)	C
Industrial	.168926***		0.16892***		0.16892***		Shock Contagion (Level Shock)	C
Con. gds	6.676481**	-.004523**	0.11331681	0.865727	-0.2711552	-3.04571	No Contagion	C
Healthcare	.000437		0.000437		0.000437		No Contagion	-
Con. Ser.	-.1141036*		-0.1141036*		-0.1141036*		No Contagion	-
Telecom	-.0052552		-0.0052552		-0.0052552		No Contagion	-
Utilities	.0066816		0.0066816		0.0066816		No Contagion	C
Technology	9.92361**	-.007136**	-0.4302877	-1.48164	-1.036822***	-3.42839	No Contagion	-
Financial	.332405***		0.332405***		0.332405***		Shock Contagion (Level Shock)	C

Global Financial Contagion of the Real Economy Sector								
Brazil			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-.2927354*		-.2927354*		-.2927354*		No Contagion	C
Basic Material	-.565809***		-.565809***		-.5658096***		No Contagion	C
Industrial	-.2404242**		-.2404242**		-.2404242**		No Contagion	C
Con. gds	-.1366311		-.1366311		-.1366311		No Contagion	C
Con. Ser.	-.832432***		-.832432***		-.8324322***		No Contagion	C
Telecom	-.396282***		-.396282***		-.3962817***		No Contagion	C
Utilities	-.527124***		-.527124***		-.5271235***		No Contagion	C
Technology	-1.479819 **		-1.479819 **		-1.479819 **		No Contagion	-
Financial	11.7901**	-.008134**	-0.0126242	-0.05189	-.7040312***	-3.7257	No Contagion (decoupling)	C

Global Financial Contagion of the Real Economy Sector

Canada			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	.205306		0.205306		0.205306		No Contagion	-
Basic Material	.445069***		.445069***		.4450694***		Shock Contagion (Level Shock)	C
Industrial	.2948048***		.2948048***		.2948048***		Shock Contagion (Level Shock)	-
Con. gds	-.255603***		-.255603***		-.2556026***		No Contagion	C
Healthcare	9.89504***	-.00668***	0.202364	1.219230457	-0.365436	-3.50192	No Contagion	-
Con. Ser.	7.3810***	-.00489***	0.2860823**	2.431654337	-0.1295422**	-1.96572	Shock Contagion (Reversal)	-
Telecom	-.094205		-0.094205		-0.094205		No Contagion	-
Utilities	.1410629**		.1410629**		.1410629**		Shock Contagion (Level Shock)	-
Technology	-.872604***		-.872604***		-.8726043***		No Contagion	-
Financial	-.0203873		-0.0203873		-0.0203873		No Contagion	C

Global Financial Contagion of the Real Economy Sector

Chile			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-.238598**		-0.2385976		-0.2385976		No Contagion	C
Basic Material	9.29237***	-.006158***	0.35711	0.064228	-0.166315	-0.02908	Shock Contagion (Transitory Shock)	C
Industrial	13.9431***	-.009283***	0.47331	2.831733	-0.3157516***	-4.00595	Shock Contagion (Reversal)	C
Con. gds	13.9509***	-.009293***	0.4673474	2.687784	-0.3225236***	-3.46853	Shock Contagion (Reversal Shock)	C
Healthcare	-.152080**		-0.1520803		-.1520803**		No Contagion	-
Con. Ser.	-.133931**		-0.1339314		-.1339314**		No Contagion	C
Telecom	-.291766***		-0.2917657		-.2917657***		No Contagion	C
Technology	.266196		0.2661955		0.266195		No Contagion	C

Financial	11.673***	-.007832***	0.3081778	2.322847	-0.35756***	-3.75652	Shock Contagion (Reversal)	C

Global Financial Contagion of the Real Economy Sector

China			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-.17290		-0.17290		-0.172901		No Contagion	C
Basic Material	-.488639**		-0.488639**		-0.488639**		No Contagion	C
Industrial	-.179876		-0.179876		-0.1798762		No Contagion	C
Con. gds	-.152828		-0.152828		-0.1528284		No Contagion	-
Healthcare	-.049038		-0.049038		-0.0490384		No Contagion	-
Con. Ser.	-.233269		-0.233269		-0.2332693		No Contagion	C
Telecom	-.213064		-0.213064		-0.2130643		No Contagion	-
Utilities	-.249063		-0.249063		-0.2490636		No Contagion	C
Technology	-.398775		-0.398775		-0.3987751		No Contagion	C
Financial	20.7013***	-.013686***	0.842798	3.292809	-0.320519	-1.4918	Shock Contagion (Transitory)	C

Global Financial Contagion of the Real Economy Sector

France			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	.4932247***		.4932247***		.4932247***		Shock Contagion (Level Shock)	C
Basic Material	.6862201***		.6862201***		.6862201***		Shock Contagion (Level Shock)	C
Industrial	.4053669***		.4053669***		.4053669***		Shock Contagion (Level Shock)	C
Con. gds	.42061***		.42061***		.42061***		Shock Contagion (Level Shock)	C
Healthcare	-.1355753		-.1355753		-.1355753		No Contagion	-
Con. Ser.	.4617216***		.4617216***		.4617216***		Shock Contagion (Level Shock)	C
Telecom	-.2028088		-.2028088		-.2028088		No Contagion	-
Utilities	.6777524***		.6777524***		.6777524***		Shock Contagion (Level Shock)	C
Technology	.4896644***		.4896644***		.4896644***		Shock Contagion (Level Shock)	C

Financial	-.0739583		-.0739583		-.0739583		No Contagion	C

Global Financial Contagion of the Real Economy Sector

Germany			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-1.63149***		-1.6315***		-1.63149***		No Contagion	-
Basic Material	-.107169		-.107169		-.107169		No Contagion	-
Industrial	-.0970055		-.0970055		-.0970055		No Contagion	-
Con. gds	.2823034**		.2823034**		.2823034**		Shock Contagion (Level)	C
Healthcare	-.136101**		-.136101**		-.136101**		No Contagion	C
Con. Ser.	-.1620355		-.1620355		-.1620355		No Contagion	-
Telecom	-.2664174*		-.2664174*		-.2664174*		No Contagion	-
Utilities	-24.5129***	.0164457***	-0.650223**	-2.41014	0.7476552***	3.30588	Recoupling contagion	-
Technology	-.0755054		-.0755054		-.0755054		No Contagion	-
Financial	-.1865879***		-.186588***		-.1865879***		No Contagion	C

Global Financial Contagion of the Real Economy Sector

Hong Kong			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	.109218		0.1092187		0.1092187		No Contagion	C
Basic Material	-.232618		-0.2326189		-0.2326189		No Contagion	C
Industrial	-.104545*		-0.104545*		-0.104545*		No Contagion	C
Con. gds	-11.5202**	.007414**	-0.76211***	-3.00732	-0.13189***	-0.68731	No Contagion	C
Healthcare	.249107		0.249107		0.2491076		No Contagion	-
Con. Ser.	-10.66151**	.007026**	-0.46678***	-2.92877	0.130426***	0.866916	No Contagion	C
Telecom	-.0591815		-0.0591815		-0.0591815		No Contagion	-
Utilities	.068836		0.0688361		0.0688361		No Contagion	-

Technology	-.325949*		-0.3259491*		-0.3259491*		No Contagion	-
Financial	10.2034***	-.00672***	0.442398***	3.005977	-0.1294056	-1.47159	Shock Contagion (Transitory)	C

Global Financial Contagion of the Real Economy Sector

India			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	.1394704***		.1394704***		.1394704***		Shock Contagion (Level)	-
Basic Material	.0427408		.0427408		.0427408		No Contagion	C
Industrial	-.1267327		-.1267327		-.1267327		No Contagion	C
Con. gds	-.062376***		-.062376***		-.0623765***		No Contagion	-
Healthcare	.001529		.0015299		.0015299		No Contagion	C
Con. Ser.	-.244454		-.244454		-.244454		No Contagion	-
Telecom	.275372**		.275372**		.275372**		Shock Contagion (Level)	-
Utilities	.1192363		.1192363		.1192363		No Contagion	-
Technology	-.0001253		-.0001253		-.0001253		No Contagion	-
Financial	.0132143		.0132143		.0132143		No Contagion	C

Global Financial Contagion of the Real Economy Sector

Indonesia			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Basic Material	.0116983		.0116983		.0116983		No Contagion	C
Industrial	.1533715		.1533715		.1533715		No Contagion	-
Con. gds	-.206911		-.206911		-.206911		No Contagion	-
Healthcare	-.213131**		-.2131318**		-.2131318**		No Contagion	-
Telecom	-.315540**		-.3155408**		-.3155408**		No Contagion	-
Utilities	-.328503		-.3285038		-.3285038		No Contagion	C
Financial	16.7417***	-.011262***	0.39999	1.547121	-0.55730***	-3.02992	No Contagion	C

Global Financial Contagion of the Real Economy Sector

Italy			First week of the crisis ($t=\boldsymbol{\tau_1}$)		Last week of the crisis ($t=\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-.1141203		-.114120		-.1141203		No Contagion	-
Basic Material	.67844***		.67844***		.67844***		Shock Contagion (Level)	C
Industrial	.1256384		.1256384		.1256384		No Contagion	C
Con. gds	.440275***		.440275***		.440275***		Shock Contagion (Level)	C
Healthcare	.30875***		.30875***		.30875***		Shock Contagion (Level)	C
Con. Ser.	8.54777***	-.00577***	0.172601	1.499647	-0.318019**	-2.58414	No Contagion	-
Telecom	.0694753		0.0694753		0.0694753		No Contagion	-
Utilities	-.0402521		-0.040252		-0.0402521		No Contagion	C
Technology	-7.64511***	.00501***	-0.36863***	-3.24972	0.0576198	0.703833	No Contagion	-
Financial	-.114120		-0.1141203		-0.1141203		No Contagion	C

Global Financial Contagion of the Real Economy Sector

Japan			First week of the crisis ($t=\boldsymbol{\tau_1}$)		Last week of the crisis ($t=\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	.122415		122415		0.1224156		No Contagion	-
Basic Material	8.09712**	-.005299**	0.40885**	2.48998	-0.041527	-0.60541	Shock Contagion (Transitory)	-
Industrial	-.087852		-.087852		-0.087852		No Contagion	-
Con. gds	-.104285		-.104285		-0.104284		No Contagion	-
Healthcare	-.126217		-.126217		-0.126217		No Contagion	-
Con. Ser.	-.079239		-.079239		-0.079238		No Contagion	-
Telecom	-.501382***		-.501382***		-0.501383		No Contagion	-
Utilities	-.138427*		-.1384267*		-0.138427		No Contagion	-
Technology	22.2929***	-.01531***	0.06978	0.363143	-1.232055***	-9.7547	No Contagion	-
Financial	.122416		.122416		0.1224156		No Contagion	-

Mexico			**First week of the crisis (t=τ_1)**		**Last week of the crisis (t=τ_2)**		**Decision**	**Model (4.1)**
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Basic Material	14.9894***	-.009932***	0.57869***	3.14306	-0.2654976	-1.4318	Shock Contagion (Transitory)	C
Industrial	-.093591		-0.0935916		-0.0935916		No Contagion	C
Con. Ser.	-.2132867**		-0.2132867		-0.2132867		No Contagion	-
Telecom	-.0576317		-0.0576317		-0.0576317		No Contagion	-
Financial	-.1043562**		-0.1043562		-0.1043562		No Contagion	C

Global Financial Contagion of the Real Economy Sector

Norway			First week of the crisis (t=τ_1)		Last week of the crisis (t=τ_2)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	.156922		0.1569223		0.1569223		No Contagion	-
Basic Material	.515448***		0.5154479***		0.5154479***		Shock Contagion (Level)	C
Con. gds	12.6816**	-.008351**	0.5645041*	2.461541	-0.1453224	-0.8116	Shock Contagion (Transitory)	-
Con. Ser.	-.3214672**		-0.3214672**		-0.3214672**		No Contagion	-
Telecom	-.2201282		-0.2201282		-0.2201282		No Contagion	-
Utilities	26.929***	-.01767***	1.28991***	4.888285	-0.21204***	-0.96249	Shock Contagion (Transitory)	C
Technology	23.6985***	-.016189***	0.207726***	0.001016	-1.168378***	-0.0054	Shock Contagion (Transitory)	C
Financial	-27.4640***	.018592***	-0.486603***	-2.95823	1.093742***	8.868686	Recoupling Contagion	C

Global Financial Contagion of the Real Economy Sector								
New Zealand			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	.0401828		0.0401828		0.0401828		No Contagion	-
Basic Material	-.0847797		-0.0847797		-0.0847797		No Contagion	-
Industrial	.1078578*		0.1078578*		0.1078578*		Shock Contagion (Level)	-
Con. gds	-8.827166**	.005854**	-0.332431**	-0.04349	0.1651924	0.020415	No Contagion	-
Healthcare	-.11474*		-0.1147449*		-0.1147449*		No Contagion	C
Con. Ser.	.0366122		0.0366122		0.0366122		No Contagion	-
Telecom	.22365*		0.22365*		0.22365*		Shock Contagion (Level)	-
Utilities	.1226466**		0.1226466		0.1226466		Shock Contagion (Level)	C
Technology	.8747107		0.8747107		0.8747107		No Contagion	-
Financial	2.98398*	-.001972*	0.1217374**	1.362364	-0.0459336	-0.689844	Shock Contagion (Reversal)	-

Global Financial Contagion of the Real Economy Sector								
Russia			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-.449684***		-.449684***		-.449684***		No Contagion	C
Basic Material	-.2647309*		-.2647309*		-.2647309*		No Contagion	C
Con. gds	-.0966464		-.0966464		-.0966464		No Contagion	-
Con. Ser.	-.1930932		-.1930932		-.1930932		No Contagion	C
Telecom	-.234709***		-.234709***		-.2347094***		No Contagion	-
Utilities	-.488424***		-.488424***		-.4884243***		No Contagion	-
Financial	-.3275292		-.3275292		-.3275292		No Contagion	-

Global Financial Contagion of the Real Economy Sector								
South Africa			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-14.0837***	.009605***	-0.146895	-0.69775	0.66953***	3.974248	No Contagion	C
Basic Material	.3428916**		.3428916**		.3428916**		Shock Contagion (Level)	C
Industrial	.0295753		.0295753		.0295753		No Contagion	-
Con. gds	-.0557462		-.0557462		-.0557462		No Contagion	C
Healthcare	.07137		.07137		.07137		No Contagion	-
Con. Ser.	-.0500749		-.0500749		-.0500749		No Contagion	-
Telecom	.1574526		.1574526		.1574526		No Contagion	C
Utilities	-.1073694		-.1073694		-.1073694		No Contagion	-
Technology	-.199709***		-.199709***		-.1997099***		No Contagion	C
Financial	-14.0837***	.009605***	-0.146895	-0.69775	0.66953***	3.974248	Kink Contagion	C

Global Financial Contagion of the Real Economy Sector								
South Korea			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-.0956565		-0.0956565		-0.0956565		No Contagion	-
Basic Material	15.8882***	-.0105***	0.585527*	2.39821	-0.310906	-1.85173	Shock Contagion (Transitory)	C
Industrial	-.313459**		-0.313459***		-0.3134594**		No Contagion	-
Con. gds	-.126378		-0.1263786		-0.1263786		No Contagion	C
Healthcare	.0086324		0.0086324		0.0086324		No Contagion	-
Con. Ser.	.2116056**		0.2116056**		0.2116056**		Shock Contagion (Level)	C
Telecom	10.7964**	-.00710**	0.4919884**	2.297755	-0.1116476	-0.8758	Shock Contagion (Transitory)	C
Utilities	.167570**		0.1675703**		0.1675703**		Shock Contagion (Level)	C
Technology	-.092116		-0.0921164		-0.0921164		No Contagion	-
Financial	-.62302***		-0.623032***		-0.623032***		No Contagion	-

Global Financial Contagion of the Real Economy Sector								
Spain			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-.1394928*		-.1394928*		-.1394928*			C
Basic Material	.283854***		.283854***		.283854***		Shock Contagion (Level)	C
Industrial	.0753426		.0753426		.0753426			-
Con. gds	-.0510151		-.0510151		-.0510151			-
Healthcare	-.0537475		-.0537475		-.0537475			-
Con. Ser.	.223111***		.223111***		.223111***		Shock Contagion (Level)	-
Telecom	-.0795231		-.0795231		-.0795231			C
Utilities	.0432102		.0432102		.0432102			-
Technology	.0434136		.0434136		.0434136			-
Financial	-.185999***		-.185999***		-.185999***			C

Global Financial Contagion of the Real Economy Sector								
Sweden			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-.073578		-0.0735788		-0.073578		No Contagion	-
Basic Material	10.7443***	-.007311***	0.1357488	0.73910	-0.48570***	-3.07635	No Contagion	-
Industrial	-.309713***		-.309713***		-.309713***		No Contagion	-
Con. gds	-.293608***		-.29360***		-.29360***		No Contagion	-
Healthcare	.1961506*		.1961506*		.19615*		Shock Contagion (Level)	C
Con. Ser.	-.1106239		-.1106239		-.1106239		No Contagion	-
Telecom	-.0653285		-.0653285		-.0653285		No Contagion	-
Technology	-.6909693***		-.690969***		-.690969***		No Contagion	-
Financial	-.273264***		-.273264***		-.273264***		No Contagion	-

Global Financial Contagion of the Real Economy Sector

Switzerland			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	.2708971		.2708971		.2708971		No Contagion	-
Basic Material	.370766***		.370766***		.370766***		Shock Contagion (Level)	C
Industrial	.288577**		.288577**		.288577**		Shock Contagion (Level)	C
Con. gds	.0965489		.0965489		.0965489		No Contagion	C
Healthcare	-.0085931		-.0085931		-.0085931		No Contagion	-
Con. Ser.	.0014796		.0014796		.0014796		No Contagion	-
Telecom	-.158447		-.158447		-.158447		No Contagion	-
Utilities	.2573081**		.2573081**		.2573081**		Shock Contagion (Level)	C
Technology	-.0471052		-.0471052		-.0471052		No Contagion	-
Financial	.2708971		.2708971		.2708971		No Contagion	C

Global Financial Contagion of the Real Economy Sector

Taiwan			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-.045242		-0.0452428		-0.0452428		No Contagion	-
Basic Material	-.103924		-0.1039246		-0.1039246		No Contagion	-
Industrial	-.574060***		-0.5740607		-0.5740607		No Contagion	C
Con. gds	-.260366***		-0.2603666		-0.2603666		No Contagion	C
Con. Ser.	-9.73052***	.0062657***	-0.638996***	-4.35755	-0.1064118*	-1.12263	No Contagion	C
Telecom	-.176952*		-0.1769522		-0.1769522		No Contagion	-
Technology	-.169696		-0.1696968		-0.1696968		No Contagion	-
Financial	.26681***		0.266812***		0.266812***		Shock Contagion (Level)	C

