VULNERABILITY IN GLOBAL FINANCIAL NETWORKS

By

Moses Kipkemei Kangogo

(M.Fin, BSc(ActuarSc))

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Declaration of Originality

This thesis is entirely the product of my scholarly work unless otherwise indicated in the text or references acknowledged. Any inaccuracies of fact or faults in reasoning are my own, and accordingly, I take full responsibility. This thesis to the best of my knowledge, is original and has not been submitted either in whole or part for another degree or diploma in any other institution.

Moses Kipkemei Kangogo

Hobart, Tasmania
28 April 2020

Preface

Authority of Access

Statement Regarding Published Work Contained in Thesis

This thesis constitutes collaborative efforts with my supervisors. Chapter 2 is co-authored with the late Professor Mardi Dungey and Dr Vladimir Volkov and some sections of this chapter published in the International Review of Financial Analysis. Chapter 3 is a joint work with Dr Vladimir Volkov. Chapter 4 is co-authored with the late Professor Mardi Dungey and Dr Vladimir Volkov and published in the ADB Economics Working Paper Series. Chapter 5 is a joint work with Dr Vladimir Volkov.

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Dedication

This thesis is dedicated to my former supervisor Professor Mardi Dungey for her mentorship, extraordinary support and encouragement in my thesis process. Thank you and may your soul rest in peace!

I also dedicate this thesis to my beloved mother for her parental love, prayers, endless support and encouragement.

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With love and gratitude.

Abstract

Vulnerability in the financial system leads to economic instability. One way to reduce economic uncertainty and ensure sufficient capital flows is by detecting, monitoring and responding to the transmission of shocks in the financial network. Interconnectedness among integrated financial markets not only provides opportunities for economic expansion, resource allocation and improved risk-sharing, it also creates channels through which vulnerabilities spread across these financial markets.

This thesis is motivated by the reoccurrences of crises such as the global financial crisis of $2007 - 2009$, and the gaps in the literature to discover means to detect, assess and respond to extreme events that lead to financial instability. Objectively, we present empirical assessments of vulnerability in financial networks and employ different approaches to detect vulnerability in the global financial system. Combined Granger causality and the Diebold-Yilmaz approach are used to measure interconnectedness. A spatial autoregressive framework in capital asset pricing model is utilised to study the impact of network exposure on structural model, and generalised historical decomposition in vector autoregression is applied to measure signed spillovers. A portfolio mimicking framework using moments conditions is used to detect contagion, while generalised historical decomposition in Markov-switching vector autoregressions is employed to detect signed spillovers under different market conditions.

Empirical evidence in this thesis reveals the changing structure of the financial network across different markets. Over time, new links are formed, and others removed due to changing relationships among different markets. These interconnections become larger and more complex acting as a channel through which shocks are transmitted and amplified throughout the entire financial system. Moreover, a growing influence of the Asian markets in spreading shocks is observed. Transitions of the network structure of different markets are discussed with emphases on individual Asian markets.

In studying the dynamics of the network exposure on equity markets, our findings highlight the role of network exposure in increasing vulnerability, with both interconnectedness and network intensity playing key roles in monitoring these exposures. Our findings also indicate evidence of changing spillovers and contagion at a given time point, implying that vulnerability in the

entire financial system changes over time.

By assessing various forms of vulnerabilities in the global economy under different economic conditions, our findings indicate that vulnerability in the financial system changes depending on the state of the market. For instance, crises are associated with intense spillover regimes while normal times are associated with moderate spillover regimes. Transmission channels of shocks become more complex with the increasing integration and globalisation within the financial system. Our empirical findings assess different levels of vulnerability with the aim of providing guidance in making policy decisions to monitor the financial system, thereby promoting financial stability.

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Abbreviations

ADB Asian Development Bank

ADF Augmented Dickey-Fuller

AIC Akaike Information Criterion

ASEAN Association of Southeast Asian Nations

BIS Bank for International Settlement

CAPM Capital Asset Pricing Model

CDS Credit Default Swap

DCC Dynamic Conditional Correlation

DR Dungey–Renault

DY Diebold–Yilmaz

EDC European Debt Crisis

EMS European Monetary System

EU European Union

ExRM Excess Market Return

FR Forbes–Rigobon

FRC Forbes–Rigobon Corrected

FTSE Financial Times Stock Exchange

FX Foreign Exchange

GARCH Generalised Autoregressive Conditional Heteroskedasticity

GCC Gulf Cooperation Council

GDP Gross Domestic Product

GFC Global Financial Crisis

GHD Generalised Historical Decomposition

GMM Generalised Method of Moments

HD Historical Decomposition

HML High Minus Low

IC Information Criterion

ICAPM Intertemporal Capital Asset Pricing Model

IMF International Monetary Fund

IR Interest Rate

IVOL Idiosyncratic Volatility

MLE Maximum Likelihood Estimation

MoM Method of Moments

MSCI Morgan Stanley Capital International

MS-EGARCH Markov-Switching Exponential Generalised Autoregressive Conditional Heteroskedasticity

MS-GARCH Markov-Switching Generalised Autoregressive Conditional Heteroskedasticity

MS-VAR Markov-Switching Vector Autoregression

NBER National Bureau of Economic Research

NID Normally and Independently Distributed

NIE Newly Industrialized Economies

OLS Ordinary Least Squares

RV Realised Volatility

SAR Spatial Autoregresive

SMB Small Minus Big

T-Bill Treasury Bill

TS Total Spillover

2SLS Two-Stage Least Squares

UK United Kingdom

US United States

VAR Vector Autoregression

VIX Volatility Index

VSTOXX Euro Stoxx 50 Volatility Index

WEO World Economic Outlook

WT Wald Test

1 Introduction

1.1 Motivation

Unexpected occurrence of crises such as the global financial crisis (GFC) of $2007 - 2009$ pose a great threat to economic and financial stability which is one of the most important means of being resilient to financial shocks. To ensure stability, it is necessary to understand how the global financial system is interrelated and to identify and monitor financial institutions that act as critical links. More specifically, identifying these critical links guides authorities such as regulators and policy makers to design appropriate policy responses and targeted interventions to promote financial stability.

Financial interconnectedness plays an important role in the emergence of financial instability events and is a broad concept that relates to inter-connections among different institutions/assets. For example, contractual obligations that are not limited to loans, derivatives, ownership and other types of contracts among different markets create interconnections between them. The growing international presence and development of interconnectedness suggests changes in a system of financial institutions or a financial network.

Interconnectedness benefits the economy in various ways. It creates opportunities for economic growth from a global perspective. It also promotes financial stability through investment and growth enhancement (Agénor, 2003; Gai and Kapadia, 2010). Accessing these financial resources through a world pool creates a better means of expanding these markets and promoting financial stability. It also creates more efficient ways to allocate resources across markets. Further, interconnectedness provides new funding and investments for markets, thereby contributing to global economic growth. It helps to diversify individual market risks. Financial integration among the different markets contributes to better sharing of risks (Agénor, 2003, 2013; Gai and Kapadia, 2010; Tonzer, 2015). In general, cross-border linkages contribute to economic growth, creating diverse opportunities for market funding options. This increasing cross-border linkages are associated with the growing global integration among different financial markets. Financial interconnectedness also contributes significantly to the propagation of systemic risks (Giudici and Spelta, 2016; Minoiu et al., 2015). For instance, distress in one institution/asset is transmitted to other institutions/assets via the financial network. With the increase in cross-border activities, the financial network grows and creates a greater chance of spreading shocks throughout the global financial system. Fragility in the economy intensifies when large shocks are transmitted through highly interconnected network (see for example Acemoglu et al., 2015; Allen and Babus, 2009; Gai and Kapadia, 2010; Tonzer, 2015).[1]

A common threat in crises is the transmission of shocks from one market to another. The challenge for policy makers and regulators is to understand how much stability is desirable and how to detect, monitor and respond to changes in the transmission of shock effects from one country to another. One step in this process is to distinguish the types of transmissions that can occur and determine how to measure them. This allows to identify which shock effect is more important by distinguishing betwen the different types of transmissions.

Theoretical frameworks that identify network structures as at least partly responsible for the transmission of financial shocks include Allen and Babus (2009), Gai and Kapadia (2010) and Acemoglu et al. (2015). Other empirical work based on real data include Billio et al. (2012), Merton et al. (2013), Giraitis et al. (2016) and Diebold and Yilmaz (2015). These papers reveal the changing nature of global financial networks over time. Other studies (Demirer et al., 2018; Dungey et al., 2019a; Giudici and Spelta, 2016; Raddant and Kenett, 2016; Wang et al., 2018) consider Asian markets and show the extent to which these markets play a role in shocks propagation.

In summary, network analysis refers to the mapping and measuring of causal relationships in the structure among different institutions/assets that may contribute to regulation and policy decision-making in the following ways:

i. Improve the transparency of complex systems.
ii. Identify the features of the system (such as centrality and critical nodes).
iii. Identify too-interconnected-to-fail nodes (see chapter 2).
iv. Provide guidance on where interventions may be applied.
v. Provide guidance on reducing complexity.
vi. Consider multi-layer interactions and multiple data sources and types.
vii. Consider the consequences of regulation designed for one network flowing to others.

Moreover, network analysis aids understanding of the channels through which the transmission of financial stress flows. Thus, it will guide policy makers and regulators in designing appro-

[1] Chapters 2 and 3 discuss interconnecteness acting as a channel of shock transmission.

priate policies to detect vulnerable markets in the network and to propose better means with which to monitor the financial network, thereby promoting financial stability and resilience.

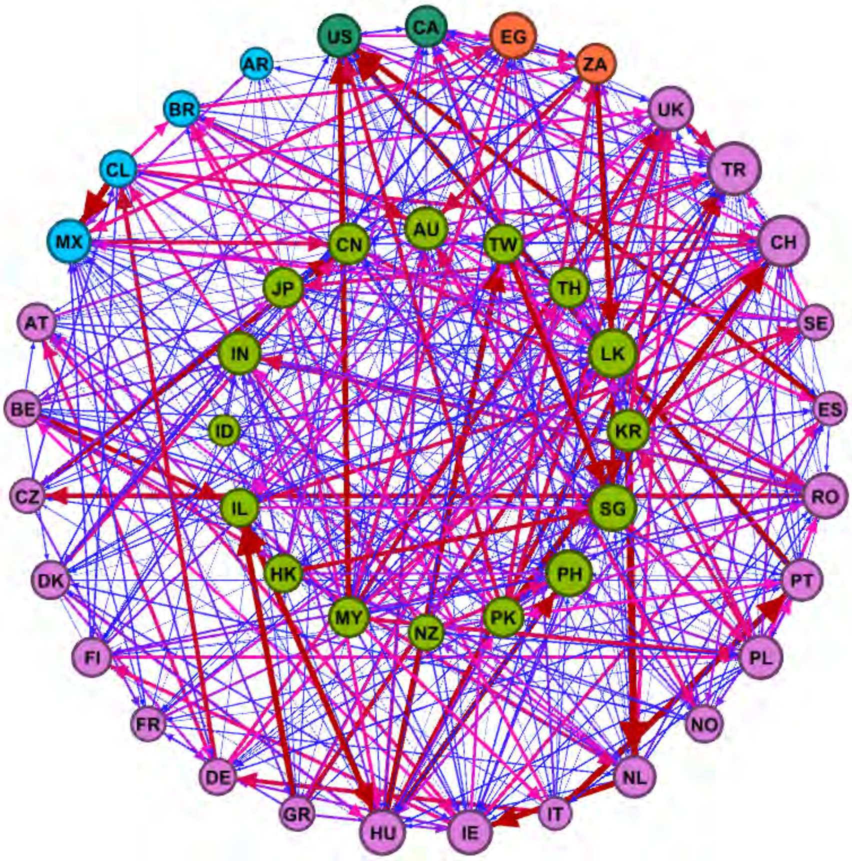


Figure 1.1: A financial network.
Notes: The network is based on cross-border liabilities for sample period 1999Q1 – 2017Q4. Regions are colour-coded: Asia–light green, Europe–magenta, North America–dark green, South America–blue, Africa–Orange. The figure displays the liability-based network of 45 markets. Edges are calculated using bivariate Granger causality tests between markets at the 5% level of significance. Edge thickness is proportional to the intensity of the edge strength and is set as: red (strongest), orange (medium) and blue (weakest). Node colour is proportion to the regional grouping while node size is proportion to its degree.

Figure 1.1 presents network diagram and cross-border exposure of the markets during 1999$Q1$ – 2017$Q4$. This plot is an example of financial exposure through liabilities, which is based on the cross-border liabilities obtained from the bank for international settlement (BIS). The size of the node is proportional to the node degree, while the size of the arrow is proportional to the strength of the links between two markets. Figure 1.1 shows the complexity of the exposures to which the financial markets are subjected. With the increasing cross-border transactions, the financial markets tend to transmit and absorb risks. The figure also shows how different economies are interlinked, with some having more links than others suggesting that each economy is subjected to different exposures from other markets, which implies that interconnectedness represents a channel of shock transmission in the global financial system. This concurs in

Haldane (2009), who asserted that interconnectedness is one of the potential channels through which shocks spread in the financial system.

Asian markets comprising mainly emerging markets depict their role as a bridge, interconnecting other regions (see Figure 1.1). Figure 1.2 presents snapshots of the Asian network in two periods. This Asian network is constructed from cross-border liabilities. These plots show narrow projection of the Asian market from the broader perspective in Figure 1.1. This indicates that apart from the Asian market being interconnected with the global markets, they are also more interconnected with each other in terms of cross-border activities that include trade and financial flow. Figures 1.2a and 1.2b show that the interconnections of Asian markets change over time, as does the strength. This implies that transmission of shocks among the Asian markets changes depending on the existing interconnections. To ensure stability in financial networks, regulators and policy makers should adopt cautious measures to investigate the transmission of shocks in existing interconnections. These global market interconnections, with emphasis on Asian economies, are examined in detail in this thesis.[2]

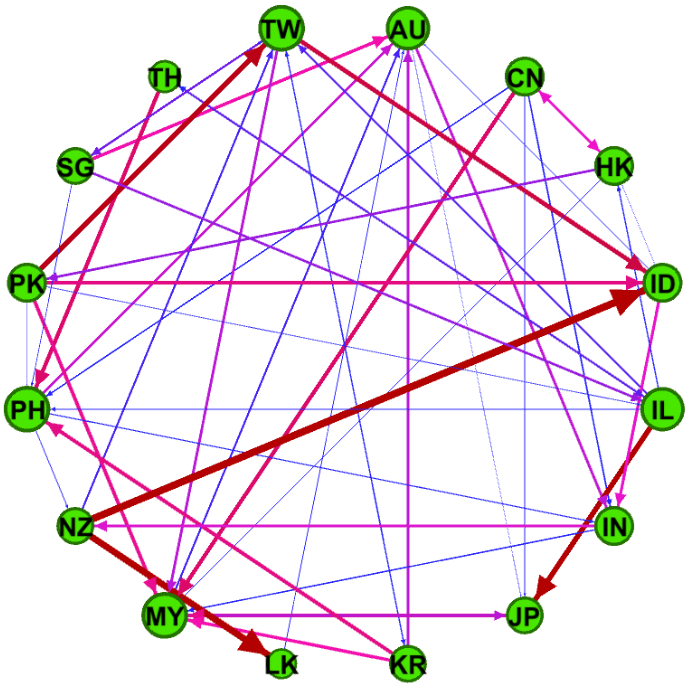
Transmission of shocks can be classified into broad groups: contagion and spillovers. According to Forbes and Rigobon (2002), contagion can be related to 'abrupt' and 'unexpected' changes of shocks. Rapidly spreading contagion severely disrupts stability in the global financial system. Specifically, its transmission reaches beyond that which would normally be anticipated. The term is generally used in a negative sense, so that true contagion refers to a case in which a shock in one market results in an unexpected decline in the performance of others. However, there may also be cases in which a shock in one market causes an unexpectedly smaller change in the performance of others. This is known as decoupling. Interdependence is maintained when markets respond to a shock by neither decoupling nor through contagion effects (no significant change of shocks).