Global Financial Contagion of the Real Economy Sector								
Thailand			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t-statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t-statistic**		
Oil	.1359527		0.1359527		0.1359527		No Contagion	-
Basic Material	.1964**		0.1964**		0.1964**		Shock Contagion (Level)	-
Industrial	-.0488954		-0.0488954		-0.0488954		No Contagion	-
Con. gds	-.0138583		-0.0138583		-0.0138583		No Contagion	-
Healthcare	-.0123391		-0.0123391		-0.0123391		No Contagion	-
Con. Ser.	-.105315		-0.105315		-0.105315		No Contagion	-
Telecom	-.1129651		-0.1129651		-0.1129651		No Contagion	-
Utilities	.0111941		0.0111941		0.0111941		No Contagion	-
Technology	-.272291***		-0.2722906***		-0.2722906***		No Contagion	-
Financial	-.373089***		-0.3730895***		-0.3730895***		No Contagion	-

Global Financial Contagion of the Real Economy Sector								
U.K.			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	.1234727		0.123472		0.1234727		No Contagion	C
Basic Material	1.5257***		1.5257***		1.5251***		Shock Contagion (Level)	C
Industrial	-.198926**		-0.198926**		-0.198926		No Contagion	C
Con. gds	5.100295**	-.003395**	0.173859**	1.587564	-0.114732*	-1.06713	Shock Contagion (Reversal)	-
Healthcare	-.088625		-0.08862		-0.088625		No Contagion	-
Con. Ser.	-21.0035***	.013950***	-0.761169***	-4.696	0.424631***	3.777213	No Contagion	-
Telecom	.1225386		0.122538		0.122538		No Contagion	-
Utilities	.3700032***		0.370003***		.370003***		Shock Contagion (Level)	C
Technology	-15.0136**	.00988**	-0.66901***	-2.33742	0.17129*	1.106275	No Contagion	-
Financial	.14893***		0.14893***		0.14893***		Shock Contagion (Level)	C

Global Financial Contagion of the Real Economy Sector								
U.S.			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**	$\hat{\beta}_{2t} = \hat{\gamma}_0 + \hat{\gamma}_1 t$	**t- statistic**		
Oil	-.03969		-0.03969		-0.03969		No Contagion	C
Basic Material	.13704		0.13704		0.13704		No Contagion	C
Industrial	-.04981		-0.04981		-0.04981		No Contagion	C
Con. gds	.07199		0.07199		0.07198		No Contagion	C
Healthcare	.110811*		0.11081*		0.11081		Shock Contagion (Level)	C
Con. Ser.	.03153		0.03153		0.03153		No Contagion	-
Telecom	7.3451***	-.004848***	0.3111***	2.9604	-0.10087	-0.9522	Shock Contagion (Transitory)	C
Utilities	.18851**		0.18851		0.18851		Shock Contagion (Level)	C
Technology	-.04516		-0.04516		-0.04516		No Contagion	C
Financial	.0625162		0.06251		0.06251		No Contagion	C

B.5: Estimation for Model (4.2): Contagion from Domestic Financial Sector

Domestic Financial Contagion of the Real Economy Sector

Australia			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\boldsymbol{\rho}}_{\mathbf{0}}$	$\hat{\boldsymbol{\rho}}_{\mathbf{1}}$	$\hat{\boldsymbol{\omega}}_{\mathbf{2t}} = \hat{\boldsymbol{\rho}}_{\mathbf{0}} + \boldsymbol{\rho t}$	**t- statistic**	$\hat{\boldsymbol{\omega}}_{\mathbf{2t}} = \hat{\boldsymbol{\rho}}_{\mathbf{0}} + \hat{\boldsymbol{\rho}}_{\mathbf{1}}\boldsymbol{t}$	**t- statistic**		
Oil	-.4004***		-0.4004***		-0.4004***		No Contagion	C
Basic Material	-.42643***		-0.42643***		-0.42643***		No Contagion	C
Industrial	4.13604*	-.0028496*	0.0012754	0.014863	-0.2409406***	-2.844768	No Contagion	C
Con. gds	-.093798		-0.0937987		-0.0937987		No Contagion	-
Healthcare	14.2187***	-.0096833***	0.1682817**	1.655220	-0.654798***	-6.289739	Shock Contagion (Reversal)	C
Con. Ser.	.090169		0.090169		0.090169		No Contagion	-
Telecom	-.1116415		-0.1116415		-0.1116415		No Contagion	-
Utilities	6.708346**	-.0045093**	0.1653517*	1.239387	-0.2179388*	-1.600125	Shock Contagion (Reversal)	-
Technology	-.0813837		-0.0813837		-0.0813837		No Contagion	-

Domestic Financial Contagion of the Real Economy Sector

Brazil			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\boldsymbol{\rho}}_{\mathbf{0}}$	$\hat{\boldsymbol{\rho}}_{\mathbf{1}}$	$\hat{\boldsymbol{\omega}}_{\mathbf{2t}} = \hat{\boldsymbol{\rho}}_{\mathbf{0}} + \boldsymbol{\rho t}$	**t- statistic**	$\hat{\boldsymbol{\omega}}_{\mathbf{2t}} = \hat{\boldsymbol{\rho}}_{\mathbf{0}} + \hat{\boldsymbol{\rho}}_{\mathbf{1}}\boldsymbol{t}$	**t- statistic**		
Oil	.389022**		0.389022**		0.389022***		Shock Contagion (Level)	C
Basic Material	.444193***		0.444193***		0.444193***		Shock Contagion (Level)	C
Industrial	.3456938***		0.345693***		0.345693***		Shock Contagion (Level)	C
Con. gds	-.1769288**		-0.176928**		-0.176928**		No Contagion	-
Con. Ser.	11.5618***	-.00746***	0.724070***	5.980198	0.0891888	0.643476	Shock Contagion (Transitory)	C
Telecom	7.084672**	-.004603**	0.404558***	2.78916	0.0132352	0.120615	Shock Contagion (Transitory)	C
Utilities	9.36142***	-.00623***	0.308343***	2.70178	-0.221988	-1.67338	Shock Contagion (Reversal)	-
Technology	1.29630***		1.29630***		1.29630***		Shock Contagion (Level)	-

Domestic Financial Contagion of the Real Economy Sector								
Canada			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	-17.8321***	.01187***	-0.60804***	-2.18719	0.400948***	1.796878	Recoupling contagion	-
Basic Material	-.89535***		-0.89535***		-0.89535***		No Contagion	C
Industrial	.1814187		0.1814187		0.1814187		No Contagion	-
Con. gds	.20367**		0.20367**		0.20367**		Shock Contagion (Level)	C
Healthcare	.0933701		0.0933701		0.0933701		No Contagion	-
Con. Ser.	-.24017***		-0.24017***		-0.24017***		No Contagion	C
Telecom	-.31799***		-0.31799***		-0.31799***		No Contagion	-
Utilities	-.1005402		-0.1005402		-0.1005402		No Contagion	-
Technology	17.50536**	-.011284*	1.1311152***	3.044625	0.1719072	0.538401	Shock Contagion (Level)	C

Domestic Financial Contagion of the Real Economy Sector								
Chile			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	1.14239***		1.14239***		1.14239***		Shock Contagion (Level)	C
Basic Material	-.0036806		-0.0036806		-0.00368		No Contagion	C
Industrial	.422270***		0.42227***		0.42227***		Shock Contagion (Level)	C
Con. gds	.200122		0.200122		0.200122		No Contagion	C
Healthcare	-11.59458**	.00807**	0.115425	0.62497	0.801400***	3.351086	No Contagion	C
Con. Ser.	.7715064***		0.771506***		0.771506***		No Contagion	C
Telecom	27.84973***	-.01863***	0.81643***	3.39454	-0.76717***	-3.17193	Shock Contagion (Reversal)	C
Technology	.0491613**	-.06201**	-89.9296***	-141.177	-95.2006***	-35.4425	-	C

Domestic Financial Contagion of the Real Economy Sector

China			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\widehat{\boldsymbol{\rho}}_{\mathbf{0}}$	$\widehat{\boldsymbol{\rho}}_{\mathbf{1}}$	$\widehat{\boldsymbol{\omega}}_{\mathbf{2}t} = \widehat{\boldsymbol{\rho}}_{\mathbf{0}} + \boldsymbol{\rho t}$	**t- statistic**	$\widehat{\boldsymbol{\omega}}_{\mathbf{2}t} = \widehat{\boldsymbol{\rho}}_{\mathbf{0}} + \widehat{\boldsymbol{\rho}}_{\mathbf{1}}\boldsymbol{t}$	**t- statistic**		
Oil	.0595361		0.0595361		0.0595361		No Contagion	C
Basic Material	.4073679 ***		0.4073679***		0.4073679***		Shock Contagion (Level)	C
Industrial	.190199*		0.190199*		0.190199*		Shock Contagion (Level)	C
Con. gds	.0007551		0.0007551		0.0007551		No Contagion	-
Healthcare	-.1858613		-0.1858613		-0.1858613		No Contagion	-
Con. Ser.	.1737032		0.1737032		0.1737032		No Contagion	-
Telecom	.345325***		0.345325***		0.345325***		Shock Contagion (Level)	C
Utilities	.1362577		0.136257		0.1362577		No Contagion	-
Technology	-8.941528*	.006115**	-0.06837	-0.00043	0.4514192	0.002665	No Contagion	C

Domestic Financial Contagion of the Real Economy Sector

France			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\widehat{\boldsymbol{\rho}}_{\mathbf{0}}$	$\widehat{\boldsymbol{\rho}}_{\mathbf{1}}$	$\widehat{\boldsymbol{\omega}}_{\mathbf{2}t} = \widehat{\boldsymbol{\rho}}_{\mathbf{0}} + \boldsymbol{\rho t}$	**t- statistic**	$\widehat{\boldsymbol{\omega}}_{\mathbf{2}t} = \widehat{\boldsymbol{\rho}}_{\mathbf{0}} + \widehat{\boldsymbol{\rho}}_{\mathbf{1}}\boldsymbol{t}$	**t- statistic**		
Oil	-.665722***		-0.6657***		-0.66572***		No Contagion	C
Basic Material	-.687846		-0.6878462		-0.6878462		No Contagion	C
Industrial	3.58736	-.00271**	-0.34716***	-3.01276	-0.57765***	-6.74545	No Contagion	C
Con. gds	3.497402	-.0027497*	-0.49241***	-3.87683	-0.72613***	-7.49251	No Contagion	C
Healthcare	-.16885		-0.168858		-0.168858		No Contagion	C
Con. Ser.	-.445035***		-0.44503***		-0.44503***		No Contagion	C
Telecom	-.49861***		-0.49861***		-0.49861***		No Contagion	-
Utilities	-.907693***		-0.90769***		-0.90769***		No Contagion	C
Technology	-.869716***		-0.86971***		-0.86971***		No Contagion	C-

Domestic Financial Contagion of the Real Economy Sector								
Germany			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\boldsymbol{\rho}}_0$	$\hat{\boldsymbol{\rho}}_1$	$\hat{\boldsymbol{\omega}}_{2t} = \hat{\boldsymbol{\rho}}_0 + \boldsymbol{\rho t}$	**t- statistic**	$\hat{\boldsymbol{\omega}}_{2t} = \hat{\boldsymbol{\rho}}_0 + \hat{\boldsymbol{\rho}}_1 \boldsymbol{t}$	**t- statistic**		
Oil	.5933332		0.5933332		0.5933332		No Contagion	-
Basic Material	.0434341		0.0434341		0.0434341		No Contagion	-
Industrial	.0800787		0.0800787		0.0800787		No Contagion	-
Con. gds	-.42094***		-0.42094***		-0.42094***		No Contagion	C
Healthcare	-.0577812		-0.0577812		-0.0577812		No Contagion	C
Con. Ser.	-6.141887**	.0041873**	-0.0661147	-0.50187	0.289805***	2.503716	Kink Contagion	-
Telecom	-.2174042		-17.2723131		-0.2174042		No Contagion	-
Utilities	17.91711**	-.011753**	17.91711***	62.7183	-0.1368804	-0.54892	Shock Contagion (Transitory)	-
Technology	-.349922**		-0.349922**		-0.349922***		No Contagion	-

Domestic Financial Contagion of the Real Economy Sector								
Hong Kong			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\boldsymbol{\rho}}_0$	$\hat{\boldsymbol{\rho}}_1$	$\hat{\boldsymbol{\omega}}_{2t} = \hat{\boldsymbol{\rho}}_0 + \boldsymbol{\rho t}$	**t- statistic**	$\hat{\boldsymbol{\omega}}_{2t} = \hat{\boldsymbol{\rho}}_0 + \hat{\boldsymbol{\rho}}_1 \boldsymbol{t}$	**t- statistic**		
Oil	17.0999***	-.01094***	1.21901***	5.436288	0.2887072*	1.217997	Shock Contagion (Transitory)	C
Basic Material	9.74095**	-.006103**	0.88448***	5.769689	0.3656668*	1.592709	Shock Contagion (Transitory)	C
Industrial	7.92766***	-.00529***	0.24607***	3.190192	-0.203917**	-1.93272	Shock Contagion (Reversal)	-
Con. gds	30.08185***	-.02013***	0.86799***	4.415771	-0.84335***	-4.11689	Shock Contagion (Reversal)	C
Healthcare	15.13527**	-.010222**	0.30242	0.857249	-0.56649*	-1.25745	Shock Contagion (Reversal)	-
Con. Ser.	19.0045***	-.01268***	0.59846***	4.983969	-0.47977***	-2.92727	Shock Contagion (Reversal)	C
Telecom	13.7481***	-.00944***	0.04985	0.245076	-0.75260***	-3.81755	Shock Contagion (Reversal)	C
Utilities	8.40581***	-.00554***	0.36538***	4.110179	-0.1056288	-0.89826	Shock Contagion (Transitory)	C
Technology	-.225889		-0.225889		-0.2258891		No Contagion	-

Domestic Financial Contagion of the Real Economy Sector								
India			First week of the crisis ($t=\boldsymbol{\tau_1}$)		Last week of the crisis ($t=\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\widehat{\boldsymbol{\rho}}_{\mathbf{0}}$	$\widehat{\boldsymbol{\rho}}_{\mathbf{1}}$	$\widehat{\boldsymbol{\omega}}_{\mathbf{2}t} = \widehat{\boldsymbol{\rho}}_{\mathbf{0}} + \boldsymbol{\rho t}$	**t- statistic**	$\widehat{\boldsymbol{\omega}}_{\mathbf{2}t} = \widehat{\boldsymbol{\rho}}_{\mathbf{0}} + \widehat{\boldsymbol{\rho}}_{\mathbf{1}}\boldsymbol{t}$	**t- statistic**		
Oil	6.805485**	-.004714**	-0.0348192	-0.33296	-0.43552***	-3.40137	No Contagion	-
Basic Material	5.414931*	-.0036108*	0.1756602**	1.829039	-0.13125**	-1.08701	Shock Contagion (Transitory)	C
Industrial	6.55657***	-.00441***	0.1485267**	2.006656	-0.22686**	-2.29948	Shock Contagion (Reversal)	C
Con. gds	8.83408***	-.0061***	-0.017012	-0.24518	-0.53551***	-6.49707	No Contagion	-
Healthcare	-.2361***		-0.2361***		-0.2361***		No Contagion	-
Con. Ser.	-.178723**		-0.178723**		-0.178723**		No Contagion	-
Telecom	9.18334***	-.00645***	-0.1808276*	-1.58412	-0.72939***	-6.13736	No Contagion	-
Utilities	12.9820***	-.00875***	0.2802562**	1.953157	-0.46381***	-3.40934	Shock Contagion (Reversal)	-
Technology	-.32894***		-0.32894		-0.32894		No Contagion	C

Domestic Financial Contagion of the Real Economy Sector								
Indonesia			First week of the crisis ($t=\boldsymbol{\tau_1}$)		Last week of the crisis ($t=\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\widehat{\boldsymbol{\rho}}_{\mathbf{0}}$	$\widehat{\boldsymbol{\rho}}_{\mathbf{1}}$	$\widehat{\boldsymbol{\omega}}_{\mathbf{2}t} = \widehat{\boldsymbol{\rho}}_{\mathbf{0}} + \boldsymbol{\rho t}$	**t- statistic**	$\widehat{\boldsymbol{\omega}}_{\mathbf{2}t} = \widehat{\boldsymbol{\rho}}_{\mathbf{0}} + \widehat{\boldsymbol{\rho}}_{\mathbf{1}}\boldsymbol{t}$	**t- statistic**		
Basic Material	13.42532**	-.00883**	0.61299***	4.246798	-0.13756	-0.50973	Shock Contagion (Transitory)	C
Industrial	.0714488		0.0714488		0.0714488		No Contagion	C
Con. gds	.0934365		0.0934365		0.0934365		No Contagion	C
Healthcare	.2077905***		0.2077905***		0.2077905***		Shock Contagion (Level)	C
Telecom	-.0796285		-0.0796285		-0.079628		No Contagion	-
Utilities	-15.4115***	.0105609***	-0.0877041	-0.42976	0.8099724***	4.250632	Kink Contagion	-

Domestic Financial Contagion of the Real Economy Sector								
Italy			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	-.048223		-0.0482231		-0.0482231		No Contagion	C
Basic Material	-.48696**		-0.48696***		-0.48696***		No Contagion	C
Industrial	-.48196***		-0.48196***		-0.48196***		No Contagion	C
Con. gds	-.64291***		-0.6429***		-0.64291***		No Contagion	C
Healthcare	-.591978***		-0.59197***		-0.591978***		No Contagion	C
Con. Ser.	.1180407		0.1180407		0.1180407		No Contagion	C
Telecom	-.1267277		-0.1267277		-0.1267277		No Contagion	-
Utilities	.0627276		0.0627276		0.0627276		No Contagion	C
Technology	-.0482231		-0.0482231		-0.0482231		No Contagion	C

Domestic Financial Contagion of the Real Economy Sector								
Japan			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	-.1721466*		-0.1721466*		-0.1721466*		No Contagion	-
Basic Material	-.191365***		-0.191365***		-0.191365***		No Contagion	-
Industrial	-.1188635**		-0.1188635**		-0.1188635**		No Contagion	-
Con. gds	-.0575742		-0.0575742		-0.0575742		No Contagion	-
Healthcare	-4.086262**	.0028089*	-0.0105481	-0.16015	0.2282084	2.053969	Kink Contagion	-
Con. Ser.	2.861237*	-.002096**	-0.180059***	-3.62423	-0.358219***	-4.45302	No Contagion	C
Telecom	-.0769862		-0.0769862		-0.0769862		No Contagion	-
Utilities	.2376792***		0.2376792***		0.2376792***		Shock Contagion (Level)	-
Technology	-.1721466*		-0.1721466*		-0.1721466*		No Contagion	-

Domestic Financial Contagion of the Real Economy Sector								
Mexico			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Basic Material	.0645409		0.0645409		0.0645409		No Contagion	-
Industrial	-.0112716		-0.0112716		-0.0112716		No Contagion	-
Con. Ser.	-.0466371		-0.0466371		-0.0466371		No Contagion	-
Telecom	-.2437473*		-0.2437473*		-0.2437473		No Contagion	-

Domestic Financial Contagion of the Real Economy Sector								
Norway			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	9.096573**	-.0061389**	0.1890291	1.03526	-0.33277***	-2.85908	No Contagion	-
Basic Material	-.2538955**		-0.2538955**		-0.2538955**		No Contagion	C
Con. gds	9.481874**	-.0062433*	0.4228457**	2.178003	-0.1078348	-0.88064	Shock Contagion (Transitory)	-
Con. Ser.	17.80147***	-.011751***	0.7503337***	3.211303	-0.248526**	-1.7825	Shock Contagion (Reversal)	-
Telecom	8.074046*	-.0056763*	-0.1622653	-0.72523	-0.64475***	-3.09632	No Contagion	C
Utilities	-.158344		-0.158344		-0.158344		No Contagion	C
Technology	-.1665574		-0.1665574		-0.1665574		No Contagion	C

Domestic Financial Contagion of the Real Economy Sector								
New Zealand			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	.374515*		0.374515*		0.374515*		Shock Contagion (Level Shock)	C
Basic Material	.5875929***		0.5875929***		0.5875929***		Shock Contagion (Level Shock)	C
Industrial	10.91419*	-.0070157*	0.7344093***	2.667291	0.1380748	0.632441	Shock Contagion (Transitory)	C
Con. gds	.485789***		0.4857895***		0.4857895***		Shock Contagion (Level Shock)	C
Healthcare	.5660061***		0.5660061***		0.5660061***		Shock Contagion (Level Shock)	C
Con. Ser.	.3739562***		0.3739562***		0.3739562***		Shock Contagion (Level Shock)	C
Telecom	-.0200624		-0.0200624		-0.0200624		No Contagion	-
Utilities	.4062832***		0.4062832***		0.4062832***		Shock Contagion (Level Shock)	C
Technology	2.563729		2.563729		2.563729		No Contagion	-

Domestic Financial Contagion of the Real Economy Sector								
Russia			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	.399745***		0.3997451***		0.3997451***		Shock Contagion (Level)	C
Basic Material	.2888739***		0.2888739***		0.2888739***		Shock Contagion (Level)	-
Con. gds	-.000277***		-0.000277***		-0.000277***		No Contagion	-
Con. Ser.	.1377057		0.1377057		0.1377057		No Contagion	-
Telecom	.2364718***		0.2364718***		0.2364718***		Shock Contagion (Level)	-
Utilities	.311118***		0.311118***		0.311118***		Shock Contagion (Level)	C

Domestic Financial Contagion of the Real Economy Sector								
South Africa			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	-.1394578		-0.1394578		-0.1394578		No Contagion	-
Basic Material	-.43743***		-0.43743***		-0.43743***		No Contagion	C
Industrial	-.18278***		-0.1827***		-0.18278***		No Contagion	-
Con. gds	6.96525**	-.004856**	-0.0809511	-0.6657	-0.493719***	-3.35088	No Contagion	-
Healthcare	-.1510717*		-0.1510717*		-0.1510717		No Contagion	-
Con. Ser.	7.069597**	-.004880**	-0.0117183	-0.10838	-0.426543***	-3.63178	No Contagion	-
Telecom	-.38548***		-0.38548***		-0.38548***		No Contagion	C
Utilities	.0376064		0.0376064		0.0376064		No Contagion	-
Technology	-.1394578		-0.1394578		-0.1394578		No Contagion	-

Domestic Financial Contagion of the Real Economy Sector								
South Korea			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	8.78625*	-.0056734*	0.5541526***	3.042328	0.0719136	0.44263	Shock Contagion (Transitory)	-
Basic Material	-.0643663		-0.064366		-0.064366		No Contagion	-
Industrial	.1615823		0.1615823		0.1615823		No Contagion	-
Con. gds	-.17275***		-0.17275***		-0.172755***		No Contagion	C
Healthcare	12.1298**	-.00814**	0.3145121	0.058901	-0.3776344	-0.06877	No Contagion	C
Con. Ser.	-.33207***		-0.33207***		-0.33207***		No Contagion	C
Telecom	-.38892***		-0.38892***		-0.38892***		No Contagion	C
Utilities	.198706**		0.198706**		0.198706**		Shock Contagion (Level)	-
Technology	-.184043**		-0.184043**		-0.184043**		No Contagion	C

Domestic Financial Contagion of the Real Economy Sector								
Spain			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	.261651***		0.26165***		0.2616518***		Shock Contagion (Level Shock)	-
Basic Material	-.20253***		-0.20253***		-0.2025386***		No Contagion	-
Industrial	17.78***	-.0117***	0.804915***	6.235834	-0.1895936**	-2.09546	Shock Contagion (Reversal)	C
Con. gds	-.182727**		-0.182727**		-0.1827271**		No Contagion	-
Healthcare	20.319***	-.01326***	1.07230***	6.263583	-0.0552164	-0.38375	Shock Contagion (Transitory)	-
Con. Ser.	14.564***	-.00972***	0.460119***	3.060767	-0.366114***	-2.69065	Shock Contagion (Reversal)	-
Telecom	-.419045***		-0.41904***		-0.419045***		No Contagion	-
Utilities	-.012792		-0.0127926		-0.0127926		No Contagion	C
Technology	12.7849***	-.00883***	-0.039818	-0.21681	-0.791099***	-5.72624	No Contagion	-

Domestic Financial Contagion of the Real Economy Sector								
Sweden			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	.0811296		0.081129		0.0811296		No Contagion	-
Basic Material	.421912***		0.42191***		0.421912***		Shock Contagion (Level)	C
Industrial	10.44252***	-.00678***	0.596324	4.617172	0.0195312	0.231788	No Contagion	-
Con. gds	-.0030495		-0.003049		-0.0030495		No Contagion	-
Healthcare	.015079		0.01507		0.015079		No Contagion	-
Con. Ser.	10.4599***	-.00715***	0.085134	0.645251	-0.52262***	-4.83748	No Contagion	C
Telecom	-.340620***		-0.3406***		-0.34062***		No Contagion	C
Technology	9.513287**	-.0062859*	0.39244**	1.866927	-0.1418554**	-0.6619	Shock Contagion (Transitory)	-

Domestic Financial Contagion of the Real Economy Sector								
Switzerland			First week of the crisis ($t=\tau_1$)		Last week of the crisis ($t=\tau_2$)		Decision	Model (4.1)
Sectors	$\hat{\rho}_0$	$\hat{\rho}_1$	$\hat{\omega}_{2t} = \hat{\rho}_0 + \rho t$	**t- statistic**	$\hat{\omega}_{2t} = \hat{\rho}_0 + \hat{\rho}_1 t$	**t- statistic**		
Oil	-.362919		-0.362919		-0.36291		No Contagion	C
Basic Material	-.409272***		-0.40927***		-0.409272***		No Contagion	C
Industrial	5.96621**	-.0041**	0.015957	0.120835	-0.33261***	-3.02512	No Contagion	C
Con. gds	-.44344***		-0.44344***		-0.44344		No Contagion	C
Healthcare	-.1525578**		-0.152558**		-0.152558		No Contagion	C
Con. Ser.	8.01042***	-.00552***	0.0042413	0.03195	-0.464763***	-3.81001	No Contagion	C
Telecom	.082247		0.082247		0.082247		No Contagion	-
Utilities	.0611233		0.0611233		0.0611233		No Contagion	-
Technology	-.362919		-0.362919		-0.362919		No Contagion	-

Domestic Financial Contagion of the Real Economy Sector								
Taiwan			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\boldsymbol{\rho}}_{\mathbf{0}}$	$\hat{\boldsymbol{\rho}}_{\mathbf{1}}$	$\hat{\boldsymbol{\omega}}_{\mathbf{2t}} = \hat{\boldsymbol{\rho}}_{\mathbf{0}} + \boldsymbol{\rho t}$	**t- statistic**	$\hat{\boldsymbol{\omega}}_{\mathbf{2t}} = \hat{\boldsymbol{\rho}}_{\mathbf{0}} + \hat{\boldsymbol{\rho}}_{\mathbf{1}}\boldsymbol{t}$	**t- statistic**		
Oil	.2124727*		0.2124727*		0.2124727*		Shock Contagion (Level)	-
Basic Material	.199975**		0.19997**		0.19997**		Shock Contagion (Level)	-
Industrial	.120845		0.120845		0.120845		No Contagion	-
Con. gds	.0418251		0.0418251		0.0418251		No Contagion	C
Con. Ser.	.377178***		0.3771787***		0.3771787***		Shock Contagion (Level)	C
Telecom	9.2314***	-.00612***	0.355074***	4.082235	-0.1649054*	-1.40811	Shock Contagion (Reversal)	-
Technology	.0183201		0.0183201		0.0183201		No Contagion	-

Domestic Financial Contagion of the Real Economy Sector								
Thailand			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\hat{\boldsymbol{\rho}}_{\mathbf{0}}$	$\hat{\boldsymbol{\rho}}_{\mathbf{1}}$	$\hat{\boldsymbol{\omega}}_{\mathbf{2t}} = \hat{\boldsymbol{\rho}}_{\mathbf{0}} + \boldsymbol{\rho t}$	**t- statistic**	$\hat{\boldsymbol{\omega}}_{\mathbf{2t}} = \hat{\boldsymbol{\rho}}_{\mathbf{0}} + \hat{\boldsymbol{\rho}}_{\mathbf{1}}\boldsymbol{t}$	**t- statistic**		
Oil	.355234***		0.355234***		0.3552337***		Shock Contagion (Level)	C
Basic Material	.1975234*		0.197523*		0.197523*		Shock Contagion (Level)	-
Industrial	.0837283		0.0837283		0.0837283		No Contagion	-
Con. gds	.173194**		0.173194**		0.1731944**		Shock Contagion (Level)	C
Healthcare	.287208***		0.287208***		0.2872077***		Shock Contagion (Level)	-
Con. Ser.	.020161		0.0201614		0.0201614		No Contagion	-
Telecom	-.240031**		-0.240031**		-0.2400307**		No Contagion	C
Utilities	-.024935		-0.0249351		-0.0249351		No Contagion	-
Technology	-.150133		-0.1501325		-0.1501325		No Contagion	C

Domestic Financial Contagion of the Real Economy Sector								
U.K.			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\widehat{\boldsymbol{\rho}}_{\boldsymbol{0}}$	$\widehat{\boldsymbol{\rho}}_{\boldsymbol{1}}$	$\widehat{\boldsymbol{\omega}}_{\boldsymbol{2t}} = \widehat{\boldsymbol{\rho}}_{\boldsymbol{0}} + \boldsymbol{\rho t}$	**t- statistic**	$\widehat{\boldsymbol{\omega}}_{\boldsymbol{2t}} = \widehat{\boldsymbol{\rho}}_{\boldsymbol{0}} + \widehat{\boldsymbol{\rho}}_{\boldsymbol{1}}\boldsymbol{t}$	**t- statistic**		
Oil	-.24055*		-0.24055*		-0.24055*		No Contagion	C
Basic Material	-.88505***		-0.88505***		-0.88505***		No Contagion	C
Industrial	7.41519***	-.0049***	0.27699	0.108802	-0.141166	-0.05392	No Contagion	C
Con. gds	-.38492***		-0.38492***		-0.38492***		No Contagion	C
Healthcare	7.74708***	-.00521***	0.18809**	1.1207	-0.254716**	-2.51123	Shock Contagion (Reversal)	C
Con. Ser.	28.2818***	-.01879***	1.0183306***	7.368728	-0.57877***	-6.88912	Shock Contagion (Reversal)	-
Telecom	-.605191***		-0.60519***		-0.6051906		No Contagion	C
Utilities	-.314001***		-0.31400***		-0.3140017		No Contagion	C
Technology	23.743***	-.01601***	0.5057**	2.176753	-0.855549***	-7.0702	Shock Contagion (Reversal)	-

Domestic Financial Contagion of the Real Economy Sector								
U.S.			First week of the crisis (t=$\boldsymbol{\tau_1}$)		Last week of the crisis (t=$\boldsymbol{\tau_2}$)		Decision	Model (4.1)
Sectors	$\widehat{\boldsymbol{\rho}}_{\boldsymbol{0}}$	$\widehat{\boldsymbol{\rho}}_{\boldsymbol{1}}$	$\widehat{\boldsymbol{\omega}}_{\boldsymbol{2t}} = \widehat{\boldsymbol{\rho}}_{\boldsymbol{0}} + \boldsymbol{\rho t}$	**t- statistic**	$\widehat{\boldsymbol{\omega}}_{\boldsymbol{2t}} = \widehat{\boldsymbol{\rho}}_{\boldsymbol{0}} + \widehat{\boldsymbol{\rho}}_{\boldsymbol{1}}\boldsymbol{t}$	**t- statistic**		
Oil	-6.616911 **	.0043845**	-0.2550015*	-1.54871	0.117681*	0.824456	No Contagion	C
Basic Material	-.2192346**		-0.2192346**		-0.2192346**		No Contagion	C
Industrial	-.2141838***		-0.214183***		-0.2141838***		No Contagion	C
Con. gds	-.4885761***		-0.488571***		-0.4885761***		No Contagion	C
Healthcare	-.381935***		-0.381935***		-0.381935***		No Contagion	C
Con. Ser.	-.2639905***		-0.263990***		-0.2639905***		No Contagion	C
Telecom	-.2891341***		-0.289134***		-0.2891341***		No Contagion	C
Utilities	-4.404169**	.002705**	-0.477908***	-4.53219	-0.2479066***	-2.80699	No Contagion	C
Technology	-.4407684***		-0.440768***		-0.4407684***		No Contagion	C

Note: Parameters stem from model (4.2): $R_{S,i,t} = \alpha_0 + \alpha_1 D_{t\,CRISIS} + \alpha_2 D_{t\,POST-CRISIS} + \beta_{1t} R_{fin,w,t} + \beta_{2t} R_{fin,w,t} D_{t\,CRISIS} + \beta_{3t} R_{fin,w,t} D_{t\,POST-CRISIS} + \omega_{1t} R_{fin,i,t} + \omega_{2t} R_{fin,i,t} D_{t\,CRISIS} + \omega_{3t} R_{fin,i,t} D_{t\,POST-CRISIS} + \varepsilon_{i,t}$, where $\omega_{1t} = \mu_0 + \mu_1 t$, $\omega_{2t} = \rho_0 + \rho_1 t$ and $\omega_{3t} = \varphi_0 + \varphi_1 t$. $R_{i,t}$ denotes stock returns in sector i at time t, $D_{t\,CRISIS}$ ($D_{t\,POST-CRISIS}$) is a dummy variable equal to one during the crisis (post-crisis) period and zero otherwise. and $R_{i,t}$ is the return on domestic financial sector. 'Constant betas model' is identical to model (4.1) but with time-invariant ω_1, ω_2, and ω_3. Insignificant trend terms (μ_1, ρ_1, φ_1) are excluded and model (4.2) is re-estimated where relevant. Error terms are modelled as a GJR-GARCH (1,1) process, corrected for autocorrelation in residuals where required. The hypotheses for shock contagion are: H_0: $\omega_2(\tau_1) \le 0$, H_1: $\omega_2(\tau_1) > 0$, for recoupling contagion: H_0: $\omega_2(\tau_1) \ge 0$, H_1: $\omega_2(\tau_1) < 0$ and H_0: $\omega_2(\tau_2) \le 0$, H_1: $\omega_2(\tau_2) > 0$, and for kink contagion: H_0: $\omega_2(\tau_1) = 0$, H_1: $\omega_2(\tau_1) \ne 0$ and H_0: $\omega_1 \le 0$, H_A: $\omega_1 > 0$.

Chapter 5. Stock Market contagion across the days of the week

5.1. Introduction

Many recent research studies have explored financial contagion among developed and emerging markets, across different crisis periods (e.g. Asian Crisis, Dot-com crisis, and global financial crisis). This includes studies (e.g. Kenourgios and Dimitriou, 2015) on how contagion differs across different stages of a crisis, depending on the conditions of the economy and investors' behaviour. It was observed in Chapter 3 and 4 of this thesis that contagion patterns are not similar across various stages of a crisis and that it affects countries and sectors heterogeneously. In this chapter, I propose to combine insights from two vast but previously disjoint strands of the finance literature, on financial contagion and on day-of-the-week effects in stock returns.

On one hand, there exists a wealth of research studies into causes, channels, and implications of financial contagion across markets (for e.g. Forbes, 2012). As mentioned in the earlier chapters of this thesis, despite a disagreement on what constitutes contagion, most authors currently apply the definition proposed by Forbes and Rigobon (2001), where contagion arises with a significant increase in comovements between stock markets following a shock to one of them. This is usually operationalised by estimating models which employ daily or weekly (e.g., Baur, 2012) data and which assume identical comovements across weekdays.

On the other hand, a large number of research studies have been devoted to calendar effects in stock returns (for e.g. Dzhabarov and Ziemba, 2010). One of the earliest and most prominent phenomena is the Monday effect, whereby returns on Mondays were found to be significantly lower than on other weekdays. Subsequent research studies demonstrated systematic effects for other weekdays, most notably Fridays, while others have suggested that the Monday effect has either disappeared, reversed or migrated to other weekdays (for e.g. Pettengill, 2003).

In this chapter, I propose a model of contagion which accounts for day-of-the-week effects. I postulate that any conclusions on the existence and severity of financial contagion derived in the existing literature may be misleading or incomplete, as current testing approaches fail to account for the existence of weekday effects in return spillovers. Firstly, if contagion occurs only on specific weekdays, any approach treating all weekdays equally may fail to recognise those contagious but infrequent days. Additionally, even if contagion can be detected by treating all weekdays as identical, a model which accounts for day-of-the-week effects in contagion, as proposed here, will generate a fuller picture of when exactly the contagion risk is most severe.

Why would one assume that spillovers and contagion can differ across weekdays? I posit that factors leading to the day-of-the-week effect in returns can also lead to uneven occurrences of contagion. For instance, the differences in intensity of short-sales activities in different economies (e.g. due to local restrictions on short-selling during the crisis), the strengthening of the 'blue Monday' effect following the crisis outbreak, and the surge in the number of investors taking a short view due to liquidity needs during the recent financial crisis might all lead to changes in the day-of-the-week effect domestically, but also affect cross-border investment decisions. Moreover, announcements of macroeconomic[14] data take place on different weekdays in different countries which could also lead to contagion effects being different across weekdays.