Spillovers reflect the 'expected' relationships between financial markets on the basis of underlying trade, financial flows or banking relationships. The critical aspect of spillovers is that they are related to anticipated shocks that transmit across the markets. This can be transmitted, for example, through balance sheets or trade and portfolio movements. In general, spillovers are stable and changes are likely to be relatively slow-moving.[3] Detecting transmission of spillovers across different markets helps to monitor the financial system.

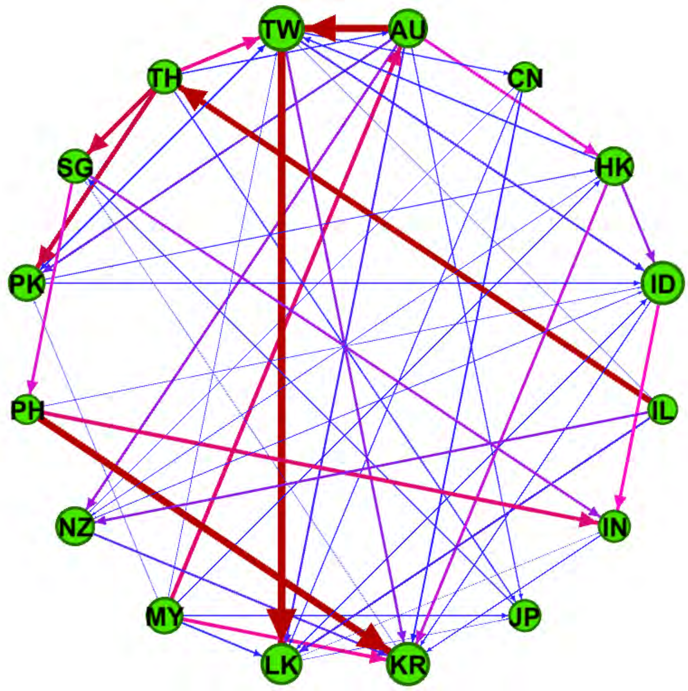
Distinctions between spillovers, contagion, decoupling and interdependence are important when

[2] Details are provided in Chapter 2.

[3] Rigobon (2019) defined volatility spillovers as causality in variance across different markets that implies vulnerability in the financial system.



(a) Asian network for 1999 to 2010



(b) Asian network for 2011 to 2017

Figure 1.2: Networks for Asian markets.
Notes: Sample period is 1999Q1 – 2017Q4. The figure displays the liability-based network of 16 markets. Edges are calculated using bivariate Granger causality tests between markets at the 5% level of significance. Edge thickness is proportional to the intensity of the edge strength and is set as: red (strongest), orange (medium) and blue (weakest). Node colour is the same, while node size is proportional to its degree.

designing policies for financial stability. It is also important to recognise that no objective criteria are available to distinguish a change that is abrupt or gradual. In other words, distinguishing spillovers from contagion can be complex and results may be disputed. Allen and Wood (2006) discussed how to determine the appropriate speed of adjustment in markets.

An asymmetric policy response may need to capture only the shocks that are likely to have negative effects on the recipient economy. In different circumstances, spillover, contagion or decoupling could either be undesirable or have useful outcomes. The problem is similar to that of research and development spillovers when offsetting effects occur from having rivals in product markets and technology spillovers (Lucking et al., 2018). Lucking et al. (2018) concluded that the positive aspects of research and development spillovers overwhelm the negative aspects in welfare analysis. A related problem is the complexity of trading of the continuous benefits of a more competitive banking sector against the costs of infrequent crises (Allen and Gale, 2004).

Although there is existing research on financial interconnectedness and its crucial role in the transmission of shocks in the global financial system, most research has focused on developed countries, not emerging markets. The recurrences of crisis events indicate the need to better understand the network structure of the financial system with particular emphasis on the Asian markets due to their increasing involvement in the global context. A stronger focus on assessing vulnerability of financial networks, specifically in emerging markets, is still needed. This will contribute to monitoring the financial system with aim of promoting financial stability. Our empirical analysis focuses on the global markets with more emphasis on the Asian contexts. We use same markets in the entire thesis except the last chapter where the number of markets reduce to 32 due to the unavailability of high frequency data for all the markets in our focus.

1.2 Objectives of the thesis

Based on the above motivation and gaps identified in the existing literature, this thesis investigates how different markets are interconnected and assesses the transmission of shocks across financial networks. This aims to monitor, detect and quantify shock transmission channels across these networks. The main focus will be on the global financial markets with greater emphasis on Asian economies.

The main goal of this thesis was motivated by the need to identify better methods of measuring systemic risk to develop better means of monitoring the financial system. Therefore, understanding the role of financial networks and how to measure them efficiently, will potentially contribute to financial stability. This thesis aims to contribute to financial and econometric modelling to measure and assess vulnerability in the global financial network. All theoretical models discussed are supported by empirical evidences using real data. To be specific, this thesis has five objectives, to:

O1. Investigate the structure and characteristics of networks among different financial markets

This objective is motivated by the GFC of $2007-2009$ that reverberated through the financial system. It seeks to study the structure of the links among different financial markets. The structure of financial networks determines the shock exposures in the financial system. These exposures vary depending on interconnectedness among different assets/markets. With the increasing interaction between different assets/markets, these interconnections become larger and more complex. The complexity of the financial system is of great concern to its stability. Specifically, this objective aims to examine the transition of financial networks during different periods. This helps to better understand the structure of the financial system, and its vulnerability to failure and resilience.

O2. Examine the emerging role of Asian markets in the global economy

This objective aims to understand the history of Asian markets based on their network structure before Asian crisis of $1997-1998$ until the end of 2016. Specifically, it focuses on explaining the evolution of the interconnections of each individual Asian market and the rest of the world over time. The characteristics of the global market structure continue to change and grow across different regions. Global integration in terms of cross-border activities has increased, leading to more possibilities of propagation of shocks across regions. The Asian crisis of $1997-1998$ highlighted the significance of Asian markets in transmitting shocks to the global market. The financial network structure of these markets has adversely changed over time.

O3. Assess the degree of network exposure among the global financial markets

It investigates the impact of network exposure on the asset pricing model. Specifically, the focus is to examine the vulnerability in the financial market from a network perspective. This is because exposures in financial system have increased tremendously with the increasing interaction between different markets. The asset pricing model highlights how a given asset reacts to common factors. Billio et al. (2015) argues that the effects of network externalities on asset pricing model become larger due to diversification. This suggests that systematic risk (undiversifiable) tends to increase with the increasing exposures from different markets.

O4. Detect the transmission of spillovers and contagion among financial markets with emphasis on Asian economies

This objective aims to assess vulnerability in the financial system by advancing methods that can be used to detect the presence of spillovers and contagion in individual Asian markets. Understanding the magnitude, and the nature of financial vulnerability and transmission channels across-borders is one way to ensure stability in the financial system. To address this issue, understanding the transmission channels, especially in Asian economies and the global market is of paramount importance.

O5. Analyse the volatility spillovers among global financial markets across different economic conditions

This objective aims to examine the magnitude of spillovers and their effects on the global market, while considering different economic regimes. This is because the nature of cross-border spillovers reflects its effects on the entire financial system. These impacts become even more severe depending on market conditions. The subprime crisis of 2007 demonstrated the increasing market chaos in the risky state implying that vulnerability in the financial system increases in risk, resulting in instability in the entire economy.

1.3 Key contributions and organisation of the thesis

To achieve the above outlined objectives, this thesis contributes by assessing vulnerability in the global financial system with greater emphasis on the Asian markets. This sub-section outlines the structure of the thesis and presents the key contributions.

Chapter 2: History of Asian markets: Financial network perspective

This chapter examines the network structure of financial markets and determines how the links between these markets change over time. It aims to investigate the history of these markets through their interconnections, with emphasis on Asian markets. This chapter employs combined Granger causality and the DY approach to establish these interconnections. Granger causality identifies statistically significant relations, while the DY approach measures the strength of these interconnections. Thus, using this combined approach, enables identification of interconnections among these markets, as well as its strength.

The findings in this chapter reveal distinct features of interconnectedness among financial markets, with emphasis on Asian markets. For instance, there are increased interconnections among different markets over time. The financial networks over the six phases show the complexity and changing nature of interconnectedness among financial markets. Further, the results demonstrate that these interconnections change from phase to phase; new links are formed while others are removed. This implies that network exposure changes over periods depending on the relationships among these markets.

Chapter 2 adds to the literature in different aspects. First, it improves understanding of the changing nature of interconnectedness among different financial markets. By splitting the sample into different phases, the study provides more information on how financial networks change before, during and after global financial crises. The study also provides more information of the new links formed and those removed from one phase to another. Thus, this detailed information would provide guidance for policy decisions to identify vulnerable markets.

Second, this chapter emphasises on individual Asian markets, which contributes to the existing literature on the history of these markets from the network perspective. With the increasing involvement of Asian markets in the global economy, focusing on these markets contributes to the literature by revealing their role in spreading shocks in the global context.

Additionally, combining the Granger and DY approaches to study the financial network contributes to the existing literature. While most of the extant literature employs one of the approaches to study spillovers, this thesis combines the two approaches. This helps to identify significant links and the strength of interconnectedness among markets.

Chapter 3: Dynamic effects of network exposure on equity markets

This chapter examines the nature of network exposure on the equity market and aims to identify the role of asset interaction in spreading shocks. Specifically, this chapter introduces the spatial autoregressive (SAR) model on the capital asset pricing model (CAPM) to study whether network exposures have an impact on the structural model.[4] Introduction of the SAR model helps differentiate between the structural exposure to common factors, structural impact to idiosyncratic shocks, the network exposure to common factors and network impact to idiosyncratic shocks.

Findings in this chapter provide detailed information on the nature of vulnerability due to network exposure. For instance, the results show that both interconnectedness and network intensity parameters play a key role in increasing network exposure.[5] Both interconnectedness

[4]Structural model captures exposures to common factors in the CAPM model.

[5]Interconnectedness is captured through connectedness matrix, W while the network intensity parameter is

and network intensity parameter monitor the effect of the linked assets. This suggests that the network intensity parameter increases during the period of stress. Therefore, an increase in network intensity parameter may be associated with extreme events, which helps monitor the financial system.

Chapter 3 contributes to the existing literature in several ways. First, it investigates the impact of network exposure to a structural model. This contributes to the literature by revealing that apart from the structural shocks in asset pricing, cross-border activities also have impact on increasing vulnerability. This highlights the role of network exposure in increasing vulnerability in the financial system. Second, this chapter contributes to the network literature by showing that it is not only interconnectedness plays a key role in increasing network exposure; but rather the network intensity parameter also plays a key role in capturing the strength of the effects of network exposure.

Chapter 4: Changing vulnerability among the Asian markets: Contagion and spillover

This chapter examines the changing vulnerability in Asian financial markets. Specifically, it distinguishes between spillover and contagion. This chapter uses both spillover and contagion methodology to study vulnerability in these markets. To detect spillovers, this chapter applies generalised historical decomposition (GHD) in vector autoregression (VAR) to identify signed spillovers across different markets. Further, we detect contagion using portfolio mimicking factor framework using the moment conditions. This chapter compares contagion measures proposed by Forbes and Rigobon (2002) and Dungey and Renault (2018).

Relying on time-varying unconditional analysis to identify spillovers, considering the conditional relationships to detect contagion, Chapter 4 finds evidence of changing vulnerability among Asian markets and global markets. Focusing on Asian markets and the United States (US) to mimic global market conditions, the findings show distinct evidence of changing spillovers over different periods with crisis periods, associated with increased effects. The findings also reveal strong evidence of contagion and decoupling using the US as the global mimicking factor.

Chapter 4 adds to the existing literature in several ways. First, this study combines both contagion and spillover methodologies to investigate vulnerability in financial markets. This contributes to both spillover and contagion literature, since most studies have focused on one of the measures independently.

captured using a spatial coefficient, ρ (see Chapter 3).

Chapter 5: Detecting spillovers in global financial markets: A Markov-switching approach

Identification of change in vulnerability in the global market in different economic regimes is achieved by measuring risk spillovers within a Markov-switching VAR framework. Chapter 5 finds that the vulnerability in the financial system changes in terms of the dynamics of 'good' and 'bad' spillovers. The findings also reveal that spillovers differ in different regimes–where an intense spillover regime is associated with a period of stress. Chapter 5 contributes to the existing literature by identifying if the sign of the spillover distinguishes the effect of the spillover. This determines whether the spillover is bad or good.

Additionally, investigating the dynamics of spillovers across different regions helps to distinguish which region need more regulations in terms of vulnerability. This creates a robust financial system and contribute to better monitoring of these regional markets.

Focusing on individual Asian markets helps determine the role played by these markets in transmitting and absorbing shocks. These countries, comprising mostly emerging markets have recently been extensively involved in the global economy.

Chapter 6: Conclusions

The final chapter summarises the major findings of this thesis and suggests future research directions.

2 History of Asian markets: Financial network perspective

Abstract

Recent international financial crises highlight the advantages of understanding the global financial system as a network of economies in which cross-border financial linkages are fundamental to the spread of systemic risk. This chapter investigates the changing network of financial markets for six periods ($1995-2016$), constructing a network that captures the concepts of the direction of links between markets, and the significance and strength of these links. Emphasis is placed on the transition of the networks before and after the Asian financial crisis of $1997-1998$ and the GFC of $2008-2009$. The analysis demonstrates the increase in interconnectedness during periods of stress and the fall in the number of links in post-crisis periods. At the same time, the results reveal a general deepening of the connections of the Asian market with the rest of the world over the past two decades. They also suggest that many of these markets have transitioned from being primarily linked to developed non-Asian markets through key bridge markets (such as Hong Kong) to developing stronger direct links with external markets, highlighting the importance of key geographical nodes in market development.

Keywords: Financial network, financial crises, Asian markets

JEL classifications: G01, G15, G10

2.1 Literature review

Finance literature has traditionally focused on interconnectedness as measured through direct exposures, which is constrained by the availability of reliable granular data. A more intuitive way is to investigate the empirical correlation of assets and the resulting implied network structure. This network helps describe the financial system, its systemic structure, and possible contagious effects. The network can provide important insights into system-level effects and uncover changes in market microstructure, bubble formation and changes in business models as some market participants withdraw from certain activities and others take their place.

This chapter relates to rapidly expanding the line of research applying network analysis tools to examine financial linkages in global markets and their implications for the emergence and management of risk contagion. This literature draws on the seminal work of Allen and Gale (2000), who used network theory to model financial interconnectedness and draw implications for system stability. The present research relates to networks as a source of shock propagation in the financial system. The notion of financial institutions being more interconnected is one of the channels through which financial stress propagates in the financial system. Recent research has focused on the structure of financial networks of a given economy. For example, Gai and Kapadia (2010) showed that shocks are transmitted more by interconnected institutions. This implies that the probability of contagion is higher in more interconnected entities. Minoiu and Reyes (2013) found that financial interconnectedness helps predict systemic risk in banking institutions. They showed that an increase within a country's interconnection and a decrease in interconnections with other banking institutions signifies a high chance of banking crises that would result in financial instability.

This chapter closely follows recently proposed connectedness measures. Billio et al. (2012) introduced Granger causality tests to measure the extent to which financial institutions are interconnected. This measure has been applied in many other studies. For example, Zhang and Broadstock (2018) used it for robustness checks and found that connectedness in global commodity prices rises following global financial crises. Cimini (2015) investigated network density among the Euro-zone entities and reported that the overall interconnection of both financial and non-financial entities reduced after the global financial crisis (GFC). Pradhan et al. (2015) examined the dynamics of the different macroeconomic variables from the G20 countries and identified a long-term economic relationship between these macroeconomic variables.[1] In the short-term, they found a complex network causal relationship.

Another widely used measure of connectedness in the financial system is the one proposed by Diebold and Yilmaz (2009) in their seminal paper. The Diebold-Yilmaz (DY) approach is based on variance decomposition from a VAR model. It has been widely accepted and applied in various studies. For example, Mensi et al. (2018) investigated volatility and connectedness among the global and regional markets and found an increased spillover to be more intensified at the beginning of the GFC. They also reported that the US is a shock transmitter, while the other economies are receivers. Ji et al. (2018a) investigated net spillover across the oil and gas

[1] G20 countries include; Argentina, Australia, Brazil, Canada, China, the European Union, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, Saudi Arabia, South Africa, South Korea, Turkey, the UK and the US.

markets and found that total connectedness has volatile characteristics over time. Zhang (2017) used this approach to study the relationship between oil shocks and six stock market indices and discovered that the global stock markets affect oil price movements, especially during periods of financial stress. Other work by Luo and Ji (2018) also studied the connectedness of the realised volatility of US crude oil and Chinese agricultural commodity and found that transmission in volatility has a leverage effect across markets. Ji et al. (2019) examined connectedness among the eight cryptocurrencies, reporting that their connectedness showed a rising trend towards the end of 2016. Ji et al. (2018b) also investigated connectedness via return and volatility spillovers across the six largest cryptocurrencies and found that each cryptocurrency return and volatility connectedness are not necessarily related to market size.

Our empirical framework relies on the network approach developed by Diebold and Yilmaz (2012, 2014) to measure financial asset connectedness, based on the variance decomposition of the h-step-ahead forecasts from a vector autoregression (VAR) model, as well as an innovative Granger causality modelling approach introduced by Billio et al. (2012). Both frameworks are able to identify and accurately measure the degree of interconnectedness and stress transmission effects among the examined economies and markets. However, this work differs from the existing literature; it examines the changing nature of the networks of interconnections over different phases, controlling for different volatility regimes (an advance from De Bruyckere et al., 2013), and includes a weighted directed network, improving on the unweighted approach of Billio et al. (2012) and the weighted approach of Diebold and Yilmaz (2012, 2014), which includes insignificant linkages.

This work extends on previous studies to investigate how the connectedness among the Asian markets has changed over time. Although there is an increasing number of studies that investigate how markets are interconnected, there is a need to investigate the behaviour of financial networks. Given the continuous increase of interconnections after the GFC, there remains a need to study the nature of these interconnections, especially in the most recent periods. Little attention is focused on emerging markets, especially in the Asian context. Thus, this chapter aims to fill the gap by focusing on Asian markets, which are becoming more significant in propagating financial shocks. It focuses on the changing network among global financial markets, with an emphasis on Asian economies to identify important links that were removed or formed in different periods.

Following recent research (such as Allen and Babus, 2009; Gai and Kapadia, 2010; Tonzer, 2015) that found transmission of shocks in the financial system increasing with more interconnections, we expect from our results more interconnections during period of financial stress. More interconnections are associated with more transmissions of shocks given one institution/market in the network is under stress. Our results reveal that there are more interconnections during crisis period and reduction of these links after the crisis period.

2.2 Financial network properties

In general, a network structure captures the interconnectedness of financial institutions. Networks visually represent the characteristics of a financial system using direct or indirect linkages. Financial networks differ in structure depending on what they depict, (e.g. inter-banking relationships in the banking sector). These interconnections are formed when institutions lend, borrow and trade financial assets to maximise profits (van Lelyveld and Veld, 2014). The complexity of these links between financial institutions is a potential source of systemic risk.

Direct interconnectedness refers to direct linkages arising from exposures between entities through financial obligations, transactions, contracts or other activities. Indirect interconnectedness refers to the mechanisms under which distress of one entity can propagate to another entity without necessarily any direct connections between the two. Inter-bank credit exposures and financial service infrastructure are examples of direct interconnectedness while exposure to common assets, information spillovers and shadow banking are examples of indirect interconnectedness (Liu et al., 2015).

Direct and indirect interconnectedness in financial networks capture how shocks are amplified and propagated in the financial system. Financial institutions, including banks, insurance companies and hedge funds, are interconnected through bilateral transactions such as assets, liabilities/debts, loans, deposits, investments and other financial obligations. These linkages extend across countries, making the financial system more complex. The network structure of these inter-linked institutions helps determine how shocks could be transmitted through the entire financial system. The structure of these networks exposures affects the potential vulnerabilities to which they expose the financial system. Understanding the role of interconnectedness in the transmission of shocks aids resilience-building in financial systems (Amini et al., 2016). This help quantify and measure linkages in the financial system, thereby promoting economic stability.

Networks have an equivalent adjacency matrix (connection matrix) representation consisting of nodes and links. Nodes (vertices) represent financial institutions, assets or markets, while links (edges) represent the bilateral exposures of the nodes. These exposures represent the maximum loss that an institution could incur when a counterparty defaults (Amini et al., 2016). Some research, (e.g. Dungey et al., 2012) uses nodes to represent volatility shocks in the financial system. These links can be either directed or indirect, weighted or unweighted. Identifying the structure of a financial network enables understanding of how shocks are transmitted from one node to another.

Bilateral linkages between institutions/assets/markets are captured by constructing an adjacency matrix W which is an $n \times n$ matrix, with elements w_{ij} taking values of 1 if node i is connected to j and 0 otherwise. The values in cell w_{ij} quantify the strength of interaction between nodes i and j. The diagonal (w_{ii}) consists of zeros reflecting the assumption of no self-loop (each node does not connect or influence itself), and that the network may not be symmetric (Billio et al., 2015). The extant research has used different approaches to construct this connection matrix.

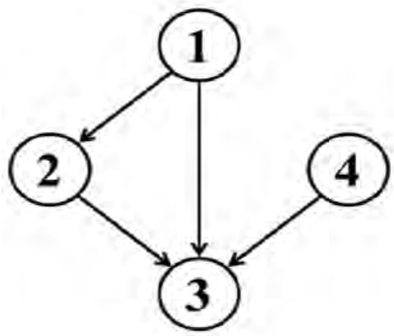
$$w_{ij} = \begin{cases} 1 & \text{existence of relation between asset } i \text{ and asset } j \\ 0 & \text{no relationship} \end{cases} \tag{2.1}$$

The aim is to construct an adjacency (connection) matrix to capture the relationship between two assets; this can be extended to represent the relationship between two institutions or countries. Assuming there are n institutions in the system (representing either a firm, an asset or a country), the adjacency matrix can be represented as

$$W = \begin{pmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,n} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n,1} & w_{n,2} & \cdots & w_{n,n} \end{pmatrix}$$

where $w_{i,j}$ captures the connection between asset/institution i and asset/institution j respectively. Figure 2.1 demonstrates how a simple adjacency matrix can be constructed for four firms. For example, Firm 1 is directly connected to Firms 2 and 3. Thus, taking the values 1 while 0 elsewhere. This is because it is not linked to Firm 4; with the assumption of no self-loop, the diagonal takes the value 0. Additionally, the adjacency matrix is not symmetrical in the sense that Firm 2 is connected to Firm 3 but the opposite is not necessarily true (i.e. Firm 3 is not connected to Firm 2). That is, the matrix shows directional sensitivity.

It is convenient to normalise the connection matrix to remove dependence on extraneous scale



w	1	2	3	4
1	0	1	1	0
2	0	0	1	0
3	0	0	0	0
4	0	0	1	0

Figure 2.1: Adjacency matrix representation for simple network of four firms. The figure shows how a simple adjacency matrix can be constructed

factors. Row normalisation of W is used such that

$$\sum_{j=1}^{n} w_{ij} = 1, \; i = 1, \cdots, n \tag{2.2}$$

With assumption of non-negative weights, each row-normalised weight (w_{ij}) can be interpreted as the fraction of all influence on asset i attributable to asset j.

2.2.1 Network measures

This chapter contributes a new way of examining the changes in financial networks over time. It tests for changes in the existence, number and strength of links between financial markets. The results demonstrate the developing profile of Asian financial markets in a global network over a 20-year period containing two important periods of crisis. It compares the evolution of the network before, during and after two crises (East Asian in $1997-1998$ and GFC in $2007-2009$) and provides statistical evidence based on weighted networks and Jaccard similarity coefficients to assess the impact of the crises, along with the increasingly interconnected Asian markets. The focus on the changing number and strengths of links (or edges) between the nodes (equity markets) in the network, differentiates this work from previous studies that focused exclusively on the net change in the number of statistically significant links, such as Billio et al. (2012) or solely on the strength (but not statistical significance) of the linkages, such as Diebold and Yilmaz (2009, 2014).

This approach extends on existing work by implementing an adjacency matrix that incorporates the spillover strengths filtered by the statistical significance of the links. This omits spuriously large but insignificant links. It considers not only the net change in links between nodes, but also the evolution of the Jaccard similarity coefficient, which provides information on the number of retained links between sample periods. The changing nature of the network led us to consider not only the degrees and centrality measures of the networks, but also to analyse the number and strength of links that are extinguished and those that are formed. For example, in terms of the weighted completeness of the network, a result that may at first appear as a net increase in links may in fact represent a reduction in strong linkages and proliferation of weaker links.

Our approach embeds existing definitions of contagion within a network representation of systemic risk. In particular, failure of links between nodes during periods of stress is evidence of the form of contagion proposed in Gai and Kapadia (2010), when the breakdown of the network results from contagion due to failing counterparty arrangements. Alternatively, new links forming between nodes during periods of stress increases the number of connections, akin to the traditional Forbes and Rigobon (2002) definition of markets becoming more interconnected during crises. To date, the literature finds evidence of both these contagion routes, but does not effectively reconcile them into a single framework. That is the aim of this background paper.

This chapter draws on the methodological approaches developed in Dungey et al. (2019a) to develop a network of financial linkages between nodes (represented by country index equity market data), in which links between them (edges) are determined by an adjacency matrix. This matrix includes both the direction and strength of those links and a measure of their statistical significance. The relative strengths of the links are determined using the DY (Diebold and Yilmaz, 2009, 2014) forecast error variance decomposition approach, in which sources of observed volatility in each return are attributed to shocks in source nodes. The DY approach has the advantage of allowing the researcher to vary the horizon of shock examined. We coupled this with the Granger-causality approach of authors such as Billio et al. (2012), who considered the statistical power of the existence of links between nodes. If one node Granger causes the other at a statistically significant level (selected by the researcher), this link is indicated as existing in the network. If Granger causality is not significant, the link is nonexistent. In this way, the Granger-causality approach is used to weed out the spuriously large (poorly estimated) linkages from the adjacency matrix provided by the DY approach. It measures existence, direction and size of the edges.

Establishing network edges via Granger causality

To measure the connectedness between entities, we identified statistically significant relations among them by applying Granger causality tests to establish the edges of network nodes. The directionality of the relationships is identified in these tests. Granger causality tests suggest causality if past values of onetime series (Y_i) stock return series: in our case, if they contain information that helps forecast another return series, Y_j.[2]

These causality links can be assessed using a VAR(L):

$$y_t = \Phi_0 + \sum_{l=1}^{L} \Phi_l \; y_{t-l} + \varepsilon_t \tag{2.3}$$

or represented in multivariate regression format as:

$$y_t = \Pi x_t + \varepsilon_t, \;\; t = 1, 2, ..., T \tag{2.4}$$

where y_t is a n-dimensional random vectors of observation, such that $y_t = (y_{1,t}, y_{2,t}, ..., y_{n,t})'$ for $t = 1, ..., T$, $x_t = (1, y_{t-1}, y_{t-2}, ..., y_{t-L})'$ and $\Pi_{2\times(2L+1)} = [\phi_0, \phi_1, ..., \phi_L]$, $l = 1, 2, ..., L$ number of lags in the model;[3] and ε_t represent the vector of residuals. Letting $\widehat{\varepsilon_t} = y_t - \Pi x_t$ be regression residuals, $\widehat{\Omega} = T^{-1} \sum_{t=1}^{T} \widehat{\varepsilon_t} \widehat{\varepsilon_t'}$ be the least square estimate of the error covariance matrix Ω, and $X' = [x_1, x_2, ..., x_T]$ be the observation matrix of the regressors in Equation (2.4).

The Wald test (WT) to test for Granger causality between stock returns has the form:

$$WT = \left[R \text{ vec}(\widehat{\Pi})\right]' \left[R \left(\widehat{\Omega} \otimes (X'X)^{-1}\right) R'\right]^{-1} \left[R \text{ vec}(\widehat{\Pi})\right] \tag{2.5}$$

where R is the $L \times 2(2L+1)$ selection matrix:

$$R = \begin{bmatrix} 0 & 1 & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & 1 & \cdots & 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 1 \end{bmatrix} \tag{2.6}$$

Each row of R picks one of the coefficients to set to 0 under the non-causal hypothesis $Y_i \to Y_j$. Then, Granger causality test results can be summarised as binary entries of matrix

$$A = [a_{ij}] \tag{2.7}$$

[2] For more information on Granger causality tests, see Granger (1969).

[3] In the empirical section, the choice of L is based on the Akaike information criterion (AIC). According to this criterion, $L = 2$.

where

$$a_{ij} = \begin{cases} 1, & \text{if } Y_i \text{ Granger causes } Y_j \\ 0, & \text{if } Y_i \text{ does not Granger causes } Y_j \end{cases} \tag{2.8}$$

note that $a_{ii} \equiv 0$ and $a_{jj} \equiv 0$. Equations (2.7) and (2.8) permit establishment of network edges.