In this chapter, I start off by looking at one of the most puzzling anomalies in calendar effects, which is the day-of-the-week effect, according to which stock returns are significantly higher on some days of the week than on others (Lakonishok and Smidt, 1988). One of the most examined day-of-the-week effects is the Monday effect, which is the focal point of this study. Cho et al. (2007) describe Monday effect as a phenomenon whereby Monday stock returns, on average, are lower than the returns on any other day of the week and returns are negative. Cross (1973) is among the authors that first studied this anomaly, and since then, extensive research has been conducted in the international equity market and the findings have suggested that Monday effect is a global phenomenon. In the 1990s, Chang et al. (1993) and Kamara (1997) confirm the presence of Monday effect. And later on, Tong (2000), Chen and Singal (2003), Cho et al. (2007) provide evidence of Monday effects in different countries. However, until now there has not been any convincing explanation for this anomaly even though there are numerous potential factors that may cause the Monday effect. The explanations include timing of corporate releases after Friday's close (e.g. Damodaran 1989), speculative short sales (e.g. Chen and Singal, 2004), statistical errors (e.g. Sullivan, Timmermann and White, 2001),

[14] Announcement of macro-economic data take place on different weekdays, for instance Federal Open Market Committee (FOMC) decisions are announced on Wednesdays and non-farm payrolls are released on Fridays. These announcements have been documented to affect asset prices. For example, Flannery and Protopapadakis (2002) examined the impact of macro-economic series' announcements on daily equity returns from 1980 until 1996 and find that 6 announcements series (i.e., CPI, PPI, Balance of Trade, Employment and Money Aggregate) do affect equity returns and increases market conditional volatility. And more recently, Birz and Lott (2011), found that there was a strong statistical relationships between S&P 500 returns and newspaper headline about unemployment and GDP from January 1991 until June 2004.
Hence, in this chapter, I hypothesize that news originating abroad will interact with those domestic announcement effects, the latter being of various intensity across countries. Hence, country-specific weekday effects in return spillovers and contagion can be observed. Moreover, even in absence of domestic announcement effects these could be carried over from an important foreign market in form of spillovers being more intensive on foreign announcement days.

information asymmetry (e.g. Foster and Viswanathan), Blue Monday hypothesis (e.g. Pettengill, 2003) and differential trading activities of market participants (e.g. Lakonishok and Maberly, 1990; Sias and Starks, 1995), amongst others.

There have also been various methodologies adopted to investigate the Monday effect phenomenon empirically. The methods range from basic OLS regressions involving F-tests and t-tests (e.g. Rogalski, 1984 and Chang et al., 1993) to more complicated and robust bootstrap procedures (e.g. Sullivan, Timmermann and White, 2001) and GARCH models (Choudry, 2000 and Chen et al., 2001). The early tests of Monday effect have been criticised on their methodology, as non-normality of data, the presence of heteroscedasticity and ARCH effects are not accounted for. More recently, the ARCH/GARCH family of models (Engle, 1982; Bollerslev, 1986) have become very common as they enable researchers to model variance as conditional on past variance and error, rather than fixed throughout the series, as in regression.

Additionally, even though there are numerous research studies, as established above, suggesting evidence of Monday effects, there have been some contradictory results, i.e. diminishing or reversal of Monday effects. For example, Kamara (1997) finds since the introduction of S&P500 futures contracts in 1982, there has been a significant reduction in the Monday effect anomaly. And more recently, the same evidence was presented by Marquering, et al., (2006) for Dow Jones Industrial Average (DIJA) from the year 1960 to 2003. While some research studies found a diminishing Monday effect, some showed a complete reversal in returns. For instance, Brusa and Pu (2000) find that returns of large U.S stocks were positive on Mondays and largest compared to any other days of the week during the 1990s. Mehdian and Perry (2001) also confirm a reversal of the anomaly for large U.S. stocks from 1987 to 1998.

Based on the efficient market hypothesis, such anomalies (Monday effect, in this case) should indeed vanish over time, as suggested by Kohers, et al. (2004), as rational investors arbitrage this opportunity away. This statement is confirmed by Mossman et al. (2015) when they find that like any stock anomaly, Monday effect also disappears in the long run. Doyle and Chen (2009) on the other hand find a wandering weekday effect, where the day of the week shows systematically higher or lower returns are very sensitive to the choice of sub-period.

Hence, this chapter is motivated by the ‘Monday effect’ puzzle as previous research studies provide mixed evidence, in terms of the existence, explanations and methods used to investigate this phenomenon and whether this has an impact of spillover and contagion effects. There also appear to be very few research studies that examine Monday effect during the recent financial crisis and are concentrated on very few markets. The Global Financial Crisis of 2007-2009 triggered by the U.S.A subprime crisis was one of the most tumultuous economic events in the recent history, which has affected both financial activities and macroeconomic conditions in numerous countries. Following, the evidence found by Urquhart and McGroarty (2014) that "Monday effect behave differently depending on certain market conditions, and that the effect is more pronounced during bear markets and market crashes, by separating their data into various periods depending on market conditions", I believe it would be interesting to see whether there is existence of Monday effect across various stock markets, and whether the effect changes (e.g. reversal or disappearance of Monday effects) under different market conditions, namely as a result of a financial crisis. One of the potential reasons for these variations might be due to changes in factors explaining Monday effects during the crisis period, including a temporary short sale restriction in several countries, different trading patterns of institutional investors, a more pronounced information asymmetry and changes in investors' perception of risk.

The aim of the paper is thus firstly to investigate whether there are any Monday effects in 13 stock markets from 24th July 2004 until 27th March 2009, and accounting for the outbreak of the 2007 financial crisis in our sample date. Having looked at the existence of Monday effect, this paper also examines how spillovers from the U.S. market differs across the day of the week during both the pre-and crisis period. Following the outbreak of the financial crisis, there have been numerous research studies on contagion effects (For e.g. Baur, 2012, Dungey and Gajurel, 2014, 2015, Fry-McKibbin et al., 2014. Beirne and Gieck, 2014, Chiu et al., 2015) in the stock market. Despite a myriad of research studies on the topic of contagion, none of them has looked at how contagion effects differ across the days of the week, i.e. whether the Monday effect has an impact on spillover across markets during normal and turmoil period. Subsequently, one of the novelty of this paper is not only limited to examining Monday effects in stock returns under different market conditions, but also looks at the impact of Monday effects on spillover from the U.S. market to other countries, and whether the pattern of Monday effect in spillover (if there is any) during the crisis period changes relative to the pre-crisis period.

The findings show evidence of disappearing Monday effect, with none and two out of thirteen equity markets showing evidence of Monday effect before and during the financial crisis, respectively. However, evidence of reversal of Monday effects is observed in some countries, whereby other days of the week (i.e. any other day apart from Monday) have the lowest return. One of the uniqueness of this chapter is that spillover from the U.S. market is investigated on a daily basis. Many of the research studies on contagion chose an arbitrary day of the week (for e.g. Tuesday or Wednesday) to examine weekly contagion effect, and as a result, might not identify contagion that might occur on specific days of the week. The findings illustrate that spillovers and contagion from the U.S. does not occur across all days of the week and occurs only on a particular day of the week or only once a week. The novel contagion model captures excess co-movement which would not have been identified by a standard contagion model, which would be only comparing average co-movement during the crisis period relative to pre-crisis period. The results can potentially add to the literature of contagion as it shows how spillovers and contagion effect are different across the days of the week. This study is also relevant for financial managers, market professionals and investors in general, and all those interested in developing trading strategies.

The remainder of the chapter is organised as follows. The next section discusses the relevant literature on Monday effects while Section 5.3 presents the Methodology Framework. Section 5.4 presents the data, while Section 5.5 reports the empirical results. Finally, Section 5.6 concludes.

5.2. Literature Review

5.2.1. Monday effect

A well-documented seasonal anomaly is the Monday effect. Since the results provided by Cross (1973) attesting that returns on the S&P index are significantly negative on Mondays, many researchers started to investigate this effect. For example, Lakonishok and Smidt (1988) examine DJIA patterns from the year 1887 until 1986. Further, Keim and Stambaugh (1984) study the S&P500 returns from 1928 to 1982, and Schwert (1990) tests the effects using different indexes from 1802 to 1987. According to the three research studies mentioned above, abnormal losses were observed on Mondays relative to other days of the week. The literature on Monday effect also attempts to explain the reasons behind this phenomenon, but the findings are quite inconclusive.

(a) <u>Potential explanations of the Monday effect</u>

- Statistical Errors

Some researchers (e.g. Connoly, 1989) suggest than a deceptive Monday effect might arise by using flawed statistical methods. One reason leading to this argument is data mining. Sullivan, Timmermann, and White (2001) question "whether apparent regularities in stock returns really imply a rejection of simple notions of market efficiency, or they are just a large, collective data-mining exercise." They apply a new bootstrap procedure (by constructing a large number of calendar trading rules using permutation arguments) and fail to identify any calendar effects. Moreover, they find that the apparent statistical significance of the best calendar effects is not robust to data-mining effects.

Moreover, a separate but related issue is that recent studies have cast doubt on the favourable evidence from the initial studies, as they found mixed evidence regarding Monday effects while employing more advanced statistical procedures. For instance, some statistical tests assume return distributions is normal despite evidence that equity return does not follow a normal distribution and ignore heteroscedasticity and ARCH effects. However, after adjustments, Monday effect might lose its significance. For example, Chien, Lee, and Wang (2002) find if heteroscedasticity is corrected for, this diminishes the weekday effect. Further, Connolly (1989) and Lin, Najand and Yung (1994) find by employing GARCH methods, the hypothesis that average returns are equal across weekdays cannot be rejected. Another example, is by using the method of rolling sample test (the least square regression model) and a GARCH model to investigate the day-of the-week anomalies in the stock returns of 28 markets around the globe, Zhang, Lai and Lin (2006) found evidence of day-of-the-week effects on the stock markets on both emerging and developed markets. In other words, they find that Monday effects are most prominent for some samples, but also identify Tuesday, Wednesday, Thursday and Friday effects are present for other markets.

- Short selling activity

Another factor that may explain the Monday effect, is short selling (Fields, 1934; Chen and Singal, 2003). According to these authors, the intuition is straightforward, “the inability to trade over the weekend causes short sellers to close their speculative positions on Fridays and re-establish new short positions on Mondays, causing stock prices to rise on Fridays and fall on the subsequent Mondays.” Their argument is that speculative short sellers are not willing to hold their position over the weekend, as it represents a long non-trading period compared to weekdays. They show that there is a temporary upward price pressure when the investors are closing their short positions on Fridays, and on the other hand, a temporary downward price pressure when and when they re-establish their short positions on Mondays. Diamond and Verrecchia (1987) and Blau, et al. (2009) posit that “a significant portion of short sales are executed by investors with information on a certain security, i.e. short sellers are informed about the true value of stocks.” Therefore short-selling activities may temporarily move the security price from its equilibrium and as a result lead to a Monday effect.

Christophe, Ferri and Angel (2003), on the other hand, show that there is no apparent pattern in daily short trade data from the NASDAQ ACT-trade reporting system for a period of 3 months. They suggest that their findings might be consistent with either of two propositions: “(1) the arbitrage opportunity available from a pattern of lower stock returns on certain days (e.g., Mondays) is not large enough to exceed the costs of short selling and, therefore, does not induce higher levels of short selling on the previous days; or (2) if a day-of-the-week effect exists, short selling is not one of several possible causes of the phenomenon.” Moreover, Blau et al. (2009) suggest that they found more short selling activity during the middle of the week, by employing short-sale transactions data for NYSE securities in 2005. Furthermore, Christophe, Ferri, and Angel (2009) find that short selling does not explain an economically meaningful portion of the weekend effect in returns. However, Gao, et al. (2015) looked at the impact of the possibility of short selling in Hong Kong Exchange Market in 1994 on Monday effect, as this activity was prohibited before 1994. They find that the anomaly exists in both sub-periods.

This study consists of two subsets in terms of the period, i.e. pre-financial crisis and financial crisis. And one of the distinguishing characteristic of the global financial crisis that has erupted in 2007 is that short selling was banned almost simultaneously across many parts of the world (Reuters, 2009 and Makintosh et al. 2009). The onset of a crisis seemed to have aroused the appetite of regulators in favour of banning short-selling opportunities and their logic is that a downward movement in stock prices will be intensified by short sellers. Several countries imposed restrictions of various durations and severity. Amongst the countries in our sample, Austria, Denmark, France, Germany, Greece, Italy, Norway, Portugal, Switzerland, U.K and U.S introduced a ban around September/October 2008, (Bohl et al., 2015). Some of them still have the short selling ban whilst other have had them removed. Countries in the Eurozone tend to have banned shorting financial stocks, with most retaining a prohibition on naked short selling well after the financial crisis. In countries such U.S. and U.K., the bans were short lived. Hence, it would be interesting to find out whether the ban on short selling across various parts of the world have had an impact on Monday effect during the recent financial crisis.

Since short selling activity may lead to a temporary price pressures and hence resulting into the lower prices on Mondays, it is crucial and interesting to investigate whether this explanation applies to other equity markets besides the U.S market, and the suspension of short selling activities during the crisis period for some countries in our sample provides a unique opportunity to investigate this issue, i.e. whether Monday effect is present before the outbreak of the crisis, and if there is any change regarding the evidence of this anomaly after the short sale ban. The result of this ban might induce investors to conduct short sales activities in markets where it is not prohibited, and subsequently, leading to an irregular contagion effect across the days of the week.

- Differential trading patterns of various market participants

There has been considerable research focused on the behaviour of individual versus institutional investors and the potential patterns which may emerge from their unique trading activities. Miller (1988) and Abraham and Ikenberry (1994), for instance posit that the behaviour of individual investors partially explains the tendency for negative Monday returns on equity. Lakonishok and Maberly (1990) also points out that there is evidence of an increase in trading activity by individual investors on Monday (especially on the sell side) while institutional investors tend to decrease their trading activity on the same day of the week. One reason that might potentially explain this behaviour is that individual investors tend to make financial decision over the weekend and as a result, are relatively more active than institutions on Mondays. In other words, individual investors are generally viewed as unsophisticated traders, who have a preference for short term investments, whereas institutional investors are viewed as being better-informed, rational traders, having a preference of a long-term investment. A second motive, according to Abraham and Ikenberry (1994) might be due to the liquidity-needs hypothesis or information-processing hypothesis. The former states that individuals are more likely to assess their need for liquidity over the weekend and place sell orders early in the week, and the latter suggests that individual investors tend to make portfolio rebalancing decisions over the weekend (which are dependent upon prevailing market conditions). In essence, the information-processing hypothesis claims that positive feedback trading (i.e. aggressive selling activity following the receipt of negative information) on the part of individual investors is a primary source of the Monday effect, which has been confirmed by Chan, Leung, and Wang (2004).

There are however some contradicting results, whereby Sias and Starks (1995) finds that Monday effect is closely related to stocks with “high institutional ownership” than to stocks with 2low institutional ownership”. Moreover, according to the findings of Wang and Walker (2000), in the Taiwanese equity market, weekday patterns are caused mostly by individual investors whereas in the Japanese market, it is the institutional investors who cause the weekday pattern and in Hong Kong, it is both types of investors that cause the weekday pattern.

Long-term investors sometimes face short term liquidity needs too and may have underestimated liquidity buffer needs during the pre-crisis era and as a result allocated to more illiquid and risky assets. And when favourable conditions are brusquely reversed and funding conditions in the market deteriorate, almost all investors have to sell their investment as soon as possible in order to raise capital. Kalemli-Ozcan et al. (2013) find that many institutional long-term investors have engaged in pro-cyclical investment actions during the recent financial crisis. Avoiding a pro-cyclical behaviour in the middle of a financial crisis may be difficult. From an individual investor perspective, pro-cyclical behaviour may be even rational, as if the investors have made risk risky investments during a favourable time and they will need liquidity in a crisis.

Hence, the change in trading pattern of institutional investors might lead to an accentuating Monday effects since they tend to disregard their long-term view and liquidate their assets on Fridays as they are more focused on liquidity needs. Following the fact that equity markets might be de-stabilised following the pro-cyclical behaviour of institutional investors in terms of preference of short term horizon over long term horizon investment, this might have an impact of contagion patterns as well.

- Information Asymmetry

Foster and Viswanathan (1990) argues that asymmetric information can explain the Monday effect anomaly. In their model, there are informed traders and two types of uninformed traders. They assume that informed traders receive private information throughout the weekend; however, public information is released only on weekdays. Hence, uninformed traders, who suffer from larger information asymmetry on Mondays, will avoid trading in the early part of the week.

"The uninformed trader knows that on Mondays the informed will exploit his information advantage in trades. The uninformed trader's best strategy is to withdraw liquidity and postpone trades until the market thickens and the price is more informative. The first type of uniformed trader trades strategically and can delay trades. The second type trades only for rebalancing reasons and does not trade strategically. Uninformed discretionary traders are unwilling to trade on Monday when the informed have greater information and these uninformed traders wait until the price is more informative and the information effect diminishes. Since, some uninformed traders believe it is best to withdraw liquidity from the market, it might potentially lead to negative returns on Mondays", (Foster and Viswanathan, 1990).

During the recent financial crisis, there has been a more pronounced degree of information asymmetry as the default risk of banks were increasing. Hence, this uncertainty might potentially lead to a more negative return on Mondays and changes in spillovers pattern across the days of the week.

- Investors' behaviour

There are also research studies which investigates psychological link to trading behaviour. Pettengill (1993), for instance, provides support for the blue Monday hypothesis in an experimental study of investor trading behaviour. According to him, the basic principle of the so called blue Monday hypothesis asserts that "investors are affected by systematic mood changes that cause price pressures on Monday and positive pressures on Friday." Further, the findings of Rystrom and Benson (1989) show that mood swings influences the decisions made by investors. An experiment was conducted by Pettengill (1993), where investors were given the choice between risky and risk-free assets. When the experiment was conducted on Fridays, investors were significantly more likely to invest in risky assets than were investors when the experiment was conducted on Mondays.

Following the outbreak of the recent financial crisis, there has been a change in investors' risk tolerance and perception which might have had altered Monday effects. According to Hoffman et al. (2013), during the crisis, there has been significant fluctuation of investors' behaviour. Guiso et al. (2013) postulate that investor's risk tolerance is time-varying, and there is evidence that in the worst months of the crisis period, investors' return expectations and risk tolerance diminishes while their risk perception increase due to uncertainty. Hence, following the outbreak of the crisis, one would expect a more pronounced "Blue Monday" effect, which would also have an impact on international investments, and hence have an effect of spillovers across the equity markets.

5.2.1.1. Reversal of Monday effects

One of the first calendar effects being discovered was the Monday effect and as mentioned above, there are numerous research studies that suggested that the effect has been quite strong. However, there are also evidence that this anomaly has reduced considerably and, in some cases, even reversed over time. The wandering and reversal of Monday effect is in line with the Adaptive Market hypothesis (AMH) which was proposed by Lo (2004). According to the AMH, market efficiency evolves over time instead of being subject to the conventional view of all-or-nothing efficiency. In other words, this theory enables market efficiency and inefficiencies to co-exist in an intellectually consistent manner.