Establishing network edges via generalised variance decomposition

The direction of edges is only one aspect of the relationship between entities in the network. Another important aspect is the strength of the relationship, which we examined by assigning weights, W_{ij}, to each significant relationship in the network. We used the Diebold and Yilmaz (2009, 2014) framework of a generalised variance decomposition to obtain these weights where the weight matrix $W_{ij} = [w_{ij}]$. The spillover measure is based on forecast error variance decompositions. Suppose that the contribution of shocks to variable j to the H-step-ahead generalised forecast error variance of entity i, $\theta^g_{ij}(H)$, is represented by:

$$\theta^g_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_\varepsilon e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_\varepsilon \Psi_h' e_i)} \quad H = 1, 2, ... \tag{2.9}$$

where Σ_ε is the variance covariance matrix for the shock vector ε_t, σ_{jj} is the standard deviation of the error term for the j^{th} equation and e_j is the selection vector, with 1 as the i^{th} element and 0 otherwise. The coefficient matrices Ψ_i are the moving average from the forecast at time t and they obey the recursion $\Psi_i = \phi_1 \Psi_{i-1} + \phi_2 \Psi_{i-2} + ... + \phi_L \Psi_{i-L}$ with Ψ_0 an $n \times n$ identity matrix and $\Psi_i = 0$ for $i < 0$. Each entry of the generalised variance decomposition is normalised by the row sum as:

$$w_{ij} = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{n} \theta^g_{ij}(H)} \tag{2.10}$$

where by construction, $\sum_{j=1}^{n} w_{ij} = 1$ and $\sum_{i,j=1}^{n} w_{ij} = n$. We denote w_{ij} as DY weights.

We can define the total spillover $TS(H)$ using the contributions from the variance decomposition as:

$$TS(H) = \frac{\sum_{i,j=1, i \neq j}^{n} w_{ij}(H)}{n} \times 100 \tag{2.11}$$

which quantifies the contribution of spillovers across different financial markets to the total forecast error variance (Diebold and Yilmaz, 2012).

Establishing network edges via combined approach

The structure of the weighted network can be defined by combining matrices A and W. As a result, the adjacency matrix $\tilde{A}$ is defined as:

$$\tilde{A} = A \odot W \tag{2.12}$$

where $\odot$ is the Hadamard product. Elements of adjacency matrix $\tilde{A}$ capture the connectedness between entities, conditional on significant causal linkages between them. Henceforth, we will call them combined Granger causality and DY weights. The system-wide completeness of the network is measured as

$$C_{ij} = \frac{\sum_{j=1,i\neq j}^{n} \tilde{a}_{ij}}{\sum_{j=1,i\neq j}^{n} w_{ij}} \tag{2.13}$$

For convenience, we let $c_{i\rightarrow j}$ represents the pairwise directional connectedness from i to j, which equals C_{ij}. Further, we introduced the total directional connectedness measures as:

i) to-connectedness, which measures the directional connectedness of from i to others defined as:

$$c_{i\rightarrow others} = \sum_{i=1,i\neq j}^{n} C_{ij} \tag{2.14}$$

ii) from-connectedness, which measures the directional connectedness of from others to i defined as:

$$c_{others\rightarrow i} = \sum_{i=1,i\neq j}^{n} C_{ij} \tag{2.15}$$

iii) net-connectedness, which measures the net total directional connectedness of i defined as:

$$c_i = c_{i\rightarrow others} - c_{others\rightarrow i} \tag{2.16}$$

iv) total connectedness, for sample n which measures the system-wide connectedness defined as:

$$c_{ij} = \frac{1}{n}\sum_{i,j=1}^{n} C_{ij} \;\forall i \neq j \tag{2.17}$$

We are interested in investigating the changing nature of the network over the sample period.

In particular, the adjacency matrix may change due to changes in the weight matrix, W, and/or the significant entries in the matrix A. Changes in the A matrix link the specification directly to the literature assessing links during crises. For example, Granger et al. (2000) assessed changing Granger causality links in Asian markets between 1986 and 1998 . To illustrate how this may apply in the current framework, consider the example of linkages between a pair of assets in a two-node example (this is for illustrative purposes only; the Granger causality relationships used in the empirical application are drawn from the VAR model of the entire system with a Wald test approach as outlined in Equations [2.5] to [2.6]). Consider a bivariate vector autoregression with one lag between Y_{1t} and Y_{2t}

$$Y_{1t} = c_1 + \vartheta_{11} Y_{1t-1} + \vartheta_{12} Y_{2t-1} + \varepsilon_{1t} \tag{2.18}$$

$$Y_{2t} = c_2 + \vartheta_{21} Y_{1t-1} + \vartheta_{22} Y_{2t-1} + \varepsilon_{2t} \tag{2.19}$$

which can be compactly written in matrix form as

$$Y_t = c + \Theta Y_{t-1} + \varepsilon_t \tag{2.20}$$

where Y_t is the vector $[Y_{1t} Y_{2t}]'$, c is the 2×1 vector of constants, Θ is the 2×2 matrix of coefficients and ε_t is the 2×1 vector of residuals.

The Granger causality test is essentially a test of significance of the off-diagonal elements of the coefficient matrix in Equation (2.20): that is, whether ϑ_{12} and/or ϑ_{21} are non-zero. To extend this test to detect evidence of contagion and the changing nature of networks, we may consider comparing these coefficients across two sample periods. If, in period 1, ϑ_{12} is statistically significant, but in period 2 it is not, then the link has been lost between the two periods. This is consistent with contagion through breakdown of linkages as per Gai and Kapadia (2010). Alternatively, if the link ϑ_{12} is insignificant in period 1, but significant in period 2, then the evidence is consistent with contagion through the formation of new linkages, such as in Forbes and Rigobon (2002).

2.2.2 Measures of centrality

There are different measures of centrality that help relate the node to the network. These measures summarise the position and role of each node in a network. Following Kubelec and

Sá (2012), we defined network centrality measures as where n is the total number of nodes in the network:

- Degree

  Degree of the network represents the total number of edges/links (c_{ij}) from or to a node. Thus, they represent the total unique connection of an asset or country. The degree for node i is defined as:

  $$d_i = \sum_{j}^{n} c_{ij} \tag{2.21}$$

  where sum is over all the nodes n in the network.

  The degree of a network can be distinguished by the number of incoming and outgoing links. The in-degree is the total number of links from node j that point to node i given by:

  $$d_i^{in} = \sum_{j}^{n} c_{ij} \tag{2.22}$$

  where $j = 1, \cdots, n$. For a direct link to exist, node j must record a nonzero liability or claim on node i. The out-degree is the total number of links departing node i that point to node j given by:

  $$d_i^{out} = \sum_{j}^{n} c_{ij} \tag{2.23}$$

  Total degree of a node i can be represented as:

  $$d_i^{tot} = d_i^{in} + d_i^{out} - c_{ii} \tag{2.24}$$

  For a direct link to exist, node i must record a nonzero liability or claim on node j (Kubelec and Sá, 2012). Gai and Kapadia (2010) asserted that the degree of a network plays a key role in governing the chance of potential spread of risk across the network.

- Closeness centrality

  Closeness of node i is the inverse of the average distance from node i to all the other nodes in the network given by:

$$Closeness_i = \left[\frac{\sum_j^n \delta(i,j)}{n-1} \right]^{-1} \tag{2.25}$$

where the distance between node i and j given by $\delta_(i,j)$ is the length of the shortest path of the links in the network.

- Betweenness centrality

  This considers the nodes that take the shortest path through the network. To be precise, if we let p_{jk} be the number of nodes on the shortest path between j and k and $p_{jk}(i)$ be the number such paths that passes through node i, we have that $p_{jk}(i)/p_{jk}$ is the probability that node i is on the shortest path from j to k. Thus, the betweenness of node i is given by:

$$Betweenness_i = \frac{\sum_{j \neq i} \sum_{k \neq i} p_{jk}(i)/p_{jk}}{(n-1)(n-2)} \tag{2.26}$$

- Clustering centrality

  It measures the probability that, given node i is directly linked to node j and k, then node j is also directly linked to node k. This is defined by:

$$Cl_i = \frac{\sum_{i,j \neq i, k \neq i, k \neq j} c_{ij} c_{ik} c_{jk}}{\sum_{i,j \neq i, k \neq i, k \neq j} c_{ij} c_{ik}} \tag{2.27}$$

  where c_{ij}, c_{ik}, c_{jk} represent the link between nodes i and j, nodes i and k, nodes j and k respectively.

- Eigenvector centrality

  This measures how a given node influences other nodes (counter-parties) in a network. Thus, it is an indicator of proximity between nodes in a network. Eigenvector centrality of each market is determined by the eigenvector centralities of the markets to which it is connected. That is, eigenvector centrality of country i, ev_i, is given by:

$$ev_i = \frac{1}{\lambda} \sum_j A_{ij} ev_j \tag{2.28}$$

  where λ is a constant that provides a nontrivial solution and A_{ij} is an adjacency matrix.[4] According to Glasserman and Young (2016), a node has high centrality when it

[4]See Bonacich (1972); Sun and Chan-Lau (2017) for details.

is connected with nodes with high centrality. Thus, eigenvalue centrality is a measure of connectedness in the entire market network. It has a similar form to the PageRank algorithm used to assess systemic risk (Dungey et al., 2013; van de Leur et al., 2017). However, because it is based on eigenvalues that do not vary much between phases, the eigenvalue centrality measure does not move between the phases. This highlights the importance of understanding the measures used; the relatively unchanging eigenvalue is consistent with Pesaran and Yang (2016), who reported that the wholesale trade sector is the dominant economic sector over multiple samples in a real economy network. (Unlike in their form, there is no individual node with an eigenvalue of greater than 0.5 in our sample that can be considered statistically dominant.)

- Network density

  Network density is a measure of connectivity that is defined as the number of connections divided by the total number of possible connections (Minoiu and Reyes, 2013). The number of connections in a network can be used to investigate how the network changes over time. The network density is given by the ratio:

$$density = \frac{\overline{n}}{n(n-1)} \tag{2.29}$$

  where $\overline{n}$ is the number of links among the nodes and $n(n-1)$ is the maximum possible number of edges/links among the nodes in a given network.[5]

2.2.3 Similarity of networks

We used the Jaccard similarity coefficient to examine how many edges identified in each subsample are retained between samples. Papers such as Billio et al. (2012) are concerned only with the net formation of new links. However, it is important to consider the gross movements to obtain a clearer picture. According to Poledna et al. (2015), Jaccard similarity coefficient quantifies the existing similarity between different networks. This measure considers what portion of the edges in two networks are formed by the same edges, and is formed as a ratio of the intersection of the sets of links in two networks, Q and R, to the union of the sets of links in two networks:

$$J(Q,R) = \frac{n(Q \cap R)}{n(Q \cup R)} = \frac{n(Q \cap R)}{n(Q) + n(R) - n(Q \cap R))} \tag{2.30}$$

[5]See Billio et al. (2015) and Chinazzi et al. (2013) for details.

When the statistically significant links in A (Equation 2.12) are weighted by DY weights, it is also possible that the W matrix may change between periods. In this way, the completeness of the network may change, due to the changes in the number of links, and/or the changes in the relative strength of those links. As we will demonstrate, this effect seems to be important in distinguishing the nature of the evolving network and seems to be particularly the case in understanding the transition from the build-up to a crisis to the crisis itself.

2.3 Dataset and descriptive statistics

The dataset includes 15 Asian daily equity market indices (in local currencies) for $1995 - 2016$ from Thompson Reuter's Datastream. These are augmented by the daily (closing) equity market indices for 27 other countries, listed by region in Table 2.1. We chose our sample of markets based on the availability of: (i) closing values, (ii) closing hours, and (iii) changes in closing prices. Our analysis of equity return spillovers is based on local currencies to avoid blurring the extent of market co-movements with fluctuations in the foreign exchange market (Mink, 2015).

The daily return (r_t) for all markets are calculated as the log differences of the total daily equity market indices of a given economy at time t. This can be expressed as:

$$r_t = \ln(P_t/P_{t-1}) \times 100 \tag{2.31}$$

Where r_t is the return at time t, P_t is the closing stock price of a given financial institution at time t, P_{t-1} is the lagged price and ln is the natural logarithm.

We studied 42 stock markets in three categories: developed, emerging, and frontier. We extended the previous research that primarily focused on a few developed or emerging markets (e.g. the G7 [Canada, France, Germany, Italy, Japan, the UK and the US] stock markets investigated by Apostolakis and Papadopoulos (2014), the 10 developed and 11 emerging markets in Asia studied by Yarovaya et al. (2016a), and Asian markets examined by Narayan et al. (2014) and did not consider all possible interconnectedness across different stock markets).

Table 2.2 presents the descriptive statistic of the daily returns for each market. The mean returns are positive for all economies with standard deviation ranging from $0.0096 - 0.0237$. The kurtosis results suggest that the daily return would be 'peaked' and have 'fat-tailed' distribution. Unit root tests revealed the usual characteristics of stationary returns in each series. The

Table 2.1: List of country-specific stock indices and their corresponding Thomson Reuters Datastream codes

Country code	Country name	Stock index	Datastream code
European			
AT	Austria	ATX – AUSTRIAN TRADED INDEX	ATXINDX
BE	Belgium	BEL 20	BGBEL20
CZ	Czech Republic	PRAGUE SE PX	CZPXIDX
DK	Denmark	OMX COPENHAGEN (OMXC20)	DKKFXIN
FI	Finland	OMX HELSINKI 25 (OMXH25)	HEX25IN
FR	France	FRANCE CAC 40	FRCAC40
DE	Germany	DAX 30 PERFORMANCE	DAXINDX
GR	Greece	ATHEX COMPOSITE	GRAGENL
HU	Hungary	BUDAPEST (BUX)	BUXINDX
IE	Ireland	IRELAND SE OVERALL (ISEQ)	ISEQUIT
IT	Italy	FTSE MIB INDEX	FTSEMIB
NL	Netherlands	AMSTERDAM MIDKAP	AMSMKAP
PL	Poland	WARSAW GENERAL INDEX 20	POLWG20
PT	Portugal	PORTUGAL PSI-20	POPSI20
ES	Spain	IBEX 35	IBEX35I
SE	Sweden	OMX STOCKHOLM 30 (OMXS30)	SWEDOMX
CH	Switzerland	SWISS MARKET (SMI)	SWISSMI
TR	Turkey	BIST NATIONAL 100	TRKISTB
UK	United Kingdom	FTSE ALL SHARE	FTALLSH
Americas			
CA	Canada	S&P/TSX COMPOSITE	TTOCOMP
US	United States	S&P 500 COMPOSITE	S&PCOMP
AR	Argentina	ARGENTINA MERVAL	ARGMERV
BR	Brazil	BRAZIL BOVESPA	BRBOVES
CL	Chile	CHILE SANTIAGO SE GENERAL (IGPA)	IGPAGEN
MX	Mexico	MEXICO IPC (BOLSA)	MXIPC35
Asia			
AU	Australia	S&P/ASX 200	ASX200I
CN	China	SHANGHAI SE COMPOSITE	CHSCOMP
JP	Japan	NIKKEI 225 STOCK AVERAGE	JAPDOWA
IN	India	S&P BSE NATIONAL 200	IBOM200
ID	Indonesia	IDX COMPOSITE	JAKCOMP
HK	Hong Kong	HANG SENG	HNGKNGI
MY	Malaysia	DJGL MALAYSIA DJTM MALAYSIA	DJMALYL
NZ	New Zealand	S&P/NZX 50	NZ50CAP
PK	Pakistan	KARACHI SE 100	PKSE100
PH	Philippines	PHILIPPINE SE I(PSEi)	PSECOMP
SG	Singapore	STRAITS TIMES INDEX	SNGPORI
KR	South Korea	KOREA SE KOSPI 200	KOR200I
LK	Sri Lanka	COLOMBO SE ALL SHARE	SRALLSH
TW	Taiwan	TAIWAN SE WEIGHED TAIEX	TAIWGHT
TH	Thailand	BANGKOK S.E.T.	BNGKSET
Africa			
EG	Egypt	MSCI EGYPT	MSEGYTL
ZA	South Africa	FTSE/JSE ALL SHARE	JSEOVER

analysis was conducted using de-meaned returns (as the mean is usually extremely close to 0 and, as we are focused on variance decompositions, this assumption is innocuous). Analysis of the complete network, consisting of 42 nodes, formed the initial benchmark for the study.