For example, Connolly (1989), Chang, Pinegar, and Ravichandran (1993) and Kamara (1997) report that the Monday effect has diminished significantly. And more recently, Nisser, and Valla (2006), Alt, Fortin, and Weinberger (2011) and Mossman et al. (2015) also found that Monday effect seems to have disappeared in the long-run.

By using average Monday returns and the average difference between Monday returns and average daily returns for the rest of the week from 1981 until 1998, Chan, Leung, and Wang (2003) suggest that the upsurge of institutional investors could have caused the Monday effect anomaly to disappear. By inference, they link the occurrence of Monday effect to the existence of individual investors. They suggest that the growth of institutional ownership may eliminate the Monday effect, as these investors actively arbitrage a seasonal pattern created by individual investors. Moreover, according to Pettengill (2003), the anomaly may re-appear due to investor inattention, or even reverse if investors overreact in their efforts to exploit the anomaly.

And on the other hand, some research studies found that there has been a complete reversal in returns. Brusa, Liu, and Schulman and Mehdian and Perry (2001) are amongst the group of researchers that find that Monday returns were positive and largest relative to any other day of the week and hence confirm a reversal effect in US stocks returns. Moreover, “contrary to the assumption that irrational effects will be automatically traded away once brought to light, there is evidence that markets over-react” (De bondt and Thaler, 1985; Lehman, 1990). If enough investors acted on the idea, “Buy Monday and sell on Friday”, this might lead to an overreaction to the anomaly which as a result might push Monday returns up beyond equilibrium, leading to a new seasonality pattern, which would eventually be reacted to, and so on. Gu (2004) also adds to this hypothesis by stating that as an anomaly becomes well-known, more investors would take act upon this anomaly to exploit excess returns. Consequently, the excess-return activities may sometimes reverse the effect or eventually make it vanish.

In addition to a diminishing and reversal Monday effect, some authors also concluded that Monday effects wander depending on market conditions. For example, Doyle and Chen (2009) showed evidence of a wandering weekday effect, using major stock markets returns from the year 1993 until 2003. Their findings show that the day of the week return were with systematically higher or lower, depending on choice of sub-periods. Likewise, by breaking their samples into bear and bull market periods, Boudreaux (1995) find weekend returns are greater than non-weekend returns only in bull markets for DJIA, S&P500 and the NASDAQ from 1976 to 2002. They argue that it is due to a wealth effect where as stock prices rise, investors gain confidence and are more likely to act upon broker recommendations during the week.

A diminishing Monday effect would mean that investors can no longer generate abnormal returns by capitalising on this anomaly. One of the reasons of possible disappearance of day-of-the-week evidence in general might be because investors took the opportunity to spot the effect and hence taken advantage of the anomaly which has priced away any advantage. Moreover, according to Wong et al. (2006), disappearance of calendar anomalies suggests that markets are more efficient, due to more knowledgeable and experienced investors and advances in information technology and communications, and lower cost of information. Also, as explained in the previous section, the use of advanced statistical procedure might be a potential reason for mixed Monday and day-of-the-week effect in general. According to Doyle and Chen (2009) there are two different ways to interpret the disappearance of Monday effects. The first one, as mentioned earlier, is that existence of public knowledge will not let seasonality effects survive, which shows that markets have become more efficient. The second reason might be because seasonal effects evolve continuously, and this may appear as a weakening seasonality effect a particular point in time, or when averaged of a period of time.

5.2.2. Summary

Early work on Monday effects in stock market was very consistent in finding significantly negative return on Mondays relative to other days of the week. And despite the fact there have been numerous explanations, (such as data mining, different flows of information, market microstructure, differential trading patterns of various market participants, investor's behaviour), researchers seem unable to fully explain the causes of this anomaly.

Over the years, researchers developed new datasets and statistical methods which recognizes the fact that returns are non-normally distributed, auto-correlated and that the residuals of linear regressions are variant over time. Henceforth, following the use of statistically robust estimation methodologies, the anomaly began to reverse, drift to other days, wander, and even disappear. Among the possible explanations for the loss of Monday effect, is the fact that early critics who dismissed the effects as spurious or being the result of data mining were correct. Another possible reason is that investors pay attention to patterns in asset prices, hence exploiting this anomaly and as a result causing those patterns to change or disappear.

5.3. Methodology Framework

This section provides a detailed overview of the methodology framework employed to investigate Monday effect, contagion effect during the crisis period and whether spillover and contagion differs across the day of the week.

Table 5.1 below shows a brief description of the coefficients pertaining to the equations below:

Eq.	Parameters	Explanations
		Monday effect
5.1	$\alpha_{i,M}$	Average Monday returns
	$\alpha_{i,D.O.W}$	Monday effect if $\alpha_{i,D.O.W} > 0$
5.2 (a)	$\alpha_{i,M}$	Average Monday returns during pre-crisis
	$\alpha_{i,D.O.W}$	Monday effect during pre-crisis if $\alpha_{i,D.O.W} > 0$
5.2 (b)	$(\alpha_{i,M} + \alpha^*_{i,M})$	Average Monday returns during crisis
	$\alpha^*_{i,M}$	Effect of crisis on Monday returns
	$\alpha_{i,D.O.W} + \alpha^*_{i,D.O.W}$	Monday effect during crisis period
	$\alpha^*_{i,D.O.W}$	Effect of the crisis on Monday effect
		Spillover effect
5.3	β_i	Spillover from U.S.
5.4	β_i	Spillover during the pre-crisis
	β^*_i	Contagion effect (crisis) if $\beta^*_i > 0$
		Spillover effect across days of the week
5.5	$\beta_{i,M}$	Spillovers on Monday
	$\beta_{i,D.O.W}$	Monday effect in spillovers if $\beta_{i,D.O.W} \neq 0$
5.6 (a)	$\beta_{i,M}$	Spillovers on Monday (pre-crisis)
5.6 (b)	$\beta_{i,M}$	Spillovers on Monday (pre-crisis)
	$\beta_{i,D.O.W}$	Monday effect in spillovers during pre-crisis if $\beta_{i,D.O.W} \neq 0$
	$\beta_{i,M} + \beta_{i,D.O.W}$	Spillovers across other days of the week during pre-crisis
5.6 (c)	$\beta_{i,M} + \beta^*_{i,M}$	Spillovers on Mondays during the crisis
	$\beta^*_{i,M}$	Contagion on Monday (during the crisis period)
5.6 (d)	$\beta_{i,D.O.W} + \beta^*_{i,D.O.W}$	Monday effect in spillover during crisis
	$\beta^*_{i,D.O.W}$	Shows how contagion is different from Mondays compared to other days of the week (during the crisis)
5.6 (e)	$\beta^*_{i,M} + \beta^*_{i,D.O.W}$	Effect of crisis on non-Monday spillovers (Contagion)

5.3.1. Monday effect

I start by estimating a basic model to test for Monday effect, by using the following equation:

$$R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W} D_{D.O.W} + \varepsilon_{i,t} \quad (5.1)$$

where $R_{i,t}$ denotes stock returns of a European country *i* at time *t*. $\alpha_{i,M}$ (the constant term) captures the mean return on Mondays. $\alpha_{i,DOW}$, on the other hand is a vector of intercepts for remaining days of the week, relative to Mondays ($\alpha_{i,DOW} = (\alpha_{i,Tu}, \alpha_{i,We}, \alpha_{i,Th}, \alpha_{i,Fr})$). $D_{D.O.W}$ is a vector of dummy variables ($D_{D.O.W}$ = (D_{Tu} , D_{We} , D_{Th} , D_{Fr})) which take the value of 1 if corresponding return for each of the following day is a Tuesday, Wednesday, Thursday or Friday, respectively, and 0 otherwise.

As mentioned above, the average Monday return is given by $\alpha_{i,M}$, as $D_{DOW} = 0$ for Mondays. And as far as non-Mondays (i.e. Tuesdays, Wednesdays, Thursdays and Fridays) are concerned, their average returns are given by $\alpha_{i,M} + \alpha_{i,D.O.W}$, as $D_{D.O.W} = 1$ for non-Mondays. For example, $\alpha_{i,Tu} \neq 0$, Tuesday returns are $\alpha_{i,M} + \alpha_{i,Tu}$. Therefore, the difference between Mondays and non-Mondays (any other particular day) average returns is measured by $\alpha_{i,D.O.W}$ and there is presence of Monday effects if any of the non-Mondays coefficients is positive and significant (i.e. $\alpha_{i,D.O.W} > 0$). A reversal in Monday effect would be detected if $\alpha_{i,D.O.W} < 0$.

Equation 5.1 is also used to test for Monday effect during two distinct periods of time, i.e. pre-crisis period (29th July 2004 until 5th August 2007) and crisis period (6th August 2007 until 27th March 2009).

Monday effect is also tested for across the whole period using the following equation:

$$R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W} D_{D.O.W} + \alpha^{*}_{i,M} D_c + \alpha^{*}_{i,D.O.W} D_{D.O.W} D_c + \varepsilon_{i,t} \quad (5.2)$$

Eq. 5.2 nests Eq. 5.1 $R_{i,t}$, $\alpha_{i,M}$, $D_{D.O.W}$ and $\alpha_{i,D.O.W}$ are as defined above. However, Eq. 5.2 differs from Eq. 5.1 in a few aspects. Firstly, Monday effects is tested across the whole sample period, i.e. (29th July 2004 until 27th March 2009) while making a distinction between the pre-crisis and crisis period, by using a dummy D_c which takes on the value of 1 during the crisis period, and 0 otherwise. Eq. 5.2 is testing whether Monday effect, defined as above is different between the pre-crisis and crisis period. And to illustrate this, Eq. 4.2 is separated into 2 parts:

(a) Return equation (pre-crisis), $D_c = 0$

$$R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W} D_{D.O.W} + \varepsilon_{i,t}$$

Here, the average return on Mondays during the pre-crisis period (whereby $D_c = 0$) is denoted by $\alpha_{i,m}$ and Monday effect is captured by $\alpha_{i,D.O.W}$ and is existent if any of the non-Monday coefficients during the pre-crisis is significant, i.e. $\alpha_{i,D.O.W} > 0$.

(b) Return equation (crisis), $D_c = 1$

$$R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W} D_{D.O.W} + \alpha^*_{i,M} + \alpha^*_{i,D.O.W} D_{D.O.W} + \varepsilon_{i,t}$$
$$= \left(\alpha_{i,M} + \alpha^*_{i,M}\right) + \left(\alpha_{i,D.O.W} + \alpha^*_{i,D.O.W}\right) D_{D.O.W} + \varepsilon_{i,t}$$

The average return on Mondays during the crisis period is represented by $\left(\alpha_{i,M} + \alpha^*_{i,M}\right)$. Therefore, the difference between average return on Mondays during the pre-crisis and crisis period is given by $\left(\alpha_{i,M} + \alpha^*_{i,M}\right) - \alpha_{i,M} = \alpha^*_{i,M}$.

Moreover, from Equation 5.2(b), it can be observed that Monday effects during the crisis is given by $(\alpha_{i,D.O.W} + \alpha^*_{i,D.O.W})$ and hence the difference between Monday effects during the pre and crisis period is $(\alpha_{i,D.O.W} + \alpha^*_{i,D.O.W}) - \alpha_{i,D.O.W} = \alpha^*_{i,D.O.W}$.

Hence, if $\alpha^*_{i,D.O.W}$ (i.e. any of $\alpha^*_{i,Tu}, \alpha^*_{i,We}, \alpha^*_{i,Th}, \alpha^*_{i,Fr}$) is significant, it means that following the outbreak of the crisis, Monday effect was affected.

5.3.2. Spillover effect

In this section, a basic model is adopted in order to test for spillover and contagion effect from the U.S. market[15] to a European equity markets and operationalises Forbes and Rigobon (2001) definition of shift-contagion as a significant increase in comovements between markets following a shock to one market (the U.S.). The equation to be estimated is as follows[16]:

$$R_{i,t} = \alpha_i + \beta_i R_{US,t} + \varepsilon_{i,t} \tag{5.3}$$

Where $R_{i,t}$ represents the stock returns of a European country *i*, and $R_{US,t}$ represents the Stock returns of U.S. α_i is the constant term and β_i captures the spillover from U.S. stock market to country *i*. Equation 5.3 is also used to test for spillover effects during two different periods of

[15] For the purpose of the chapter, I am looking at spillovers from U.S. stock market instead of World Stock market (as in the previous sections) as time-aligned data retrieved from DataStream is being employed to test for day of the week effects in spillovers. And it is not possible to find time-aligned stock prices for World Stock market

[16] Unlike Chapter 3 and 4 of this thesis, a simple model to estimate contagion is employed instead of a model with trend, as the aim of this chapter is to only test for contagion across the days of the week.

time, i.e. pre-crisis period (29th July 2004 until 5th August 2007) and crisis period (6th August 2007 until 27th March 2009). There are spillover effects if β_i is significant i.e. $\beta_i \neq 0$.

Spillovers can also be tested across the whole period, allowing for a change during the crisis period by using the following:

$$R_{i,t} = \alpha_i + \alpha_i^* D_c + \beta_i R_{US,t} + \beta_i^* R_{US,t} D_c + \varepsilon_{i,t} \quad (5.4)$$

Eq. 5.4 nests Eq. 5.3 and hence $R_{i,t}$, α_i and β_i can be defined as above. Eq. 5.4 looks at whether there is any difference in the spillovers from U.S. stock market to other markets during the crisis period, as compared to the pre-crisis period. Hence, the crisis dummy (D_c), defined previously, is added to the equation. β_i^* captures the excess spillover during the crisis period, relative to the pre-crisis one from U.S equity market to Country *i*. Contagion effects during the crisis period will be determined if β_{us}^* is positive and significant.

One of the drawbacks of approaches represented by (5.3) and (5.4) is that they average out spillover and contagion effects across the days of the week. Accordingly, models such as (5.3) and (5.4) may not detect contagion if there is an increase in spillovers only during a specific day of the week but this is offset by a decline during other days of the week, hence potentially concealing the day-specific contagion effect. Another issue arises when (5.3) and (5.4) show evidence of contagion during the crisis period (therefore, necessarily, existence of contagion across all days of the week, on average), but where in reality contagion only occurs on particular days of the week, a phenomenon which would remain undetected when using (5.3) and (5.4).

Hence, in the next section, contagion effect is tested for during the different days of the crisis.

5.3.3. Spillover effect across days of the week

In this section, both the day-of-the-week effect and spillover effects are combined in order to determine whether there are significant changes in spillovers across the days of the week.

$$R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W} D_{D.O.W} + \beta_{i,M} R_{US,t} + \beta_{i,D.O.W} R_{US,t} D_{D.O.W} + \varepsilon_{i,t} \quad (5.5)$$

Equation 5.5 is used to test for changes in spillover effects across the days of the week during two distinct periods of time, i.e. pre-crisis period (29th July 2004 until 5th August 2007) and crisis period (6th August 2007 until 27th March 2009). $R_{i,t}$, $\alpha_{i,M}$, $\alpha_{i,D.O.W}$ and $D_{i,D.O.W}$ are as defined previously.

β_i captures the spillover from U.S. stock market to country *i* on Mondays, as $D_{i,DOW} = 0$ for Mondays. And as far as non-Mondays (i.e. Tuesdays, Wednesdays, Thursdays and Fridays) are concerned, the spillovers are captured by $\beta_{i,M} + \beta_{i,D.O.W}$, as $D_{D.O.W} = 1$ for non-Mondays (For example, on Tuesdays, the average spillovers can be denoted by $\beta_{i,M} + \beta_{i,Tu}$. Hence, it can be said that $\beta_{i,D.O.W}$ measures by how much non-Monday spillovers are different from Monday spillovers. Therefore, if $\beta_{i,D.O.W}$ for any non-Monday is significant (i.e. $\beta_{i,Tu}, \beta_{i,We}, \beta_{i,Th}$ or $\beta_{i,Fr} \neq 0$), there is a day-of-week effect in spillovers.

Eq. 5.6 below nests Eq. 5.5. $R_{i,t}, \alpha_{i,m}, D_{i,D.O.W}, \alpha_{i,D.O.W}, \beta_{i,M},$ are defined as above. However, Eq. 5.6 differs from Eq. 5.5 in the sense that we are testing for spillover effects during the different days of the week across the whole sample period i.e. 29th July 2004 until 27th March 2009 in order to determine whether there are any changes in the spillover effects pattern across the days of the week during the crisis period, as compared to the non-crisis period, whereby $D_c = 1$ during the crisis period and 0 otherwise.

$$R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W} D_{D.O.W} + \beta_{i,M} R_{US,t} + \beta_{i,D.O.W} R_{US,t} D_{D.O.W}$$

$$+\alpha^*_{i,M} D_c + \alpha^*_{i,D.O.W} D_{D.O.W} D_c + \beta^*_{i,M} R_{US,t} D_c + \beta^*_{i,D.O.W} R_{US,t} D_{D.O.W} D_{c_t} + \varepsilon_{i,t} \qquad (5.6)$$

$\alpha^*_{i,m}$ and $\alpha^*_{i,D.O.W}$ are the changes in parameters for Mondays and non-Mondays, respectively due to the crisis period. By employing Eq. 5.6, I estimate whether the pattern of spillovers effects on Mondays and the other days of the week are different between the pre-crisis and crisis period. Additionally, the pattern across the other days of the week (i.e. from Tuesdays to Fridays) during the two distinct periods are also examined.

And to demonstrate this, we separate Eq. 5.6 into 5 parts:

(a) Spillover on Mondays during pre-crisis ($D_{D.O.W} = 0$ and $D_c = 0$)

$$R_{i,t} = \alpha_{i,M} + \beta_{i,M} R_{US} + \varepsilon_{i,t} \qquad (5.6a)$$

From Eq. 5.6(a), it can be observed that during the pre-crisis period, spillover from U.S. market to country *i* on Mondays are denoted by $\beta_{i,M}$, as $D_{D.O.W} = 0$ and $D_c = 0$.

(b) Spillover on Monday vs non-Mondays during pre-crisis ($D_{D.O.W} = 0$ vs $D_{D.O.W} = 1$ and $D_c = 0$)

The equation below shows spillovers from U.S. to country *i* before the crisis period:

$$R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W} D_{D.O.W} + \beta_{i,M} R_{US} + \beta_{i,D.O.W} R_{US} D_{D.O.W} + \varepsilon_{i,t} \qquad (5.6b)$$

On non-Mondays, as $D_{i,D.O.W} = 1$, the spillover is represented by $\beta_{i,M} + \beta_{i,D.O.W}$. Hence it can be said that $(\beta_{i,M} + \beta_{i,D.O.W}) - \beta_{i,M} = \beta_{i,D.O.W}$ measures by how much non-Monday spillovers are different from Monday spillovers before the crisis period. Therefore, if $\beta_{i.D.O.W} \neq$

0 (i.e. $\beta_{i,Tu}, \beta_{i,We}, \beta_{i,Th}$ or $\beta_{i,Fr}$ is significant), there is evidence of a day-of-the-week effect in spillovers, as this indicates Monday ($\beta_{i,M}$) and non-Monday ($\beta_{i,D.O.W}$) spillovers are different.

(c) Excess spillover (contagion) on Mondays during crisis ($D_{D.O.W} = 0$ and $D_c = 1$)

$$R_{i,t} = \alpha_{i,M} + \alpha^*_{i,M}D_c + \beta_{i,M}R_{US,t} + \beta^*_{i,M}R_{US,t} + \varepsilon_{i,t} \tag{5.6c}$$

From the above equation, it is assumed that $D_{i,D.O.W} = 0$ and $D_c = 1$ and it can be observed that spillover effects on Monday during the crisis is given by $(\beta_{i,M} + \beta^*_{i,M})$. Therefore, the difference between the spillovers on Mondays pre-crisis compared with spillovers during the crisis on Mondays is given by $(\beta_{i,M} + \beta^*_{i,M}) - \beta_{i,M} = \beta^*_{i,M}$. $\beta^*_{i,M}$shows how spillovers from the U.S. market on Mondays is different during the crisis period as compared with the pre-crisis. It can therefore be said that if $\beta^*_{i,M}$ is significant, it means that following the outbreak of the crisis, the spillovers on Mondays were affected, and hence showing evidence of contagion on Mondays.

(d) Spillover on Mondays versus non-Mondays during crisis ($D_c = 1$)

$$R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W}D_{i,D.O.W} + \alpha^*_{i,M} + \alpha^*_{i,D.O.W}D_{i,D.O.W} +$$
$$\beta_{i,M}R_{US,t} + \beta_{i,D.O.W}R_{US,t}D_{i,D.O.W} + \beta^*_{i,M}R_{US,t} + \beta^*_{i,D.O.W}R_{US,t}D_{i,D.O.W} + \varepsilon_{i,t} \tag{5.6d}$$

From the equation above, it can be deduced that spillovers on non-Mondays during the crisis period are denoted by $(\beta_{i,M} + \beta_{i,D.O.W} + \beta^*_{i,M} + \beta^*_{i,D.O.W})$. And Monday effect in spillovers during the crisis period are then captured by $(\beta_{i,M} + \beta_{i,D.O.W} + \beta^*_{i,M} + \beta^*_{i,D.O.W}) - (\beta_{i,M} + \beta^*_{i,M})$ = $(\beta_{i,D.O.W} + \beta^*_{i,D.O.W})$. Thus, the impact of the crisis on the day-of-the-week effect in spillovers can be expressed as $(\beta_{i,D.O.W} + \beta^*_{i,D.O.W}) - \beta_{i,D.O.W} = \beta^*_{i,D.O.W}$.

(e) Spillovers across non-Mondays before the crisis vs non-Mondays during the crisis

$$R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W}D_{i,D.O.W} + \alpha^*_{i,M}D_c + \alpha^*_{i,D.O.W}D_{D.O.W}D_c +$$
$$\beta_{i,M}R_{US,t} + \beta_{i,D.O.W}R_{US,t}D_{D.O.W} + \beta^*_{i,M}R_{US,t} + \beta^*_{i,D.O.W}R_{US,t}D_{D.O.W} + \varepsilon_{i,t} \tag{5.6e}$$

Spillovers on non-Mondays during the pre-crisis period are denoted by $\beta_{i,M} + \beta_{i,D.O.W}$ and during the crisis, it is represented by $(\beta_{i,M} + \beta_{i,D.O.W} + \beta^*_{i,M} + \beta^*_{i,D.O.W})$. The excess spillover (i.e. contagion) during the crisis period for non-Mondays hence given by $\beta^*_{i,M} + \beta^*_{i,D.O.W}$. Contagion effects on Mondays relative to other days of the week during the crisis period is different if, $\beta^*_{i,Tu}$, $\beta^*_{i,We}$, $\beta^*_{i,Th}$, or $\beta^*_{i,Fr} \neq 0$ (i.e. $\beta^*_{i,D.O.W} \neq 0$). And contagion on non-Mondays is determined if $\beta^*_{i,M} + \beta^*_{i,D.O.W} < 0$.

5.4. Data and Methodology

For the purpose of this chapter, stock market indices from 13 countries[17] are used namely from Austria, Denmark, France, Euro Index, Germany, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, Switzerland, U.K. and U.S. The daily prices denoted in local currency are obtained from DataStream for the period from 29th July 2004 until 27th March 2009. The sample consists of 1217 observations for each equity markets and begins on 29th July 2004, consistent with the previous tightening cycle in the monetary policy cycle in the US, and ends in March 2009 (Dungey and Yalama, 2010). To examine Monday effects and how it affects spillover effects from the U.S. market to other markets in our sample, a synchronized dataset of 16:00 GMT market prices is used, as the timing of collected data is an important determinant of contagion results.

Moreover, the period is also divided into non-crisis and crisis samples, delineated by the start of the crisis period, in 6th August 2007. The start of the crisis period is determined by considering major financial and economic events from the timeline provided by the Bank for International Settlements (Filardo et al., 2009).

In view of the effect of heteroscedasticity for the stock return rate, it is not enough to employ the least square regression method when fitting the conditional residuals. The conditional residuals should be fitted via generalized error distribution as well in order to draw a comparatively consistent conclusion. Hence similar to Chapter 3 and 4, Eq. (5.1) to (5.6e) are estimated within a GJR-GARCH framework, as the OLS estimation technique may provide not only inefficient but also biased parameter estimates.

[17] A synchronised dataset (16.00 GMT, in this case) is employed in Chapter 5 to test for days of the week effect on contagion, as it is more suitable to capture shocks that are transmitted due to the crisis. Time-aligned dataset (i.e. 16.00 GMT) of the indices used in Chapter 3 and 4 are not available on DataStream. Hence, I employ a synchronised dataset that was readily available on DataStream for Chapter 5, consisting of the main European equity market indices and U.S market indices from 24th July 2004 until 27th March 2009, which I believe was substantial enough to test for day of the week effect in contagion

5.5. Empirical Results

5.5.1. Descriptive Statistics

Table 5.2 below reports the descriptive statistics for returns of each market, in terms of means and standard deviations across the whole period. An examination of the characteristics displayed shows that overall, average daily returns on Mondays are not lower relative to other days of the week. And the lowest average daily returns occur on Thursdays. Moreover, the descriptive statistics table shows that the presence of the day of the week effect on stock market return can be shown in terms of standard deviation, as the volatility is higher on Mondays, followed by Fridays as compared to other days of the week.

	Mondays		**Tuesdays**		**Wednesdays**		**Thursdays**		**Fridays**	
	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.
Austria	.00028	.01855	-.00033	.01669	.00008	.01666	-.00067	.01622	-.00009	.01694
Denmark	.00047	.01593	.00049	.01280	-.00026	.01439	-.00102	.01237	-.00016	.01279
Eurostoxx	.00010	.01597	.00028	.01268	.00005	.01383	-.00085	.01178	-.00060	.01478
France	.00008	.01618	-.00018	.01280	.00029	.01432	-.00103	.01233	-.00009	.01497
Germany	.00064	.01656	.00060	.01329	-.00046	.01416	-.00008	.01261	-.00029	.01434
Ireland	-.00076	.01667	-.00010	.01433	.00005	.01497	-.00078	.01184	.00034	.01551
Italy	-.00014	.01526	-.00068	.01265	.00054	.01308	-.00068	.01096	-.00089	.01375
Netherlands	.00041	.01711	-.00015	.01244	-.00031	.01439	-.00114	.01221	-.00035	.01414
Portugal	.00008	.01293	-.00037	.01086	.00047	.01013	-.00111	.00977	.00024	.01106
Spain	-.00036	.01489	.00017	.01306	.00051	.01394	-.00038	.01202	.00013	.01450
Switzerland	.00015	01466	.00030	.01177	-.00026	.01176	-.00048	.01121	-.00019	.01319
U.K.	-.00034	.01283	-.00051	.01296	.00034	.01262	.000103	.01191	.00066	.01243
US..	00061	.01553	-.00043	.01077	.00044	.01375	-.00082	.01172	-.00093	.01533

Descriptive statistics of the stock returns for 13 equity markets across the different days of the week

Before estimating the different models in the previous section to investigate for Monday effect, spillover and contagion effect across the days of the week, the data pertaining to our sample is subject to a battery of tests to ensure that Eq. 5.1 to 5.6 are correctly specified. The results from the ADF test, tabulated in Appendix C.1 suggest that the log indices of the 13 stocks are non-stationary and the returns on the other hand are stationary. Further, the Johansen test is used to identify co-integrating vectors for all pairs of stock prices (i.e. U.S. with other countries in our sample). From Appendix C.2 in the appendix it can be observed that the Schwaz Bayesian Information Criterion (SBIC) indicates that there are no co-integrating vectors for all pairs of stock prices. In addition to this, Eq. 5.6 is estimated using an OLS method and tested for homoscedasticity of residuals by using the White General Heteroscedasticity of residuals. It can be seen from Appendix C.3 in the appendix that the null hypothesis of no heteroscedasticity is rejected for all at 1% indicating that there is significant amount of heteroscedastic while estimating Eq. 5.6 through an OLS model. In addition to this, the non-normality, all the equations in the previous section is re-estimated assuming a student-t distribution or a GED distribution. Appendix C.4 displays the findings from Shapiro Wilk test from Eq. 5.6. And, after having re-estimated the model with the correct error term follows a t-distribution or the residuals are tested for autocorrelation, and in cases where it is found, the errors are modelled as an ARMA process of an appropriate order. Finally, the Engle's LM ARCH test shows that there is no ARCH effects in residuals after estimating all the models within a GJR GARCH framework. Appendix C.5 shows that the p-value observed are greater than the chosen alpha (at 5% significance level, in this case) for Eq. 5.6, indicating no remaining ARCH effects in residuals.

5.5.2. Monday effect

In this section, evidence of Monday effect is investigated across 13 stock markets. Table 5.3(a) and 5.3(b) below shows the estimated results from Eq. 5.1 and reports the findings pertaining to Monday effect during the pre-crisis and crisis period respectively. As established in the Methodology Framework section, Monday effect is observed if any of the non-Monday coefficients is positive and significant (i.e. $\alpha_{i,D.O.W} > 0$). It can be seen from Table 4.2(a) that there are some significant non-Monday coefficients $(\alpha_{i,D.O.W} \neq 0)$ for Germany, Italy, Netherlands, Spain and U.K. The non-Monday coefficients are negative in all cases, except for Fridays in U.K. For instance, $\alpha_{i,Tu} < 0$ for Germany, Italy, Netherlands, Spain and U.K. This indicates wandering Monday effect. And as far as other countries (7 out of 13) in our sample are concerned, there is no Monday effects, as $\alpha_{i,D.O.W} = 0$, showing a disappearing Monday effect in these markets.

Table 5.3: Estimating days of week effects in stock returns (Based on Eq. 5.1)

a. $R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W} D_{D.O.W} + \varepsilon_{i,t}$ (Pre-crisis period, i.e. from 29th July 2004 until 5th August 2007)

	Austria	Denmark	Eurozone	France	Germany	Ireland	Italy	Netherlands	Portugal	Spain	Switzerland	U.K.	U.S.
$\boldsymbol{\alpha_{i,M}}$	.00178*** (2.57)	.00009 (0.16)	.00099* (1.79)	.00073 (1.15)	.00151** (2.26)	.00102 (1.65)	.00105** (2.21)	.00137** (2.37)	.00075** (2.13)	.00115** (2.23)	.00093* (1.76)	.00107** (2.31)	.00024 (0.67)
$\boldsymbol{\alpha_{i,Tu}}$	-.00097 (-1.03)	.00012 (0.21)	-.00101 (-1.22)	-.00115 (-1.36)	-.00153* (-1.70)	-.00033 (-0.41)	-.00146** (-2.16)	-.00145* (-1.88)	-.00023 (-0.49)	-.00119* (-1.67)	-.00110 (-1.53)	-.00104* (-1.73)	-.00061 (-1.01)
$\boldsymbol{\alpha_{i,We}}$	.00019 (0.21)	-.00002 (-0.03)	-.00020 (-0.25)	-.00019 (-0.23)	-.00046 (-0.52)	1.40e-06 (0.00)	.00023 (0.34)	-.00115 (-1.49)	.000569 (1.22)	.00030 (0.44)	-.00012 (-0.18)	.00010 (0.16)	.00029 (0.54)
$\boldsymbol{\alpha_{i,Th}}$	.00032 (0.35)	-.00009 (-0.10)	-.00017 (-0.20)	-.0000528 (0.950)	-.00020 (-0.23)	.00050 (0.61)	-.00014 (-0.20)	-.00065 (-0.87)	-.00054 (-1.06)	.00005 (0.07)	-.00047 (-0.65)	.00082 (1.33)	.00080 (1.42)
$\boldsymbol{\alpha_{i,Fr}}$	.00005 (0.06)	-.00006 (-0.07)	-.00006 (-0.07)	.0003913 (0.252)	-.00020 (-0.22)	.00057 (0.71)	-.00008 (-0.12)	-.00064 (-0.85)	.0006 (1.26)	.00009 (0.13)	.00014 (0.20)	.00110* (1.79)	-.00003 (-0.06)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (for a two-tailed test)
$\alpha_{i,M}$ represent the mean return on Mondays, and $\alpha_{i,Tu}$, $\alpha_{i,We}$, $\alpha_{i,Th}$, and $\alpha_{i,Fr}$ captures the excess mean return on Tuesdays, Wednesdays, Thursdays, and Fridays respectively, as compared to Mondays during the pre-crisis period

b. $R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W} D_{i,D.O.W} + \varepsilon_{i,t}$ (crisis period, i.e. from 6th August 2007 until 27th March 2009)

	Austria	Denmark	Eurozone	France	Germany	Ireland	Italy	Netherlands	Portugal	Spain	Switzerland	U.K.	U.S.
$\boldsymbol{\alpha_{i,M}}$	-.00197 (-1.07)	-.00181 (-0.95)	-.00144 (-1.06)	-.00136 (-0.86)	-.00088 (-0.67)	-.00232 (-1.25)	-.00270* (-1.81)	-.00189 (-1.30)	-.00222* (-1.82)	-.00190 (-1.23)	-.00144 (-0.91)	-.00150 (-0.83)	-.00038 (-0.28)
$\boldsymbol{\alpha_{i,Tu}}$	.00047 (0.18)	.00115 (0.45)	.00078 (0.38)	-.00046 (-0.20)	.00086 (0.44)	.00007 (0.03)	.000430 (0.21)	.00055 (-0.27)	.00050 (0.30)	.00209 (0.93)	.00031 (0.14)	.00066 (0.26)	-.00166 (-0.84)
$\boldsymbol{\alpha_{i,We}}$	.00363 (1.47)	.00177 (0.65)	.00332* (1.75)	.00399 (1.88)	.00214 (1.16)	.00289 (1.16)	.00368* (1.88)	.00466 (2.40)	.00156 (0.91)	.00236 (1.13)	.0017 (0.76)	.00204 (0.80)	.00199 (1.06)
$\boldsymbol{\alpha_{i,Th}}$	-.00004 (-0.02)	-.000486 (-0.18)	-.00116 (-0.58)	-.00273 (-1.19)	-.00102 (-0.53)	-.00229 (-0.78)	-.00023 (-0.12)	-.00136 (0.56)	-.00019 (-0.12)	-.00039 (-0.17)	.00174 (-0.56)	-.00001 (-0.01)	-.00296 (-0.44)
$\boldsymbol{\alpha_{i,Fr}}$	.00069 (0.28)	.00051 (0.20)	.00011 (0.06)	-.00010 (-0.05)	.00058 (0.31)	.00130 (0.52)	.001947 (0.96)	.00189 (-1.30)	.00209 (1.28)	.00146 (0.66)	-.00104 (-0.48)	-.00097 (-0.37)	-.00082 (-0.28)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (for a two tailed test). $\alpha_{i,M}$ represent the mean return on Mondays, and $\alpha_{i,Tu}$, $\alpha_{i,We}$, $\alpha_{i,Th}$, and $\alpha_{i,Fr}$ captures the excess mean return on Tuesdays, Wednesdays, Thursdays, and Fridays respectively, as compared to Mondays during the crisis period

Table 5.3(b), on the other hand, shows the estimated results from Eq. 5.1 during the crisis period (i.e. from 6th August 2007 until 27th March 2009). Monday effect ($\alpha_{i,D.O.W} > 0$) is present only for Euro Index and Italy during that period. And as far as the remaining countries (11 out of 13) in our sample are concerned, they showed no evidence of Monday effect during the recent financial crisis, as $\alpha_{i,D.O.W} = 0$.

Despite the fact that there was a short sale activity ban imposed by the government in Italy and several other European countries during the recent financial crisis, the findings indicate the presence of Monday effect in Euro Index and Italy. The result of the ban was that speculative short sellers would not take the risks of holding their positions during the weekend, which would otherwise mean that they will close out their position on Friday and reopen their position on the following Monday, hence contributing to the Monday effect. And as hypothesized by Chen and Singal (2003) "the behaviour of short sellers contributes to the occurrence of Monday effect due to the increasing selling pressure on Monday, and that the closing of short positions on Friday and the opening of these positions on the following Monday".

Potential reasons for the above two markets experiencing Monday effect might be due to the exuberance of the blue Monday hypothesis. The basic premise of this hypothesis asserts that investors are affected by systematic mood changes that cause negative pressures on Mondays (Rystrom and Benson, 1989). And since during a financial crisis, fear and emotions have a more widespread impact across investors, this might lead to high uncertainty avoidance, which would have a more prominent effect on Monday effect.

However, unlike French (1980) and Kamara (1997), the findings from Eq. 5.1 show evidence of a disappearing and wandering Monday effect for most cases. According the authors, the wandering Monday effect refers to "a situation whereby the pattern of the day seasonality within a market may shift overtime, in a manner that is distinguishable from a random process." According to Doyle and Chen (2009), seasonal effects continually evolve, especially since the way investment was conducted the 1970s is different from now, and hence the conditions that promoted Monday effects may no longer be present. For instance, the days on which key economic indicators were announced have changed and there is now the availability of electronic trading. Moreover, the overreaction of markets might be another reason of the change in seasonality pattern, according to De Bondt and Thaler (1985) and Lehman (1990). This might happen if enough people act upon "buy on Monday and sell on Friday", and consequently, overreaction to calendar effects might potentially push Monday returns up beyond equilibrium, hence leading to a new pattern of seasonality, which will eventually be reacted upon.

The results from Eq. 5.2 is not reported as it is simply the estimation of Eq.5.1 for whole period in our sample (i.e. Aug.t 2007 until March 2009), by adding coefficients (i.e. $\alpha^{*}_{i,M} D_c + \alpha^{*}_{\boldsymbol{i,D.O.W}} D_{\boldsymbol{D.O.W}} D_c$) and a dummy variable (i.e. $D_c = 1$) representing the financial crisis.