To construct our network, we used the data with its recorded local closing time date. The choice of time-zone treatment can have dramatic effects; no single choice is dominant due to the complications of wanting to test for two-way causality. Other researchers have used the dates as provided with the data (Wang et al., 2018), averaged data over consecutive days (Forbes and Rigobon, 2002) or used time-matched data series (Kleimeier et al., 2008). Although the last of these is arguably the most appropriate, it is difficult to obtain these data for the markets examined here and to control for problems associated with out-of-local trading time liquidity effects (most markets have different price-impact effects during local and non-local trading). The averaging procedure used by Forbes and Rigobon (2002) introduced a moving average bias into the problem, and, with Granger-causality testing, created additional problems with the performance of the statistic. Further, it is debated whether the use of lagged or non-lagged samples introduces or reduces noise in the process. Sensitivity analysis to different choices of date-lagging produced important differences; the most pronounced of these is that when the US data are lagged, there is virtually no evidence of transmission from the US to Asia, which seems at odds with our understanding of international financial markets and the transmission of shocks. Consequently, this chapter uses the convention of actual day dating in its analysis.

We first examined the evolution of the unweighted and weighted networks over the sample period and augmented this analysis with scenarios based on alternative clustering of markets, as per the Asian Development Bank member countries and the role of regional groupings, including the Association of Southeast Asian Nations (ASEAN) with other regions across the globe.

2.4 Financial network representation

Figure 2.2a is a graphical representation of the statistically significant links between each country node in the sample using just the Granger causality test results over the entire sample period ($1995 - 2016$). The figures show regional groupings of sample markets (using the groupings in Table 2.1), which immediately pointed to the complexity of the relationships between nodes–there are $1,722 = (42!/40!)$ possible connections between the nodes. It is evident that the markets involved are heavily interconnected, but it is difficult to comment further (ana-

Table 2.2: Descriptive statistics of daily return for each market

Country	Mean	Min	Max	Std. dev	Kurtosis	Skewness	ADF test	No. obs.
AT	0.0002	–0.0974	0.1277	0.0135	10.7384	–0.2140	–71.1573**	5739
BE	0.0003	–0.0829	0.1087	0.0111	9.9523	0.0112	–70.3872**	5739
CZ	0.0002	–0.1494	0.1316	0.0132	14.8753	–0.1718	–69.4570**	5739
DK	0.0004	–0.1091	0.0986	0.0113	9.7303	–0.2713	–71.1096**	5739
FI	0.0004	–0.0897	0.0973	0.0152	6.5627	–0.1113	–73.8211**	5739
FR	0.0003	–0.0904	0.1118	0.0143	7.8396	0.0829	–77.0792**	5739
DE	0.0004	–0.0849	0.1140	0.0147	7.5954	–0.0077	–76.5194**	5739
GR	0.0000	–0.1902	0.1327	0.0189	10.6342	–0.1824	–68.5693**	5739
HU	0.0007	–0.1650	0.1459	0.0166	13.5187	–0.2345	–71.7532**	5739
IE	0.0003	–0.1303	0.1022	0.0129	11.3909	–0.5090	–71.4974**	5739
IT	0.0001	–0.1272	0.1161	0.0149	7.8602	–0.0388	–76.8145**	5739
NL	0.0003	–0.0950	0.0830	0.0124	7.4651	–0.4448	–68.6160**	5739
PL	0.0003	–0.1320	0.1469	0.0168	7.4476	0.0083	–74.4086**	5739
PT	0.0001	–0.0986	0.1073	0.0118	9.9042	–0.2103	–68.3531**	5739
ES	0.0003	–0.1235	0.1443	0.0146	8.9329	0.0124	–74.0971**	5739
SE	0.0004	–0.0842	0.1165	0.0147	7.2704	0.1721	–77.0466**	5739
CH	0.0003	–0.0867	0.1139	0.0118	9.5391	–0.0438	–73.2515**	5739
TR	0.0013	–0.1768	0.1856	0.0237	9.3668	0.3075	–73.9692**	5739
GB	0.0002	–0.0834	0.0921	0.0108	9.3767	–0.0988	–75.9863**	5739
AR	0.0006	–0.1684	0.1775	0.0224	9.3782	0.1776	–70.0926**	5739
BR	0.0006	–0.1312	0.2796	0.0188	18.5465	0.7545	–72.1713**	5739
CL	0.0002	–0.0710	0.1475	0.0106	14.8593	0.4589	–63.2493**	5739
MX	0.0006	–0.1334	0.1292	0.0146	10.6563	0.2751	–68.8651**	5739
CA	0.0003	–0.0932	0.0982	0.0105	12.5107	–0.5306	–74.9890**	5739
US	0.0003	–0.0903	0.1158	0.0117	11.6484	–0.0660	–80.9848**	5739
AU	0.0002	–0.0834	0.0589	0.0096	8.5885	–0.3593	–77.1427**	5739
CN	0.0004	–0.1639	0.3099	0.0175	25.8061	0.7424	–73.9442**	5739
IN	0.0005	–0.1187	0.1631	0.0149	10.0010	–0.1242	–69.1956**	5739
ID	0.0005	–0.1195	0.1403	0.0151	11.8284	0.0327	–65.6407**	5739
JP	0.0001	–0.1141	0.1415	0.0149	8.7971	–0.1237	–78.7296**	5739
HK	0.0003	–0.1370	0.1882	0.0160	14.7057	0.3911	–76.4475**	5739
MY	0.0002	–0.2071	0.2344	0.0127	65.9316	1.8058	–69.8174**	5739
NZ	0.0001	–0.1507	0.1179	0.0104	15.9717	-0.3705	–76.3666**	5739
PK	0.0007	–0.1238	0.1361	0.0147	9.9650	–0.1841	–69.2419**	5739
PH	0.0002	–0.1278	0.1769	0.0148	15.0100	0.5099	–66.7017**	5739
SG	0.0001	–0.0936	0.1160	0.0126	9.9460	0.1695	–71.7193**	5739
KR	0.0003	–0.1196	0.1572	0.0180	9.3491	0.2213	–72.4785**	5739
LK	0.0004	–0.1297	0.2007	0.0105	42.2018	0.9596	–61.2101**	5739
TH	0.0001	–0.1484	0.1202	0.0152	10.9150	0.2835	–70.1885**	5739
TW	0.0001	–0.0980	0.0961	0.0149	6.0186	0.0605	–74.3705**	5739
ZA	0.0005	–0.1278	0.0816	0.0118	9.5149	–0.4721	–69.8633**	5739
EG	0.0007	–0.1552	0.1385	0.0162	10.0429	0.0050	–68.2147**	5739

Notes: The sample period is January 1995 – December 2016. The augmented Dickey-Fuller (ADF) statistic tests for unit root.** indicate statistical significance at a 5% level.

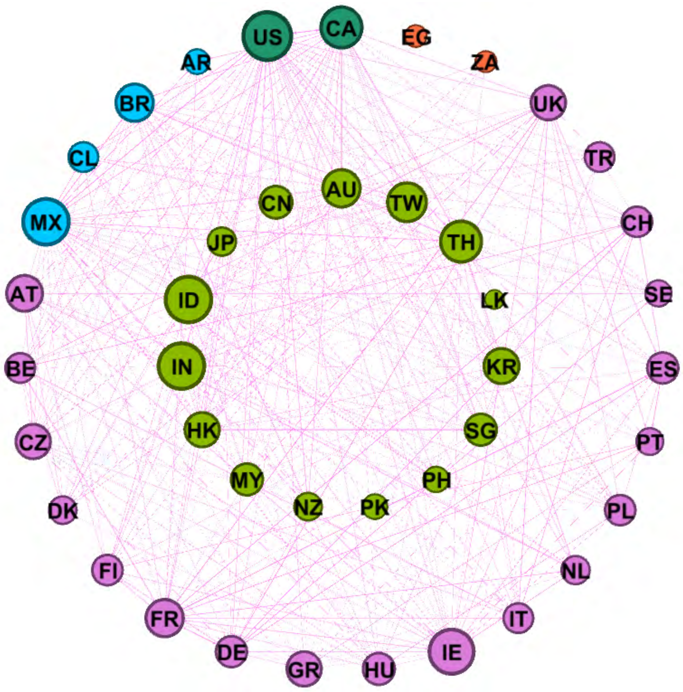
lytically) from this diagram. The primary focus of this paper is Asian economies, which are represented in light green, primarily to the left of figure. The sizes of each node reflect the number of links in and out of that node, so it is evident, for example, that the US has many connections over the sample period.

The methodological section of the paper showed how we augmented these simple directional graphs with weights drawn from the DY method to obtain a weighted directional network of the nodes. Figure 2.2b provided the weighted network equivalents of Figure 2.2a and identified both the nodes with largest connections and statistically significant links. The figure indicated relatively strong significance of the relationships between the European markets in the sample, particularly those that are members of the Euro region. The linkages between the markets are also directional, as signified by the arrows at the ends of each edge. While some are double-ended implying Granger causality in both directions (such as Hong Kong and Singapore), others are not (the link between Thailand and Malaysia is shown running in one direction only).

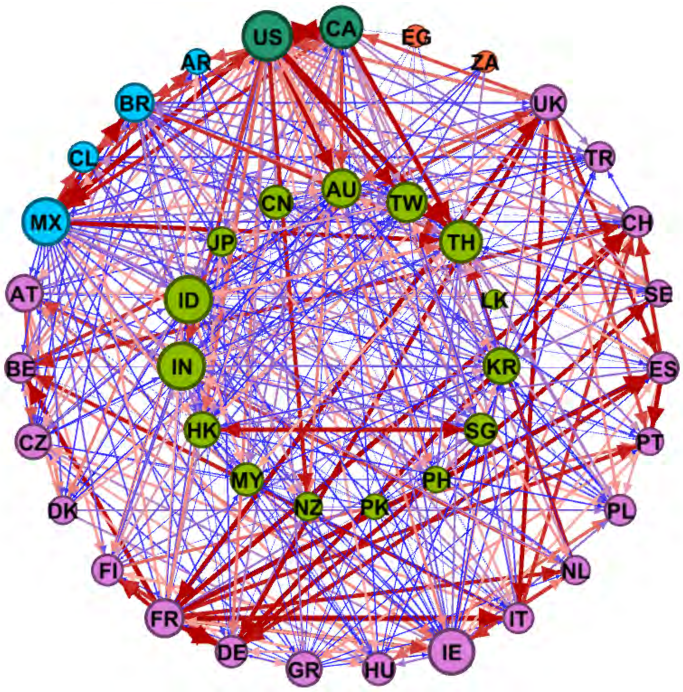
The thickness of the lines in Figure 2.2b indicates the relative strength and statistical significance of the links. Thus, it is immediately evident that the US and France are strongly connected to others (a similar role for France is found in Wang et al., 2018). Within the Asian focus of this chapter, there are clearly strong links between Hong Kong and the US, and slightly less so for Hong Kong to Canada. Hong Kong is also strongly linked to each of Malaysia and Singapore, snd slightly less strongly to a raft of other economies. Other distinctly strong linkages are clear between European countries such as Finland and Sweden, the UK and Italy and so on. The links between the European countries are stronger (in terms of the DY weights) than those detected for most Asian economies. This is likely unsurprising, as many were members of a common currency union for a large part of the sample period.

A distinct disadvantage of Figure 2.2 is the span of the sample covered. There were many changes in world financial markets in this period, including the introduction of the Euro, the floating of many Asian currencies, increasing financialisation of emerging markets in Asia, Africa and South America, further liberation of international capital markets and capital deepening in many areas. In addition, there were several financial crises.

We consequently divided our sample into six periods. Figures 2.3a to 2.3f represent the networks in each phase. The phases were selected based on a desire to examine how the network of Asian markets has altered over the sample period. The sample periods are divided as represented in the Table 2.3.



(a) Unweighted with regions indicated



(b) Weighted with regions indicated

Figure 2.2: Weighted and unweighted networks for entire sample.
Notes: Sample period: 1 March 1995 – 30 December 2016. Regions are colour-coded: Asia (light green), Europe (magenta), North America (dark green), South America (blue) and Africa (orange), as defined in Table 2.1. The figure displays the returns-based network of 42 equity markets. Edges were calculated using bivariate Granger causality tests between markets at the 5% level of significance. Edges in Figure 2.2a are unweighted and allocated equal weights. Edge thickness in Figure 2.2b is proportional to the intensity of the edge strength and is set as: red (strongest), orange (medium) and blue (weakest). Node colour is proportional to the regional grouping, while node size is proportional to its degree.

Table 2.3: Subsample periods in our data

Phases	Time period	Representing	Observations
All phases	01.03.1995 – 30.12.2016	Pre-Asian crisis period	5,738
Phase 1	01.03.1995 – 01.07.1997	Pre-Asian crisis period	650
Phase 2	02.07.1997 – 31.12.1998	Asian crisis period	391
Phase 3	01.01.1999 – 31.12.2002	Post-Asian crisis period	1,042
Phase 4	01.01.2003 – 14.09.2008	Lead up to the global financial crisis	1,287
Phase 5	15.09.2008 – 31.03.2010	Global financial crisis	602
Phase 6	01.04.2010 – 30.12.2016	Post IMF program approval in Greece	1,761

To avoid complications in naming our choice of periods in the literature, particularly with respect to choosing end points for each sample, each subperiod is referred to simply as a phase within the total sample. The number of time-series observations in each subsample is given in Table 2.3. The total number of observations in the whole sample is 5,738. The number of observations in each subsample varied with Phase 2 having the lowest (391) and Phase 6 having the largest (1,761). However, some of these phases strongly correspond with periods of particular interest.