5.5.3. Spillover effect

The findings pertaining to Table 5.4 below on the other hand is estimated from Eq. 5.4 is based upon the whole period in this study (i.e. July 2004 until March 2009). The results from Eq. 5.3 are not reported since we wish to investigate for contagion effects (i.e. the excess spillover during the crisis period, relative to the pre-crisis period) instead of just comparing the spillovers across two distinct periods.

The estimated results show how the spillover from the U.S. market is different in the crisis period relative to the pre-crisis period, as there is a dummy variable taking the value of 1 during the crisis period, and 0 otherwise. In other words, Eq. 5.4[18] is used to estimate contagion effect, that is, the excess co-movement during the crisis period, relative to the pre-crisis period.

It can be observed from Table 5.4 that there is positive and significant spillover from the U.S. during the pre-crisis period, i.e. $\beta_i > 0$ for all the markets in our sample (except for Denmark). Following the outbreak of the 2007 Financial crisis, there seem to be contagion effects from the U.S. market to Austria, Denmark, Portugal and U.K., as $\beta_i^* > 0$. However, there is a lower spillover effect during the crisis period, relative to the pre-crisis one for Euro Index, France and Germany, given that $\beta_i^* < 0$. And as far as other markets (i.e. Ireland, Netherlands, Spain and Switzerland) in our sample are concerned, there has not been an impact on the spillover effect caused by the crisis, i.e. $\beta_i^* = 0$.

[18] Note that Eq. 5.4 is a basic contagion model unlike the ‘Globalisation model’ in Chapter 3 and 4.

Table 5.4: Estimating spillover and contagion effect during the pre-crisis and crisis respectively (Based on Eq. 5.4)

$R_{i,t} = \alpha_i + \alpha_i^* D_c + \beta_i R_{US,t} + \beta_i^* R_{US,t} D_c + \varepsilon_{i,t}$

	$\boldsymbol{\alpha_i}$	$\boldsymbol{\beta_i}$	$\boldsymbol{\alpha_i^*}$	$\boldsymbol{\beta_i^*}$
Austria	.00113** (4.13)	.75046*** (16.35)	-.00105** (-1.96)	.16416*** (2.94)
Denmark	.000089 (0.43)	.02034 (0.90)	-.000170 (-0.35)	.77030*** (21.48)
Eurozone	.000198 (1.46)	.98168*** (37.54)	-.0002718 (-1.03)	-.12121 (-3.82)
France	.000238* (1.74)	.97535*** (33.74)	-.00023 (-0.83)	-.06632 (-1.94)
Germany	.00041** (2.37)	1.0651*** (35.92)	-.00019 (-0.56)	-.29573 (-8.03)
Ireland	.00059*** (2.70)	.66186*** 18.37)	-.00086* (-1.69)	.011255 (0.25)
Italy	.00033** (2.08)	.77138*** (27.14)	-.00074** (-2.13)	.02375 (0.71)
Netherlands	.00024 (1.49)	.88473*** (34.20)	-.00038 (-1.13)	-.02007 (-0.58)
Portugal	.00058*** (3.32)	.32647*** (12.17)	-.00128*** (-3.09)	.18166*** (5.61)
Spain	.00057*** (3.38)	.8029*** (29.38)	-.0007** (-2.03)	.00499 (0.15)
Switzerland	.00037*** (2.66)	.74924*** (25.83)	-.00053* (-1.74)	.02834 (0.80)
U.K.	-.00086** (5.31)	.62688*** (22.30)	-.00102** (-2.56)	.1782*** (4.82)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

β_i represent the spillover from U.S. to a European Country i on during the pre-crisis period. β_i^* represents the excess spillover (i.e. contagion) during the crisis period over the crisis period. Evidence of contagion is observed if $\beta_i^* > 0$ (one-sided test).

5.5.4. Spillover effect across days of the week

From the previous section, spillovers during the pre-crisis period, crisis period, and excess spillovers (i.e. contagion) during the crisis as compared to the pre-crisis period could be observed. One of the drawbacks of Eq. 5.4, is that it looks only at the excess average co-movement during the crisis as compared to the pre-crisis period. However, spillovers might differ across the days of the week and contagion might not occur during all days of the week, but only on certain days of the week. As a result, Eq. 5.4 might not detect contagion effect, if a positive spillovers during a particular day of the week is met by a negative spillover on another day during that same week, hence eliminating the effect. Another instance might be whereby Eq. 5.4 shows evidence of contagion during the crisis period (i.e. existence of contagion overall), but actually this contagion is occurring on a particular day during the crisis period, which can be shown by using Eq. 5.6. Henceforth, Eq. 5.6 is employed to capture spillovers across the different days of the week and investigate how the crisis changes the spillover patterns. Moreover, there might be occasion whereby Eq. 5.4 shows no contagion, but Eq. 5.6 shows evidence of contagion.

Table 5.5 below is based on Eq. 5.6 and the results shows the spillovers for Mondays until Fridays from the U.S. market for the whole sample period (i.e. July 2004 until March 2009). Most importantly, the findings illustrate how the spillovers across the different days of the week during the crisis period differ from the pre-crisis period, and whether a day-of-the-week effect can be reflected while estimating spillovers.

As established previously in this chapter, I define the day-of-the-week effect in spillovers as a significant difference between Monday and non-Monday spillovers, i.e., $\beta^*_{i,D.O.W} \neq 0$. In addition, the day-of-the-week effect in contagion (i.e., contagion differs significantly across weekdays) can be observed if 1) either there was contagion on Mondays ($\beta^*_{i,M} > 0$) and spillovers change significantly on any remaining weekday ($\beta^*_{i,D.O.W} \neq 0$), or 2) there was no contagion on Mondays but spillovers changed significantly on any remaining weekday such that the resulting non-Monday effect ($\beta^*_{i,M} + \beta^*_{i,D.O.W}$) is significantly positive (positivity assures existence of contagion).

Firstly, day-of-the-week effects in spillovers before the crisis first is examined. Most of the markets (except for Denmark) in our sample experienced a positive and significant spillover from the U.S. market on Mondays during the crisis period, i.e. $\beta_{i,M} > 0$. Further, Monday spillovers tend to remain at a constant level across the week, as $\beta_{i,D.O.W}$ parameters are mostly insignificant, except for a few exceptions affecting only three countries (Austria, Portugal, and the U.K.). Hence, the overall evidence is not supportive of the hypothesis that *pre-crisis* spillovers from the U.S. varied in intensity across days of the week.

Following the crisis outbreak, there is some evidence of financial contagion from the U.S. The baseline model (5.4) detected contagion for Austria, Denmark, Portugal, and the U.K. Model 5.6 gives a deeper insight into the nature of this phenomenon. Firstly, it confirms that U.S. spillovers have had a stronger effect on each of these countries, on some days of the week.

The coefficients $\beta^*_{(us)m}$ and $\beta^*_{(us)m} + \beta^*_{(us)D.O.W}$ represent excess spillover (i.e. contagion) on Monday and other days of the week respectively during the crisis period, relative to the pre-crisis period. It can be observed that there has been contagion effect only on Mondays (as $\beta^*_{(us)m} > 0$) for U.K. and Austria during the crisis period. On the other hand, for Denmark and Portugal contagion occurred for more than one day during the week. It can be observed from Table 5.4 that Denmark is experiencing contagion from U.S. on Mondays and Tuesdays, as $\beta^*_{(us)m} > 0$ and $\beta^*_{(us)tu} > 0$ whereas Portugal shows evidence of contagion on Tuesdays until Fridays, i.e. $\beta^*_{(us)tu} > 0, \beta^*_{(us)w} > 0, \beta^*_{(us)th} > 0$ *and* $\beta^*_{(us)f} > 0$ This is one advantage of this model, as it enables us to determine contagion effects across different days of the week effect, instead of just having an overall overview of whether a market has experienced contagion during the crisis period.

Moreover, from Table 5.4, it can be seen how Eq. 5.6 outperforms Eq. 5.5 in terms of examining contagion. Eq. 5.6 allows one to detect contagion daily, whereas Eq. 5.4 investigates for contagion across the whole crisis period and assumes that all days of the week are identical, which is a general viewpoint that has been adopted by most financial contagion literatures (e.g. Forbes and Rigobon, 2002; Baele et al., 2012; Zhang et al., 2013).

For remaining countries, the result of no contagion, on average, from model (5.4) is not rejected for any weekday by model (5.6), i.e., although theoretically possible, I did not observe any case where contagion would prevail only on some weekdays but would be undetected when estimated for all weekdays treated as identical.

Table 5.5: Estimating days of the week effect and spillovers across the days of the week (Based on Eq. 5.6)

$$R_{i,t} = \alpha_{i,M} + \alpha_{i,D.O.W}D_{i,D.O.W} + \beta_{i,M}R_{US,t} + \beta_{i,D.O.W}R_{US,t}D_{D.O.W} + \alpha^{*}_{i,M}D_c + \alpha^{*}_{i,D.O.W}D_{D.O.W}D_c + \beta^{*}_{i,M}R_{US,t}D_c + \beta^{*}_{i,D.O.W}R_{US,t}D_{D.O.W}D_{c_t} + \varepsilon_{i,t}$$

	Austria	Denmark	Eurozone	France	Germany	Ireland	Italy	Netherlands	Portugal	Spain	Switzerland	U.K.
$\alpha_{i,M}$	.00158** (2.59)	-.0000209 (-0.05)	.000141 (0.39)	.000039 (-0.10)	.0007141* (1.72)	.0006027 (1.13)	.000611 (1.62)	.0006986* (1.76)	.0004498 (1.29)	.000599 (1.62)	.0003697 (0.91)	.000809** (2.24)
$\alpha_{i,Tu}$	-.0011682 (-1.41)	.0002441 (0.48)	-.0002734 (-0.53)	-.0004929 (-0.90)	-.001028* (-1.78)	-.0003357 (-0.49)	-.0012177** (-2.34)	-.0008409 (-1.51)	.0000193 (0.04)	-.000577 (-1.10)	-.0004937 (-0.87)	-.000941** (-2.01)
$\alpha_{i,We}$	-.0007327 (-0.86)	.0002768 (0.55)	.0000458 (0.09)	-.0000308 (-0.05)	-.0005283 (-0.95)	-.0000293 (-0.04)	.0001973 (0.38)	-.0008385 (-1.55)	.0004343 (0.95)	.000286 (0.56)	.0000352 (0.06)	-.000544 (-1.11)
$\alpha_{i,Th}$	-.0003464 (-0.41)	-8.63e-06 (-0.01)	-.0003612 (-0.72)	-.0002615 (-0.48)	-.000622 (-1.09)	-.0000465 (-0.06)	-.000651 (-1.26)	-.0007802 (-1.49)	-.0005976 (-1.25)	-.0003503 (-0.65)	-.0003234 (-0.57)	.000264 (0.53)
$\alpha_{i,Fr}$	-.0000371 (-0.04)	.0000546 (0.08)	.0008405 (1.58)	.0011901** (2.10)	.0005037 (0.84)	.0004275 (0.59)	.0002238 (0.43)	.0000651 (0.11)	.0007705* (1.67)	.0004913 (0.93)	.0007817 (1.34)	.001169** (2.32)
$\beta_{i,M}$	.43848*** (4.06)	.025794 (0.40)	.966516*** (13.99)	.980926*** (12.35)	1.076843*** (13.32)	.547689*** (5.42)	.7649304*** (9.58)	.909981*** (12.53)	.459642*** (6.70)	.82934*** (11.76)	.761135*** (10.34)	.577952*** (8.19)
$\beta_{i,Tu}$	.407851*** (2.65)	.0116108 (0.16)	.1751853* (1.84)	.1535927 (1.45)	.1017662 (0.94)	.0687791 (0.52)	.1028064 (0.94)	.1090963 (1.08)	-.233798** (-2.43)	.0744446 (0.74)	.1326065 (1.20)	.0483277 (0.50)
$\beta_{i,We}$	.3203197** (2.33)	.0389958 (0.58)	-.0564873 (-0.68)	-.1245274 (-1.30)	-.0778679 (-0.83)	.0586138 (0.48)	-.0227893 (-0.24)	-.1256546 (-1.45)	-.1230269 (-1.48)	-.0767313 (-0.91)	-.051137 (-0.56)	.0416042 (0.48)
$\beta_{i,Th}$	.398464*** (2.59)	-.0156605 (-0.17)	.059528 (0.67)	.0320496 (0.32)	.0522866 (0.50)	.2004877 (1.48)	.0586207 (0.56)	-.0021539 (-0.02)	-.1166037 (-1.30)	-.0271348 (-0.29)	-.0266279 (-0.28)	.182259* (1.93)
$\beta_{i,Fr}$	.37438*** (2.74)	-.0156447 (-0.17)	-.0235095 (-0.27)	-.009837 (-0.10)	-.0585002 (-0.58)	.1963585 (1.58)	-.0552561 (-0.58)	-.0298806 (-0.33)	-.17438** (-1.98)	-.0420241 (-0.46)	-.0227793 (-0.24)	-.0647647 (-0.72)
$\alpha^{*}_{i,M}$	-.00232* (-1.83)	-.0010248 (-0.83)	-.0011529 (-1.49)	-.0004181 (-0.47)	-.0009759 (-1.09)	-.0006245 (-0.52)	-.0016115** (-1.96)	-.0012738 (-1.54)	-.002031** (-2.55)	-.0015339* (-1.68)	-.0006805 (-0.81)	-.00249*** (-2.91)

$\alpha^*_{i,Tu}$	.001889 (1.09)	.0029854*** (2.05)	.0022102** (1.97)	.0015318 (1.27)	.0027904** (2.25)	-.0010603 (-0.64)	.0020325* (1.73)	.0014476 (1.24)	.0014567 (1.38)	.002708** (2.18)	.0017663 (1.37)	.003066** (2.54)
$\alpha^*_{i,We}$	.0018304 (1.10)	.0001868 (0.12)	.000751 (0.71)	.0006616 (0.57)	.0004049 (0.34)	.0009067 (0.56)	.0008663 (0.77)	.0019554* (1.71)	-.000524 (-0.50)	-.0002317 (-0.19)	.0000867 (0.07)	.003544** (2.92)
$\alpha^*_{i,Th}$	.0013279 (0.76)	-.0004568 (-0.27)	.0013847 (1.28)	.0001382 (0.12)	.0012293 (0.99)	-.0020814 (-1.24)	.0010209 (0.82)	.0003537 (0.30)	.001281 (1.16)	.0007449 (0.58)	.0004988 (0.41)	.0013103 (1.07)
$\alpha^*_{i,Fr}$	.0013787 (0.77)	.0009888 (0.55)	.0000447 (0.04)	-.0005917 (-0.49)	-.0001011 (-0.08)	.000978 (0.59)	.0002142 (0.19)	.0009933 (0.78)	.0013834 (1.23)	.0006467 (0.52)	.0004988 (-1.28)	.0004284 (0.34)
$\beta^*_{i,M}$	.4199*** (3.34)	.7842973*** (8.88)	-.1282976 (-1.52)	-.104829 (-1.09)	-.253793 (-2.68)	.0628367 (0.54)	.045004 (0.52)	-.0338083 (-0.40)	-.0802557 (-1.06)	-.0738379 (-0.89)	.0243865 (0.30)	.1433326* (1.74)
$\beta^*_{i,Tu}$	-.222362 (-1.19)	.2198267** (1.96)	-.051747 (-0.45)	-.0160836 (-0.13)	-.0679983 (-0.52)	-.0066469 (-0.04)	-.0264572 (-0.21)	-.011675 (-0.10)	.444667*** (3.97)	.0550478 (0.46)	-.0569092 (-0.42)	.1773258 (1.47)
$\beta^*_{i,We}$	-.2473809 (-1.49)	-.0530849 (-0.45)	.0840004 (0.81)	.1260893 (1.08)	-.0679983 (-0.41)	.1645257 (1.13)	.0252833 (0.23)	.0948455 (0.89)	.2287566** (2.36)	.1519217 (1.42)	.0024633 (0.02)	.0322887 (0.30)
$\beta^*_{i,Th}$	-.289782 (-1.54)	-.0019902 (-0.01)	-.0784631 (-0.69)	-.0320409 (-0.25)	-.1157546 (-0.89)	-.1773466 (-1.07)	-.1259895 (-1.01)	-.0377242 (-0.30)	.294565*** (2.64)	.0317307 (0.27)	-.0124764 (-0.11)	-.0628615 (-0.51)
$\beta^*_{i,Fr}$	-.38843** (2.35)	-.1199377 (-0.94)	.0492604 (0.47)	.0266069 (0.23)	-.0006821 (-0.01)	-.1756042 (-1.21)	-.0030027 (-0.03)	-.0221981 (-0.20)	.355591*** (3.46)	.1073624 (0.99)	.0000613 (0.00)	.0833874 (0.79)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

$\alpha_{i,M}$ represent the intercepts of Eq. 6 on Mondays, and $\alpha_{i,Tu}$, $\alpha_{i,We}$, $\alpha_{i,Th}$, and $\alpha_{i,Fr}$ captures change in intercepts on Tuesdays, Wednesdays, Thursdays, and Fridays respectively, as compared to Mondays during the pre-crisis period.

$\alpha^*_{i,M}$ represent the intercepts during the crisis period over the pre-crisis period on Mondays. $\alpha^*_{i,Tu}$, $\alpha^*_{i,We}$, $\alpha^*_{i,Th}$ and $\alpha^*_{i,Fr}$ captures change in intercepts on Tuesdays, Wednesdays, Thursdays, and Fridays respectively, as compared to Mondays during the crisis period over the pre-crisis crisis period.

$\beta_{i,M}$ represent the spillovers from U.S. to Country *i* on Mondays, and $\beta_{i,Tu}$, $\beta_{i,We}$, $\beta_{i,Th}$, and $\beta_{i,F}$ captures the excess spillovers on Tuesdays, Wednesdays, Thursdays, and Fridays respectively, as compared to Mondays during the pre-crisis period. $\beta^*_{i,M}$ represent the contagion during the crisis period over the pre-crisis period on Mondays. Day of the week effect on contagion on non-Mondays can be identified by $\beta^*_{i,M} + \beta^*_{i,D.O.W}$.

When the results from Table 5.4 and Table 5.5 are compared, it can be observed from the former that there is evidence of contagion for Austria, Denmark, Portugal and U.K. However, Table 5.4 illustrates that this contagion effect might occur only during certain days of the week, and not necessarily across all days of the week. As discussed in the previous chapters, the fact there is an uneven occurrence of contagion across the week might be due factors leading to the Monday effect anomaly and the release of macro-economic data on particular days of the week. For instance, the ban of short sales activities in certain economies (leading to international investors might have shift their short selling in countries where it was not banned), an accentuating blue Monday hypothesis, and the surge in the number of investors taking a short view due to liquidity needs during the recent financial crisis might lead to a Monday effect and this effect might be transferred to other markets during a turmoil period. Moreover, the announcement of macro-economic data such as the release of nonfarm payrolls on Fridays, FED Decision on Wednesdays, ECB rate decision of Thursdays, Employment figures on Wednesdays might lead to contagion effect being different across the days of the week.

5.6. Conclusion

This paper explores the possible existence of Monday effects and contagion effects during different days of the week across 13 countries before and during the financial crisis, using time-aligned data (i.e. 4 p.m. GMT). Following the fact that there were continuous changes in economic policies and conditions (e.g. ban on short selling activities, changes in institutional investors' trading pattern, and changes in investors' behaviour pertaining to uncertainty in the market) during the recent global financial crisis, this might have had an impact on Monday effect, and contagion effect.

The results of this chapter support the literature on weakening Monday effect (for e.g. Kohers et al., 2004; Gu, 2004; Marquering et al., 2006). Before the outbreak of the crisis all countries in our sample are either experiencing a reversal or disappearing Monday effect. And during the crisis period, there are only two markets (i.e. Euro Stocks and Italy) that showed evidence of contagion effect. One reason attributed to the effect of this anomaly in the two above mentioned stocks might due to the growing uncertainty and more pronounced blue Monday hypothesis during the crisis period, leading to investors liquidating their positions on Monday or delay their trades. The findings pertaining to this chapter show very little evidence of Monday effects, but there is still significant general weekday effect, which provides evidence for market inefficiency. This "twist" in Monday effect is expected as the way business and investment strategies were conducted forty years ago is different from how it is done today, for instance settlement procedure and the days key economic indicators are publicly released has changed (Steeley, 2001). Moreover, the availability of electronic trading has the potential to alter the significance of each of the day of the week. Therefore, many forces may drive this wandering seasonality effect. Hence it can be said that the findings pertaining to this chapter is in line with the adaptive market hypothesis, a state whereby anomalies can still exist, but underlie cyclical variations which can be due to changes in investment styles, trends and investor behaviour (Lo, 2004).

Having looked at Monday effect across 13 equity markets, a novel contribution of this paper is that, spillover and contagion effect across the different days of the week is also examined from U.S. market to other economies during the pre-crisis and crisis period. Most contagion research studies look at the average spillover over a certain period of time, and this might not be an effective way of detecting contagion effect as it can be observed from the estimations that spillovers differ across the days of the week. From the preliminary model of contagion, it can be observed that there is contagion effects in four countries, namely, Austria, Denmark, Portugal and U.K. However, while using the robust model to test for spillover and contagion across the different days of the week, it can be noticed that the countries mentioned above did not experience contagion consistently during every day of the week, but instead the excess co-movement was happening only during certain days of the week.

There are various reasons why exploring Monday effect is important, despite the fact that it is indeed a well-researched topic. First, model specifications may have been inadequate for the detection of Monday effect. For the purpose of this chapter, a robust model (more precisely, a GJR GARCH model) is used and non-normality of residuals, autocorrelation, ARCH effects and heteroscedasticity is accounted for. Moreover, this study covers many countries, and since the period of our study covers the recent financial crisis, I believe that it is important to see whether there has been any change about how markets are affected by such anomaly during such a turmoil period. Furthermore, it is also interesting to examine whether spillovers differ across the days of the week, which is an important contribution towards the literature pertaining to contagion effect.

APPENDIX C

C.1: Augmented Dicker Fuller test

ADF Test	Stock Prices				Stock Returns			
	T Stats	1% C.V	5% C.V	10% C.V	T Stats	1% C.V	5% C.V	10% C.V
		-3.430	-2.860	-2.570		-3.430	-2.860	-2.570
Austria	-0.487				-32.451			
Denmark	-0.695				-32.649			
Euro Index	-0.118				-36.725			
France	-0.182				-36.801			
Germany	-1.382				-36.656			
Ireland	-0.179				-33.172			
Italy	0.819				-34.368			
Netherlands	0.387				-35.153			
Portugal	-0.316				-32.989			
Spain	-1.154				-35.679			
Switzerland	-0.554				-35.283			
U.K.	-1.273				-32.449			
U.S.	-0.163				-37.487			

ADF test is conducted for the daily log and aggregate stock market returns for each of the 13 countries for the full sample (July 2004-March 2009). The lag length is selected using SIC, and the t-statistics and critical values are compared in order to test the null hypothesis of non-stationarity.

C.2: Johansen Test using Schwaz Bayesian Information Criterion (SBIC)

	SBIC	HQIC	AIC	Number of lags
Austria				2
Max Rank: 0	-11.73233*	-11.74802*	-11.7575*	
1	-11.72341	-11.74695	-11.76116	
2	-11.71762	-11.74377	-11.75956	
Denmark				2
Max Rank: 0	-12.29094*	-12.30663	-12.3161*	
1	-12.28638	-12.30991*	-12.32412	
2	-12.28109	-12.30724	-12.32303	
Eurostoxx				2
Max Rank: 0	-12.86862*	-12.88433*	-12.89381*	
1	-12.8579	-12.88146	-12.89569	
2	-12.85207	-12.87826	-12.89407	
France				2
Max Rank: 0	-12.81544*	-12.83113*	-12.84061*	
1	-12.80237	-12.82591	-12.84011	
2	-12.79657	-12.82272	-12.83851	
Germany				2
Max Rank: 0	-12.54066*	-12.55635*	-12.56582*	
1	-12.52901	-12.55255	-12.56676	
2	-12.5236	-12.54976	-12.56554	
Ireland				1
Max Rank: 0	-11.77849*	-11.78372	-11.78687*	
1	-11.772	-11.78508*	-11.79298	
2	-11.76641	-11.7821	-11.79157	
Italy				3
Max Rank: 0	-12.75233*	-12.77848*	-12.79427*	
1	-12.73984	-12.77384	-12.79436	
2	-12.73447	-12.77108	-12.79318	
Netherlands				2
Max Rank: 0	-12.64711*	-12.6628	-12.67228*	
1	-12.64068	-12.66422*	-12.67843	
2	-12.63493	-12.66108	-12.67687	

Portugal				1
Max Rank: 0	-12.61005*	-12.61528*	-12.61844*	
1	-12.59901	-12.61208	-12.61998	
2	-12.59319	-12.60888	-12.61835	
Spain				2
Max Rank: 0	-12.56123*	-12.57693*	-12.5864*	
1	-12.55121	-12.57475	-12.58896	
2	-12.54568	-12.57184	-12.58762	
Switzerland				2
Max Rank: 0	-12.74758*	12.76327* -	12.77274*	
1	-12.73315	-12.75669	-12.7709	
2	-12.72741	-12.75356	-12.76935	
U.K.				3
Max Rank: 0	-12.47053*	-12.49668*	-12.51247*	
1	-12.45714	-12.49114	-12.51167	
2	-12.45131	-12.48792	-12.51003	

Johansen test is conducted for the for all pairs of each 12 countries' weekly log indices with the World stock market portfolio log indices for the period from (July 2004-March 2009). The test uses SBIC to indicate whether the pairs are co-integrated or not.

C.3 Heteroscedasticity from an OLS model (based on Eq. 5.6)

	Chi(2)	**P Value**
Austria	352.13	0.0000
Denmark	252.56	0.0000
Euro Index	80.01	0.0000
France	89.69	0.0000
Germany	67.29	0.0000
Ireland	49.29	0.0000
Italy	161.98	0.0000
Netherlands	148.79	0.0000
Portugal	269.59	0.0000
Spain	91.43	0.0000
Switzerland	115.35	0.0000
U.K.	252.53	0.0000

The White's (1980) test is used to test the null hypothesis of homoscedasticity against heteroscedasticity. The null hypothesis is rejected all countries at 1% level which means that there is a substantial amount of heteroscedasticity from an OLS model.

C.4: Normality Test

	W	V	Z	Prob>z
Austria	0.93496	123.576	12.478	0.000
Denmark	0.96119	73.716	11.140	0.000
Eurostoxx	0.95706	74.662	11.136	0.000
France	0.96376	127.370	12.831	0.000
Germany	0.95481	114.669	12.414	0.000
Ireland	0.93504	168.670	13.435	0.000
Italy	0.95079	93.679	11.762	0.000
Netherlands	0.94989	95.385	11.808	0.000
Portugal	0.94989	95.385	11.808	0.000
Spain	0.02014	3153.494	21.264	0.000
Switzerland	0.94479	194.059	13.946	0.000
U.K.	0.95289	141.153	13.033	0.000

Shapiro Wilk test is conducted after modelling equation (5.6) to test for the normality of the error terms. Given the p-values are compared to the 5% significance level in order to determine whether the hypothesis of normality should be rejected or not.

C.5: ARCH LM effects tests after GJR GARCH estimation

	Lags	Chi2	Df	Prob>chi2
Austria	1	0.097	1	0.7553
Denmark	1	0.002	1	0.9675
Eurostoxx	1	0.005	1	0.9459
France	1	0.024	1	0.8773
Germany	1	0.003	1	0.9556
Ireland	1	0.001	1	0.9794
Italy	1	0.032	1	0.8583
Netherlands	1	0.151	1	0.6979
Portugal	1	0.008	1	0.9269
Spain	1	0.000	1	0.9897
Switzerland	1	0.000	1	0.9951
U.K.	1	0.034	1	0.8545

Engle's ARCH LM test is conducted after modelling equation (5.6) for ARCH effects. Given the p-values are compared to the alphas (5% significance level) in order to determine whether there are any remaining ARCH effects in the residuals after estimating Model 5.6 with a GJR GARCH framework.

Chapter 6. Summary and Conclusions

6.1. Conclusion

This thesis explores financial contagion across developed and emerging equity markets, financial and non-financial sectors across the globe. Given the controversies on the different definitions and methods used to test for contagion, this thesis develops and employs a more robust method and realistic definition in order to detect financial contagion during the recent financial crisis. Moreover, since contagion is not a phenomenon that occurs consistently over a turmoil period, this thesis investigates the occurrence of contagion from U.S. to 12 European equity markets on a daily basis, in order to determine whether contagion manifests itself more on a particular day relative to others.

Apart from the Introduction and Conclusion chapter, this thesis consists of four other chapters, with chapter 2 being a literature review on financial contagion whereas the other three chapters are based on the empirical analysis of contagion. Chapter 2 describes the literature of contagion in details. Firstly, the different definitions and disagreements upon how to detect contagion throughout. As established in chapter 2, the most commonly used meaning of contagion is the one proposed by Forbes and Rigobon (2002) who describe it as a significant increase in cross-market linkages after a shock is transmitted from one country to another. Moreover, the different channels through which a crisis can be propagated is discussed in detail and can be categorised into fundamental and behavioural causes. The former consists of factors such as trade and financial linkages, global nature of businesses and common shocks (e.g. increase in world interest rates), whereas behavioural causes is made up of liquidity problem, investors behaviour, information asymmetries and wake-up calls. Further, the factors that contribute towards an intensification of a crisis, such as financial innovations and liberalization of financial services are also discussed. In the last part of this chapter the empirical methods used in previous literature to investigate financial contagion, together with their advantages and limitations are discussed. The methods include probability models, correlation analysis, VAR models and ARCH/GARCH frameworks.

The third chapter is based on developing a new model to distinguish between genuine contagion and growing interdependence between both developed and developing equity markets with the world stock market portfolio. This method accounts the pre-existing time-varying integration process between markets, which consequently leads to a novel definition of contagion, whereby it refers to an increase in co-movement in asset prices following the outbreak of a crisis relative to what the co-movement would have been if the crisis did not occur and the same integration process as the pre-crisis period was being followed. This model also enables us to identify how the recent financial crisis has unfolded in 25 equities market, i.e. whether the crisis has hit a particular country at the first stage of the crisis period (a situation which I describe as 'shock' contagion) or at a later phase (whereby the term 'recoupling' or 'kink' contagion can be used to describe such instances). The findings of contagion being confined into specific phases of the crisis period correspond well with, for example, Dungey and Gajurel (2014), Kenourgios and Dimitriou (2015) and Dungey et al. (2015), but in our approach these phases emerge endogenously from model estimation. The most common contagion type identified here is shock contagion. This type of market reaction at crisis' onset corresponds to the "wake up call" hypothesis of contagion by Goldstein (1998) but could also be generated by irrational changes in investors' sentiment, especially when combined with their herding behaviour. A GJR GARCH model is used and the empirical findings show the 18 instances of contagion from the world stock market portfolio, with some market showing contagion effects temporarily or across the whole crisis period. In addition to this, the results also show that during a crisis, economies tend of dis-integrate but, once economies around the world show signs of recovery, the integration process goes back to what is was before the outbreak of the crisis period.

The fourth chapter focuses on contagion across the financial sector and real economies across 25 countries. The literature on financial contagion has been mostly focused on equity markets and little attention has been paid to contagion at a sectoral level. The fact that the return dynamics of sectors are not identical and some real economy sectors (e.g. those that involve tradable goods) are more susceptible to shocks, it is interesting to test for genuine contagion. The same definition and empirical method as the last chapter is employed to examine financial contagion across different sectors. This chapter also sheds light on the potential causes that lead to contagion at a sectoral level and it includes dependency on external financing, industries' valuation and investment, trade channel, information asymmetry and risk aversion amongst others. The results show that the real economy was mostly affected by the global financial sector relative to domestic financial sectors. This demonstrate that the recent financial crisis had a direct impact on the real economies, especially if the later were borrowing and lending globally, or the sectors involve tradable products. Moreover, sectors across developed countries were more vulnerable towards the crisis as compared to emerging markets. In addition to this, similar to Baur (2012), Kenourgios and Dimitriou, (2015) and Bekaert et al., (2014), it is observed from our findings that basic materials and the financial sector are the one depicting highest occurrences of contagion across the 25 countries, and technology and healthcare showing less vulnerability towards the recent crisis. This chapter contributes to the literature of real economy contagion in terms of way it is modelled, i.e. using a time-varying method hence allowing one to know at what point during the crisis were the sectors affected. For instance, the basic material sector was affected at the beginning of the crisis period and experienced contagion throughout the whole crisis period for almost all countries examined, whereas the utilities sector in Germany experienced contagion at a much later stage of the crisis. Overall, this study shows that sectors were affected mostly at the start of the financial crisis. This sectoral level analysis is important for investors and portfolio managers as it suggests that diversification benefits may exist in certain markets even in periods of severe global turmoil.

Chapter 5 combines calendar anomalies together with the examination of financial contagion. More specifically, this chapter looks at the Monday effect puzzle for a period of approximately 5 years (July 2004 until March 2009) and investigates whether there is indeed a lower return on Mondays relative to other days of the week in 13 developed equity markets or whether there has been a disappearance or reversal of this effect. In addition to this, the impact of the recent financial crisis on this puzzle is also explored. By employing a GJR GARCH model, it is shown that most markets in this sample show a reversal or a wandering Monday effect. And, the most important and novel part of this chapter is the examination of contagion effects across the different days of the week. The main motivation of this chapter is in conjuncture with the previous two chapters, i.e. contagion does not occur consistently. Some markets are affected immediately after the outbreak of a crisis, given the vulnerability of the economy (in terms of trade and financial linkages or current account deficit amongst others), investors' risk perception, and the actions taken by the country in order to deal or lessen the effect of the crisis. However, there are some equity markets or sectors experiences a shock at much later phase of the crisis. Hence, it can be postulated that contagion (i.e. a significant increase in co-movement during the crisis period, relative to the pre-crisis period) might been different across the days of the week due to short selling activities, investors' risk perception, or major macro-economic news announcement on a particular day of the week. The empirical findings show that contagion from U.S. to 12 European equity markets might occur only during certain days of the week, and not necessarily across all days of the week. More specifically, the results show that during the pre-crisis period, the majority of economies experience a positive spillover from the U.S. on Mondays relative to other days of the week. However, as the crisis struck, most of the countries examined were not showing any signs of contagion, except for four of them. U.K. and Austria were experiencing contagion effects only on Mondays whereas other two economies were showing evidence of contagion effects only during a few days of the week. The findings contribute to the literature in the sense that it provides a more detailed picture of financial contagion as compared to a more traditional approach. It reveals that in countries for which contagion was found, it was not a persistent phenomenon but rather concentrated on specific days of the week and show how the weekly pattern differ and are universal across countries.

A deepening international integration around the world has led to greater risk sharing, which as a result promoted economic development. However, growing interdependence has also led to heightening risk of contagion. The findings of the Chapter 3, 4 and 5 of this thesis contribute to academic literature and suggest implication for both investors and financial regulators, especially during times of uncertainties and while restructuring their portfolio. Chapter 3 and 4 show the time-varying integration process and it is essential for portfolio investors to have information about time-varying linkages between asset markets and how the impact of these unpredictable and fast changing linkages can be minimized, in order to devise safer investment strategies for their client. For example, in presence of kink contagion the change in comovements between markets is minimal initially and gives investors the time to rebalance their portfolios, whereas shock contagion changes these comovements abruptly and investors should rather try to predict/hedge against it ex ante. Chapter 5 is also of crucial importance for investors as it shows whether there is any pattern in contagion, i.e. whether day-of-the-week effect has an impact on contagion results. For instance, the release of macro-economic data (e.g. Non-Farm payroll) on a specific date of the week may have an impact on U.S equity markets, and spillover to the other equity markets.

> Moreover, the results of thesis can have a significant impact on international portfolio diversification, as it is shown in the thesis which country or sector has been least affected by the crisis and the time-varying co-movements depicts at which stage of the crisis was the country or sector was affected. For instance, in the presence of recoupling contagion, a country or sector does not show signs of contagion only at the beginning of the crisis but instead shows a disintegration with the world economy followed by showing evidence of contagion at a later stage of the crisis. . This information might also help regulators in the sense that they might not implement measures such as capital controls if contagion is only temporary in certain sectors.

6.2. Limitations

Like any other research studies, this thesis has some limitations, which are as follows:

- In chapter 3 and 4, prices for the equity markets, financial and non-financial sectors are collected from DataStream from 27th October 1979 until 27th March 2012, resulting in 1693 weeks of observation. However, due to data unavailability for certain equity markets or sectors, there are less weeks being observed, which makes the pre-crisis period shorter, but the crisis and post crisis period is consistent across the whole sample.
- Moreover, Chapter 3 and 4 assumes that there is a linear time-varying integration process amongst markets. However, despite the fact that, in reality the linkages are non-linear, the model still captures positive and negative interdependence trends, enabling us to identify genuine contagion.
- While using GARCH framework to examine contagion at a sector level, there were some issues encountered in terms of non-convergence for a few sectors, as the prices available from DataStream were not available across the complete pre-crisis and crisis period. Moreover, there are some sectors which are non-existent in certain countries.
- In chapter 3 and 4, a novel approach was used to contagion in terms of definition and method to detect this phenomenon. However, in chapter 5, the definition proposed by Forbes and Rigobon (2002) is used as the aim of this chapter is only to show that contagion does not occur consistently across all days of the week, and not to detect genuine contagion as the previous empirical chapters of this thesis.

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