Phase 1 represents the period in the lead-up to the Asian crisis of 1997 – 1998 and Phase 2 covers the generally accepted duration of that crisis.[6] Phase 4 covers the recognised lead-up to the GFC pre-2008, and Phase 5 the period of the GFC itself.[7] Consequently, Phases 1 and 4 both represent periods of lead-up to crises. Phases 2 and 5 are periods of crisis, and Phases 3 and 6 are to some extent, recovery periods, although this is clouded by the dot-com crisis in 2001 in Phase 3 and the stress in sovereign debt markets post-2010. Our area of interest is not only the networks in those periods, but also the transitions that occur in these networks between the different phases. This enabled us to develop generalisations about the number of characteristics of networks as they enter and exit crisis conditions. Our findings are reinforced by those for the large network (107 nodes) of credit default swap (CDS) issuers examined in Dungey et al. (2019a), despite the fact that market coverage in that paper was more specifically geared towards individual financial institutions and sovereign issuers rather than the equity market indicators used here.

The next stage of analysis was examination of the changing nature of the network over time, the importance of particular sources of shock, and a geographical examination of the relationship of non-Asian and within the Asian region.

[6]See, Dungey et al. (2005).

[7]See Dungey et al. (2015).

2.4.1 Changing network links over time

Figure 2.3 illustrates the changing nature of the weighted financial network over the six phases defined in Section 2.4. The key network statistics are presented in Table 2.4. We observed the network density as high during crises, (with the GFC presenting the largest network density) while low during the pre-crisis period. The results also show that the average degree of the network is evident during the crisis periods and low during pre-crisis periods. These findings suggest that the exposures are larger during the crisis period. Table 2.5 provides the associated network statistics that aided our analysis.

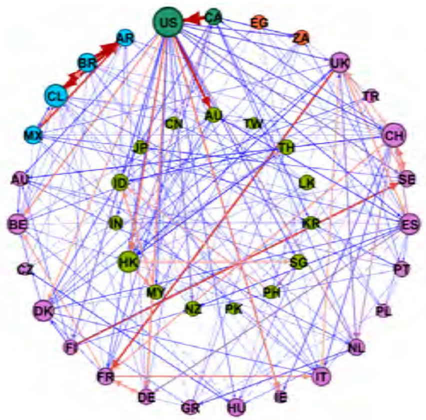
Table 2.4: Key network statistics for the whole sample period

Key network statistics	**All phases**	**1**	**2**	**3**	**4**	**5**	**6**
Average degree	11.52	5.00	7.26	5.10	5.64	9.26	7.29
Network density	0.27	0.12	0.18	0.12	0.14	0.23	0.18
Network diameter	5	5	5	5	5	5	5
Average path length	1.80	2.53	2.17	2.64	2.46	1.99	2.20
Average clustering coefficient	0.38	0.17	0.24	0.20	0.20	0.36	0.30

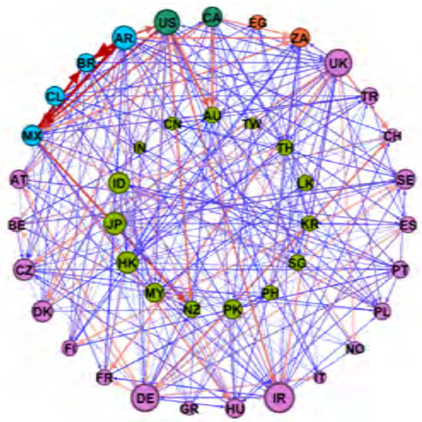
The sample period was 1 March 1995 – 30 December 2016.

The first impression from Figures 2.3a – 2.3f is that the density of the network changed substantially over time. The figures give the impression of becoming darker and thicker– that is, more connected, in a similar manner to the changes noted by Billio et al. (2012) and Merton et al. (2013) for several forms of financial intermediaries in the US and European markets. However, Table 2.5 reveals that the number of statistically significant edges in the network has grown less monotonically than the panels may suggest. In Phase 1, 210 of the possible 1,722 linkages were statistically significant. This is only 12.2% of all possible linkages. However, this number grew dramatically by 45% to 305 links in Phase 2, before returning to close to the pre-crisis period numbers in Phase 3. In Phase 4, the build-up to the GFC, the number of links increased in the system, up by 10%, but in Phase 5 the number of links jumped dramatically to 389, an increase of almost 65%. After that period, the links reduced again but remained at about the same level in Phase 6 (as evident in the crisis of 1997 – 1998).

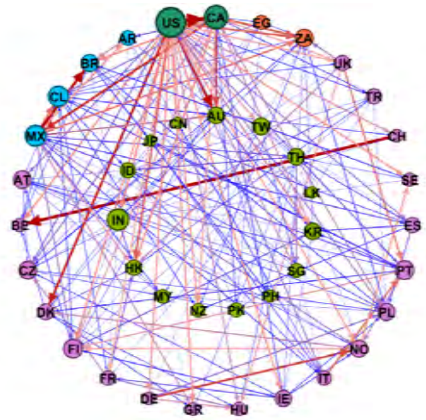
The Jaccard statistics, which compare the networks in a phase to that in the previous phase summarise one aspect of the changing numbers of linkages (see Table 2.6). The first row of Table 2.6 indicates the proportion of links that existed in the earlier period that were removed in the transition to the next period. The second row indicates the proportion of links that formed between the two phases as a proportion of the latest phase's links. This appproach



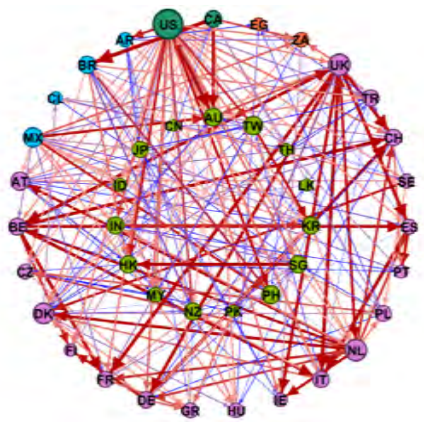
(a) Phase 1



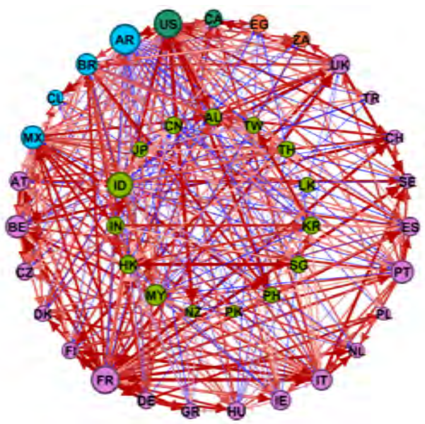
(b) Phase 2



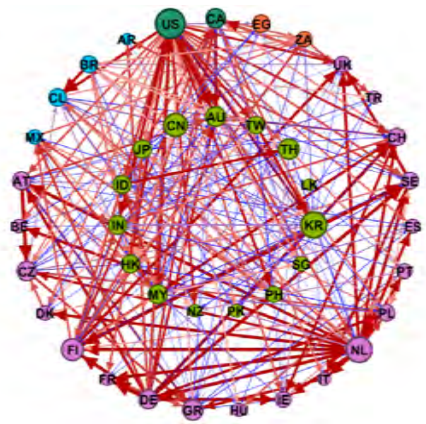
(c) Phase 3



(d) Phase 4



(e) Phase 5



(f) Phase 6

Figure 2.3: Evolution of weighted networks with regional groupings.

Notes: Sample period: 1 March 1995 – 30 December 2016. Regions are colour-coded: Asia (light green), Europe (magenta), North America (dark green), South America (blue) and Africa (orange), as defined in Table 2.1. The figures display the returns-based network of 42 equity markets. Edges are were calculated using bivariate Granger causality tests between markets at the 5% level of significance. Edge thickness is proportional to the intensity of the edge strength and is set as: red (strongest), orange (medium) and blue (weakest). Node colour is proportional to the regional grouping while the node size is proportional to its degree.

Table 2.5: Network statistics used in the analysis of the network structures (all countries) in each phase

Panel A						
	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Phase 6
Average strength	0.0260	0.0235	0.0236	0.0276	0.0260	0.0225
Number of edges	210	305	214	237	389	306
Completeness	0.2570	0.2252	0.1820	0.2034	0.2734	0.1990
Panel B						
Edges Formed						
	1 – 2	2 – 3	3 – 4	4 – 5	5 – 6	
	0.0194	0.0169	0.0208	0.0225	0.0211	
	264	159	180	306	233	
	0.1608	0.0968	0.1163	0.1864	0.1424	
Edges Removed						
	Phase 1 – Phase 2	2 –3	3 – 4	4 – 5	5 – 6	
	0.0206	0.0196	0.0180	0.0207	0.0229	
	169	250	157	154	316	
	0.1640	0.1536	0.1020	0.0994	0.1957	

Notes: The average link strength was estimated from the connectedness of each respective network. The number of edges was calculated using bivariate Granger causality tests between network nodes.

enabled a clear view of the composition of the elements of the Jaccard statistic listed in the third row of the column. The Jaccard statistics are low; that is relatively few links are common between two phases. This partly reflects that the network is growing significantly in terms of number of links over the sample period, with 45% more links in Phase 6 than Phase 1. This growth results in a reduction in the Jaccard statistic by construction. The first two rows show that in general, the network exhibits greater stability, in terms of the retention of edges, as time progresses. Setting aside the post-crisis period of Phase 6, it is apparent that the proportion of links lost during each of the sample shifts is falling, from 80% to 65%. The edges are becoming more likely to be retained over the sample period. The growth of the network is still apparent, however, there is drop in the number of new links as a proportion of the total in each phase remains relatively more stable at or over 75% of each phase.

Table 2.6: Jaccard similarity statistics for all countries in the sample (%)

	Phases				
	1 − 2	2 − 3	3 − 4	4 − 5	5 − 6
Edges removed as proportion of Phase t-1	80.48	81.97	73.96	64.98	81.23
Edges formed as proportion of Phase t	86.56	74.3	75.95	78.66	76.14
Jaccard statistic for all edges	8.65	11.85	14.47	15.29	11.74

The transitions around the GFC period, involving Phase 5, paint a complementary picture to the analysis above. During Phase 5 a relatively lower proportion of existing links in Phase 4 were retained, and the very many that formed during the crisis period were subsequently not retained in Phase 6. Thus, the crisis period had increased density associated with the high degree of net formation of new links. This is consistent with the dominance of the Forbes and Rigobon (2002) form of contagion.

The examination of the transition from the built-up in pre-crisis to the crisis period identified a rapid increase in the number of statistically significant edges in the network, supporting the notion that during periods of stress, markets become more interconnected. This finding is consistent with the literature, which contains considerable evidence of contagion. In our analysis, sample variances were separately controlled in the different phases; thus, changes in correlation are not a symptom of the changing variance.[8]

The average link is weaker in the crisis period than in the lead-up period. Panel B of Table 2.5 demonstrates this evolution. The top part of the panel describes the mechanism of formation of edges between each of the phases, while the bottom section describes the edges removed. A

[8]See Forbes and Rigobon (2002) for details.

relatively large number of average weaker linkages were formed (264 edges formed of average strength 0.0194) while a smaller number of stronger edges were removed (169 edges removed of average strength 0.0206). Dungey et al. (2019a) observed declines in the average strength of the links between the periods leading to crises and the crisis periods themselves for CDS markets.

A similar pattern was observed in the transition between the pre-GFC period and in the crisis itself when comparing the results for Phases 4 and 5. There were 306 links formed between Phases 4 and 5, and 154 links removed. That is, the number of links formed outweighed the number of links removed (the total number of links recorded in Phase 5 was 389, so that a full 64% of the links in Phase 4 were removed in Phase 5). The Jaccard statistic for Phase 5 compared with Phase 4 is 11.74% (see Table 2.6). The new links were, on average, slightly stronger than those that were removed. The completeness statistics for the network rose due to increases in average strength of the link and number of links.

The net change in the number of edges reported is not sufficient to characterise the changing nature of the network; edges removed are just as important as edges formed in understanding the transmission of crises, as these are both forms of contagion between markets. The complications of using completeness statistics to understand the evolution of a network were also revealed. Completeness may fall due to the increased number of edges being outweighed by the fall in their average strength as in the Asian crisis example. Alternatively, it may rise due to the overwhelming increase in the number of edges, which is evident in the GFC period. Knowing which edges are removed may be critical–for example, the collapse of Bear Stearns in 2007. Policy makers will clearly wish to understand both possibilities for removed edges and formed edges in periods of stress and have alternative plans available for each.

The post-crisis periods in the sample also revealed interesting contrasts. Both periods also included crisis periods in other parts of the network–in Phase 3, the dot-com crisis, and in Phase 6, the European sovereign debt crisis–making it difficult to classify these periods as pure post-crisis conditions. However, the transitions from the main crises of focus in this analysis were informative. From Phase 2 to 3, the number of links reduced, as it did from Phase 5 to 6. That is, after our main crisis period, the number of edges fell. In the first case, from Phase 2 to 3, this was achieved by a reduction in the number of links (loss of 250 links and gain of only 159) and a lower average strength of the new links than those that were removed. These factors both contributed to a lower completeness statistic in Phase 3. Similarly, in the transition from Phase 5 to Phase 6, more links were removed than were formed. The links that were removed were stronger than those formed, contributing to a lower completeness statistic in Phase 6.

Identifying which of the links existed prior to a crisis, were lost during the crisis, and reformed in post-crisis has policy implications. Were these linkage losses due to deliberate isolation of nodes, or due to their vulnerability? To address this question more specifically, we analysised the links themselves.

2.4.2 The changing involvement of nodes over time

As shown in Table 2.5, not only does the net number of linkages between nodes changes between subperiods, but it also masks changes in the existence of specific linkages. Table 2.7 provides descriptive statistics of the form of the network in each phase. The first statistics are the degree of the network. in-degree is the number of links that directionally point towards each node, and out-degree is the number of links pointing away from each node.

The average in-degree and out-degree for the network over the entire sample period is given in the first panel of Table 2.7, and shows that the means were identical. However, the median in-degree for the network exceeded that of the out-degree and had a much lower standard deviation–the range of the out-degree for each node was far higher. For the entire sample every, node had an in-degree of at least 5, meaning that each node received transmissions from at least five other nodes, directly; the maximum in-degree is 18. In contrast, not all nodes transmitted shocks (a minimum out-degree of zero).

To consider the changing nature of the in-degree and out-degree, Figure 2.4 provides a histogram of the numbers of nodes for out-degree and in-degree respectively by 5 degree intervals for each phase. The first bar in each column of Figure 2.4 is the number of nodes recording 5 or fewer (including zero) edges in that phase, with subsequent categories rising in increments of 5. It was immediately apparent that in-degree by phase had fewer nodes with fewer connections than out-degree by phase. This was marked during the two crises, Phases 2 and 5, which had the fewest nodes registering low in-degree or out-degree. This means that nodes connected during the periods of stress have links to more other nodes than those which are connected during periods of less stress. The in-degree for any node involved in the system never exceeded 15, indicating that each node received shocks from sources that specific, and perhaps identifiable. However, the out-degree for each phase was more diverse. Table 2.7 shows that the maximum out-degree generally increased over the sample; the figures reveal the extent to which the distribution of higher connected nodes increased in times of stress. In Phases 2 and 5, there were discernibly

Table 2.7: Summary statistics of various network measures (all countries)

	Mean	Med	Std. dev	Min	Max
	All phases (01.03.1995 – 30.12.2016)				
In-degree	11.52	11	3.27	5	18
Out-degree	11.52	8	9.18	0	37
Betweenness centrality	21	12.84	21.18	1.32	90.41
Eigenvector centrality	0.02	0.02	0.01	0.01	0.04
	Phase 1 (01.03.1995 – 01.07.1997)				
In-degree	5	5	2.55	0	10
Out-degree	5	4	3.85	1	22
Betweenness centrality	36.71	22.88	43.35	3.78	227.12
Eigenvector centrality	0.02	0.02	0.01	0.01	0.06
	Phase 2 (02.07.1997 – 31.12.1998)				
In-degree	7.26	7	3.19	0	14
Out-degree	7.26	6	5.52	0	22
Betweenness centrality	28.48	19.59	27.28	1.9	105.77
Eigenvector centrality	0.02	0.02	0.01	0.01	0.04
	Phase 3 (01.01.1999 – 31.12.2002)				
In-degree	5.1	5	2.18	1	10
Out-degree	5.1	4	5.28	0	28
Betweenness centrality	36.19	17.42	53.48	0	307.61
Eigenvector centrality	0.02	0.02	0.01	0	0.06
	Phase 4 (01.01.2003 – 14.09.2008)				
In-degree	5.64	6	2.43	0	12
Out-degree	5.64	4	5.91	0	31
Betweenness centrality	33.43	21.29	43.67	0	263.65
Eigenvector centrality	0.02	0.02	0.01	0.01	0.06
	Phase 5 (15.09.2008 – 31.03.2010)				
In-degree	9.26	9	2.96	1	15
Out-degree	9.26	5.5	9.49	0	35
Betweenness centrality	24.71	10.56	38.47	0.52	196.03
Eigenvector centrality	0.02	0.02	0.01	0	0.05
	Phase 6 (01.04.2010 – 30.12.2016)				
In-degree	7.29	7	2.99	0	13
Out-degree	7.29	5	7.4	0	34
Betweenness centrality	28.14	14.52	43.21	0	211.56
Eigenvector centrality	0.02	0.02	0.01	0.01	0.05

Note: We used network measures of in-degree, out-degree, betweenness centrality and eigenvector centrality to capture the centrality of a country's position in the global financial network and its closeness to all other countries in these networks.

more nodes involved with a higher out-degree; that is, they were involved in transmitting shocks to (more) other nodes. However, this does not necessarily mean that they were source nodes for the shocks.

Shocks may transmit between nodes via other nodes. A measure of the extent of this effect is betweenness centrality, which effectively assesses the substitutability of a node. This measures the number of times a given node acts as part of the shortest path between two other nodes. It helps to determine how important a node may be in transmitting information through a network. A node with a normalised betweenness centrality measure of 1 is involved in the shortest path between all nodes in the network; hence, its removal could be of substantial importance for the network (this node does not obviously need to be the largest in the network or the source of a shock; Bear Stearns is a good example of this type of risk during the GFC). A market with a betweenness measure of 0 is unimportant in retaining the network. Table 2.7 shows that the average betweenness centrality of the network increased dramatically in Phase 3 of the sample, but in Phase 5, it drops from the previous pre-crisis sample period. Betweenness clearly differs across the phases, pointing to the different structures of core nodes during the different periods.

There is little information in the eigenvalue centrality measure to assess the changing nature of a network of nodes in financial markets over time. Table 2.8 provides the betweenness centrality, closeness centrality and eigenvalue centrality figures for each individual node assessed over the entire sample. There was no great variation in the closeness and eigenvalue centrality measures across different countries. In contrast Wang et al. (2018) derived a variety of centrality and closeness measures for 57 international equity markets and observed patterns consistent with crisis periods, although the range of their statistics did not vary greatly over time.

So far, we have established that: i) the number of connections between nodes changed between phases; ii) some edges were removed from the system; iii) some edges were formed each time; iv) the connectedness of nodes as measured by in-degree and out-degree changed in what appears to be a discernible way, increasing during periods of stress; v) the nodes that were more or less involved in the network during various phases may change and that vi) measures of centrality do not provide definitive information about changing financial networks during periods of stress. This information is gleaned from the summary measures of the network for each phase. We will now examine individual nodes.

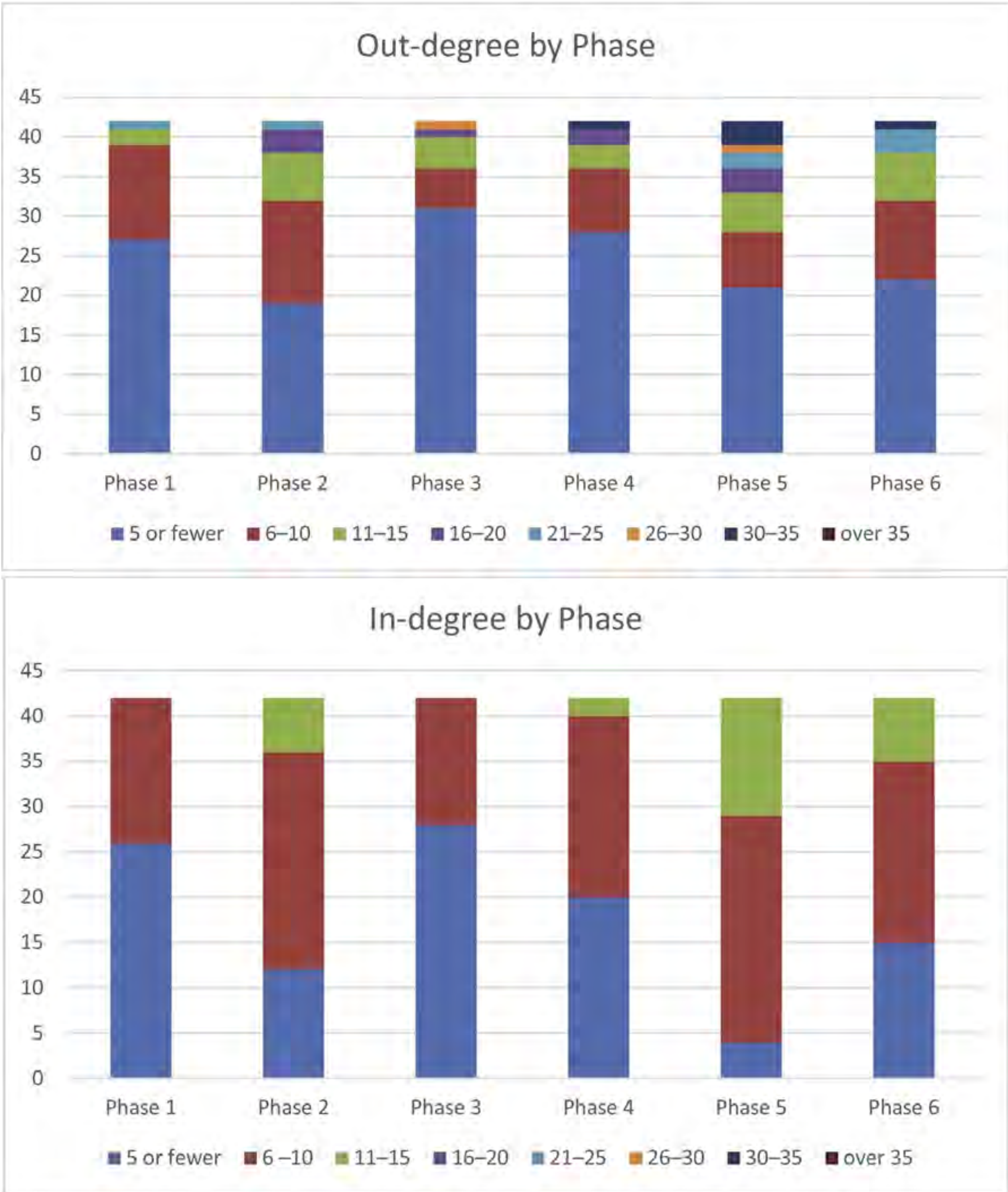
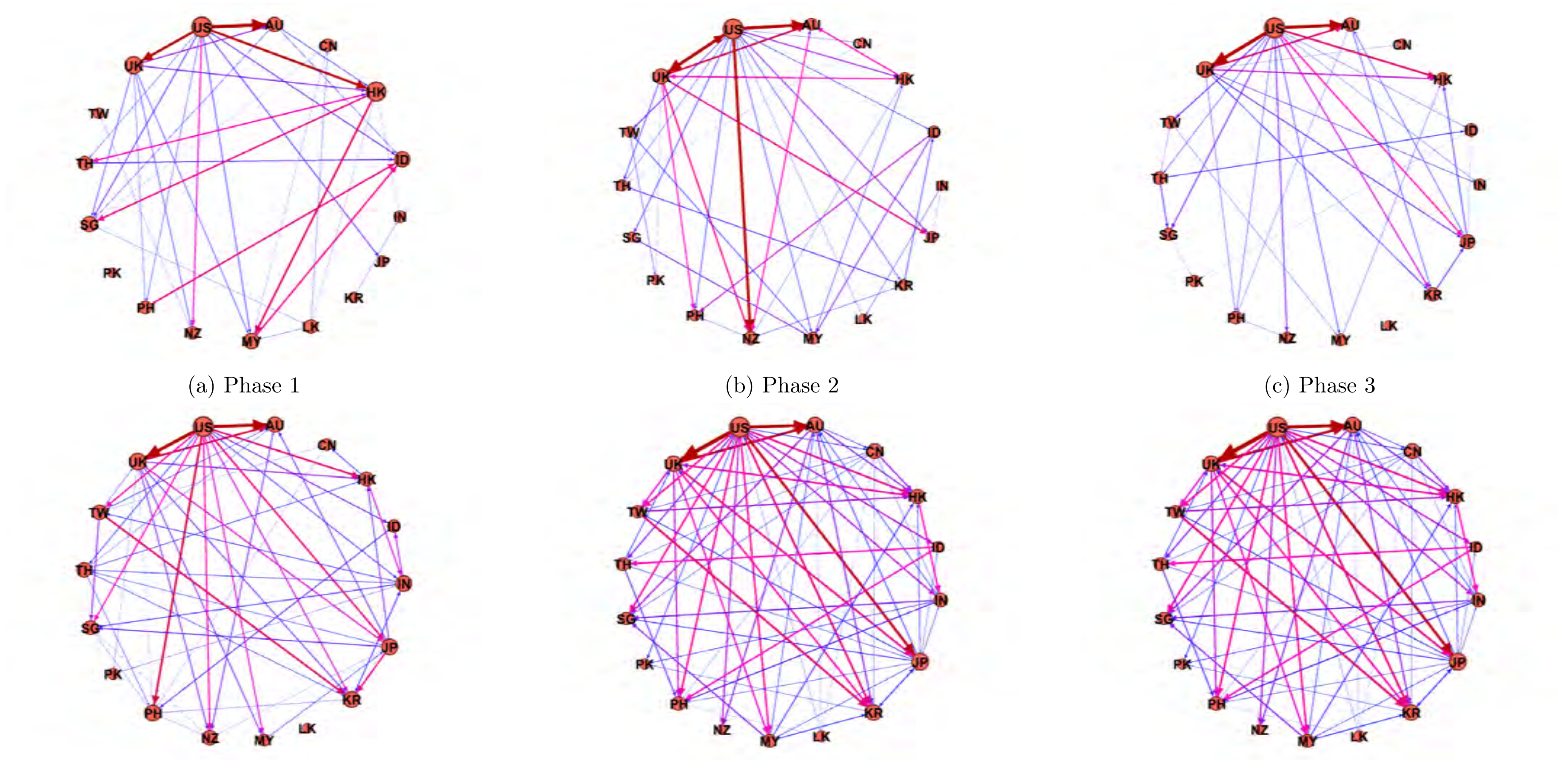


Figure 2.4: In-degree and out-degree by phases

Table 2.8: Completeness statistics for the whole sample (all phases: 01.03.1995 – 30.12.2016)

Country	**In-degree**	**Out-degree**	**Betweenness**	**Closeness**	**Eigenvector**	**Clustering**
Argentina	7	4	6.5658	0.0139	0.0113	0.3111
Australia	18	13	24.3210	0.0179	0.0309	0.3600
Austria	14	13	32.6658	0.0169	0.0261	0.3202
Belgium	11	7	9.6903	0.0149	0.0189	0.4190
Brazil	11	19	36.7235	0.0185	0.0318	0.3029
Canada	11	24	52.5183	0.0200	0.0360	0.3175
Chile	12	6	9.7601	0.0154	0.0211	0.3713
China	6	16	12.7719	0.0156	0.0204	0.2908
Czech Republic	15	10	20.6217	0.0164	0.0252	0.3405
Denmark	9	6	4.4163	0.0149	0.0197	0.4667
Egypt	9	7	6.6775	0.0147	0.0174	0.4011
Finland	12	7	8.1179	0.0154	0.0217	0.4081
France	10	19	53.7337	0.0179	0.0275	0.2908
Germany	11	9	8.4845	0.0154	0.0213	0.4044
Greece	7	18	21.7494	0.0164	0.0239	0.3286
Hong Kong	17	8	18.1500	0.0164	0.0259	0.3881
Hungary	12	9	15.3452	0.0159	0.0235	0.3743
India	11	6	9.2375	0.0152	0.0195	0.3917
Indonesia	15	28	56.8902	0.0208	0.0381	0.3004
Ireland	10	29	58.3729	0.0200	0.0352	0.2954
Italy	9	9	11.1405	0.0156	0.0217	0.3725
Japan	13	29	50.0405	0.0196	0.0344	0.2871
Malaysia	15	6	14.3542	0.0159	0.0235	0.3713
Mexico	5	37	76.6419	0.0222	0.0406	0.2905
Netherlands	10	7	1.3214	0.0141	0.0158	0.5364
New Zealand	9	6	9.0325	0.0149	0.0185	0.3762
Pakistan	6	5	4.4446	0.0137	0.0108	0.2778
Philippines	10	2	1.8190	0.0143	0.0163	0.4924
Poland	15	4	8.2548	0.0156	0.0228	0.4085
Portugal	13	1	2.4349	0.0145	0.0176	0.4744
Singapore	13	8	12.9077	0.0156	0.0222	0.3627
South Africa	14	7	17.6159	0.0159	0.0235	0.3977
South Korea	18	9	15.7321	0.0167	0.0271	0.3658
Spain	13	7	11.3760	0.0156	0.0221	0.4020
Sri Lanka	6	0	1.8586	0.0132	0.0068	0.2333
Sweden	9	4	2.8124	0.0143	0.0177	0.4744
Switzerland	14	5	10.1012	0.0154	0.0210	0.3824
Taiwan	13	13	19.8328	0.0167	0.0260	0.3225
Thailand	16	12	25.2410	0.0172	0.0279	0.3351
Turkey	11	7	10.1564	0.0154	0.0208	0.3566
United Kingdom	14	11	17.6546	0.0169	0.0281	0.3696
United States	10	37	90.4137	0.0222	0.0398	0.2725



(a) Phase 1 (b) Phase 2 (c) Phase 3

(d) Phase 4 (e) Phase 5 (f) Phase 6

Figure 2.5: Evolution of weighted networks for Asian markets, the US and UK.

Notes: Sample period: 1 March 1995 – 30 December 2016. Regions are colour-coded: Asia (light green), Europe (magenta), North America (dark green), South America (blue), Africa (orange), as defined in Table 2.1. The figure displays the returns-based network of 42 equity markets. Edges were calculated using bivariate Granger causality tests between markets at the 5% level of significance. Edge thickness is proportional to the intensity of the edge strength and is set as: red (strongest), orange (medium) and blue (weakest). Node colour is proportional to the regional grouping while node size is proportional to its degree.

2.4.3 Focus on the Asia-Pacific region

Figures 2.5a to 2.5f illustrate the subnetwork within the Asia-Pacific region, including a few key non-regional source shocks (notably the US and UK). That is, we reduced the information in Figure 2.3 to make this more tractable analytically. The system statistics are given in Table 2.9 for each phase; we treated each 'region' as a single node when counting the in-degree and out-degree.

It is readily apparent from Figure 2.5 that the US had the greatest number of connections of each node considered (omitting all European links from the diagram provides this clarity). Further, Sri Lanka and Pakistan were relatively isolated. The dominant direction was an out-link from the US to other markets. We proceeded to the sub-sample analyses to understand more clearly the changing nature of the network within the Asia Pacific.

Figure 2.5a reveals the network for Phase 1, prior to the Asian crisis. Here, it is apparent that the network was quite sparse. The links from the US directly to Asian markets were dominated by the direct link to Hong Kong. This provides an evidently important conduit from Hong Kong to and from other Asian markets Hong–Kong has links to Malaysia, Singapore, Thailand and Australia. There were also direct links from the US to Singapore, which again provides a conduit to other Asian markets that are not as strongly connected, such as China and Australia. Thus, both Hong Kong and Singapore provided a bridge node for transmissions to other Asian markets. Even more evident is the role of the UK and Australia in receiving links from the US and distributing them to Asian markets. The Australian node transmitted between Indonesia and Hong Kong, while there was a clear expression of links from the UK into Asia-Pacific markets–New Zealand, Hong Kong, Malaysia, Singapore, and the Philippines. A particularly interesting facet of the network in this phase is that Japan was connected to the US, but did not provide a bridge for these shocks into Asian markets.

By Phase 2 (the Asian crisis, shown in Figure 2.5b), links from the US directly to Asian-Pacific markets were evident for a wider range of markets than in the previous phase. The link between the US and UK remained strong, with ongoing links to other market. However, during this crisis period, while the links to Australia and New Zealand from the US were strong, the inwards projection of shocks from these sources to other Asian markets was not as pronounced as in Phase 1. However, the network did not indicate that shocks emerging from the Asian markets travel directly to the US; in this case, they tended to transmit around the Asian market and then developed markets via the conduit of regional hubs such as Hong Kong. For example,

Table 2.9: Summary statistics of various network measures for the Asian, plus the US and UK

	Mean	Med	Std. dev	Min	Max
	All phases (01.03.1995 – 30.12.2016)				
In-degree	5.65	6	1.92	1	9
Out-degree	5.65	5	4.21	1	16
Betweenness centrality	6.94	3.95	14.67	0	39.94
Eigenvector centrality	0.06	0.06	0.02	0.02	0.09
	Phase 1 (01.03.1995 – 01.07.1997)				
In-degree	2.18	2	1.7	0	5
Out-degree	2.18	1	2.72	0	10
Betweenness centrality	15.53	3	22.07	0	69.89
Eigenvector centrality	0.06	0.05	0.04	0	0.13
	Phase 2 (02.07.1997 – 31.12.1998)				
In-degree	2.47	2	1.55	0	6
Out-degree	2.47	2	2.65	0	11
Betweenness centrality	13.65	3	32.23	0	134.33
Eigenvector centrality	0.06	0.06	0.03	0.01	0.14
	Phase 3 (01.01.1999 – 31.12.2002)				
In-degree	2.06	2	1.14	0	4
Out-degree	2.06	1	3.31	0	13
Betweenness centrality	12.12	1.33	29.07	0	119
Eigenvector centrality	0.06	0.05	0.04	0	0.15
	Phase 4 (01.01.2003 – 14.09.2008)				
In-degree	3.35	2	3.39	0	13
Out-degree	3.35	3	1.8	0	7
Betweenness centrality	8.24	3.43	9.97	0	33.79
Eigenvector centrality	0.06	0.06	0.03	0	0.11
	Phase 5 (15.09.2008 – 31.03.2010)				
In-degree	4.35	4	2.06	0	7
Out-degree	4.35	3	3.71	0	15
Betweenness centrality	6.47	4.75	9.03	0	39.02
Eigenvector centrality	0.06	0.06	0.02	0	0.1
	Phase 6 (01.04.2010 – 30.12.2016)				
In-degree	4.06	4	1.92	2	8
Out-degree	4.06	3	4.21	0	16
Betweenness centrality	8.47	2.94	14.67	0	60.59
Eigenvector centrality	0.06	0.06	0.02	0.02	0.1

consider a shock originating in Malaysia–one route for this to affect the developed markets of the US, UK, New Zealand or Australia is via the link from Malaysia to Hong Kong and then to the developed markets.

Figure 2.5c shows the much-reduced network in the post-crisis period. Compared with the pre-crisis period of Phase 1, more Asian markets were directly linked to the US. The role of the UK in providing a further conduit into Asian markets was also evident. Japan was more integrated into the network, receiving shocks from all of developed markets (bar New Zealand) directly, and passing them to Hong Kong and Indonesia directly. China was still relatively isolated, receiving effects from the rest of the network only through the UK. Sri Lanka was a completely isolated node. In the build-up to the GFC, in Phase 4, the network was much denser than in previous periods. In Figure 2.5d, the links directly from Asian markets to the more developed markets were becoming clear–for example, Taiwan and Malaysia. Importantly, China was now connected via an Asian bridge–the Hong Kong market, and directly to the UK node. The role of Japan in transmitting shocks continued to grow. While it continued to receive shocks quite strongly from other developed markets–and distributed them via Hong Kong and Singapore–there were also additional direct links from Malaysia, to Thailand and to South Korea.

The increasing density of the Asia-Pacific network continued into the GFC period, Phase 5 (as shown in Figure 2.5e). China in this case became a source of inputs to the network but was not linked directly to the shocks emanating from the US, evidence of the differences in outcomes for China and Western developed markets during this period. Conversely, the role of Japan continued to increase in importance as a bridge to Asian markets. In contrast, the role of Hong Kong showed primarily inward linkages from Asian markets (it remained connected in both directions to many markets, but compared with earlier phases, there was a higher degree of inward linkages) and acted as a bridge to markets such as the US and UK. Hong Kong remained an important bridge market between Asian markets and others. Singapore had a similar experience. As with the existing analyses of changing networks during the GFC, the completeness of the network in the GFC increased dramatically.[9]

In Phase 6 (see Figure 2.5f), the density of the network decreased from the crisis period but the greater connectivity of Asian markets from many sources remains prevalent; for example, South Korea received links from a much wider portion of the network than it had previously. China was clearly more connected than it had been previously; there were links outward from

[9]See Billio et al. (2012) and Merton et al. (2013) for details.

China to many Asian markets–Hong Kong, Taiwan, Thailand, South Korea and Singapore–but it still only received inward links from Australia and the US. Japan and Hong Kong functioned as hubs for receiving and distributing shocks to and from Asian markets.

The network between the Asia-Pacific markets and the association of Southeast Asian nations (ASEAN) markets were aggregated to a single block, to examine the evolution of the network between both ASEAN and the rest of the Asian block and also with the rest of the world (see Appendix A.1.1) .

2.4.4 Individual histories of Asian markets

This section presents the illustrated history of the six phases of the sample, highlighting the connections of each individual market in the Asian sample (Australia and New Zealand were omitted from this analysis but figures are provided for completeness). Figures 2.6 to 2.18 have a similar form; a – f representing the six different phases. Each phase was overviewed before drawing together the lessons learnt from the extensive graphical analysis of this section.

- China (see Figure 2.6)

  Unsurprisingly China was poorly connected with other markets in the early part of the sample. There was a direct relationship with the US in Phases 1 and 2, perhaps reflecting the fixed exchange rate regime. China was linked with Singapore and Malaysia in Phase 1, but even these links are dropped during Phase 2 of the Asian crisis–a phenomenon that China was largely sheltered from due to its policies at the time. Phases 3 and 4 continued to reflect a relatively isolated Chinese market. With restrictions on investment by foreigners and maintenance of strict financial controls, it is not unreasonable that the influential links were limited. In Phase 5, however, during the GFC, China is far more connected. As well as direct influences from European markets and the US (drivers of these shocks), China was also connected to global markets via Japan, Indonesia and India. Note the absence of most ASEAN markets in helping facilitate this link–reflecting that China, due to its dominant economy, had not used a bridge economy to build relationships. As with India, China expanded its linkages between Phases 5 and 6, representing its rapid emergence in the world financial market. In the last phase, China was the dominant spreader in the network, with more out-degree links than any other market except the US and the Netherlands.

- Hong Kong (see Figure 2.7)

Hong Kong acts as a bridge between markets in Asia and the rest of the world. The markets of Sri Lanka and Thailand were not connected to the US or Germany directly (nor to European markets), but had a bridge to these global influences via Hong Kong (and to some extent Singapore) in the initial phase. As a market central to the geographical locus of the Asian crisis of 1997 – 1998, Hong Kong played an important role in bridging Asian and non-Asian markets, as evident in Phase 2. The strong links with the US and UK were expected, particularly given the problems with the 'double-play' on the Hong Kong stock market/currency market of August 1998 – September 1998, when the Hong Kong government ended up owning more than half of the Hong Kong stock market to foil speculation on the Hong Kong dollar (see Goodhart et al., 2003). Post this episode, it is apparent how much more connected Hong Kong was to non-Asian markets in Phase 3 and 4 than to Asia. Direct links with Hong Kong from Asia were more limited, and involved the more developed or fastest growing markets (such as Australia, Singapore, Malaysia and India). Although the direct links with Hong Kong grew in Phases 5 and 6, the Asian links were again limited to the more developed and fastest growing markets–this time including China. The markets that were not part of ASEAN seemed to be able to bypass Hong Kong as the primary first-degree link to other markets.

- India (see Figure 2.8)

  Although a large economy, India was a relatively isolated market in the first three phases of the study. In Phase 4, it is apparent that India established first-degree connections with a diverse group of markets, including others who were experiencing rapid growth during this boom period, such as Ireland, Brazil, Argentina, Turkey and Mexico. Within Asia, India had relatively limited contact with ASEAN markets, linking only with Indonesia. It appeared to be pursuing expansion of its international financial networks directly to the world's largest developed markets. During Phases 5 and 6 India continued to expand its first-degree network, expanding to include other ASEAN markets and China. While it connected directly to several developed European markets, and to the US (all major consumers of Indian production) in Phase 6, the financial market links to markets such as Australia, Singapore, New Zealand, the UK and some South American markets (Chile) were notable by their absence.

- Indonesia (see Figure 2.9)

  In Phase 1, Indonesia was connected to global markets both directly via the developed markets of the US and Australia and through links with other ASEAN economies

(Malaysia, Thailand and the Philippines). As one of the economies at the epicentre of the East Asian crisis in 1997 – 1998 in Phase 2 the number of direct links to non-Asia increased considerably (evidence of Forbes and Rigobon style contagion, as documented in, for example Dungey et al. (2006). Interactions with ASEAN markets remained intact, and included Singapore. Hong Kong and South Korea; two economies also indicated at the core of the crisis were also directly involved. However, after the crisis, in Phase 3, the direct links involving Indonesia shrank dramatically, and in Asia region were represented by Thailand, Japan and Pakistan. The addition of Japan, the major developed market of the region, is the earliest evidence present for a developing Asian market linked directly to outside markets via Japan. This was not sustained into Phase 4, in which a direct link to the US markets was evident. In Phase 5, the GFC, direct links to and from Indonesia with connections outside Asia exploded compared with previous periods. Links to Thailand, Malaysia and Australia remained in place, but the Japanese link was again missing. However, for the first time, China and India featured as directly connected nodes, likely reflecting their growing importance in global markets. In the aftermath of the GFC, Indonesia retained its links with China, Thailand, Malaysia and the Philippines, but not Indian. Japan link was now evident. Links to European economies in the sample were generally to periphery markets, some of which experienced considerable problems that could be viewed as sources of ongoing troubles (such as the Czech Republic, Spain and Portugal). Over the phases examined, Indonesia retained its first-degree links with Thailand and Malaysia consistently, frequently with the Philippines and the US. The most recent periods indicated links with China and Japan. Like most markets linked to China in Phase 6, Indonesia was a recipient of shocks transmitted from China. It was also observed that Indonesia was among the dominant spreaders in the network in Phase 5, having more out-degree links (27) than any other market except the US, Argentina and France.

- Japan (see Figure 2.10)

  With the exception of connections with South Korea, the Japanese node remained remarkably unconnected with other Asian markets in the first two phases of the sample. It was connected with other major markets in the world, particularly the US, and in Phase 2 with many European markets. Not until Phase 4, the period prior to the GFC, did Japan connect more extensively with Asian markets, and even then, the links were limited to the more developed markets in the set. In Phase 5, Japan had direct links to China for the first time, and only in Phase 6 was Japan more comprehensively connected to a wide variety of Asian markets (showing direct connections with 10 of the 14 other Asian markets examined; exceptions were the three markets from South Asia Pakistan, India, Sri Lanka and New Zealand). Japan appeared not to have formed bridge relationships with developing Asian financial markets over the longer term, but direct links emerged in the second half of the sample. These results are consistent with those of Wang et al. (2018), who identified a key role for Japan between Asia and the rest of the world using a sample that began in 2005.

- Malaysia (see Figure 2.11)
  The Malaysian results demonstrate how a policy to protect markets from contagion of stress during a crisis may evolve. In Phases 1 and 2, Malaysia was the third-most directly connected market from Asia–behind Hong Kong and Indonesia. In Phase 3, however, the direct connections in the network involving Malaysia shrank dramatically, perhaps reflecting the more restrictive capital regimes in place at the end of Phase 2. Malaysia was the only case in the Asian sample where capital markets did not move in a single direction towards greater liberalisation over the sample period. In Phase 5, direct linkages of Malaysia with other global markets expanded rapidly, almost tripling the number reported in Phase 4. There was some reduction in linkages to European markets, particularly in Phase 6 and some changes in the direct Asian market partners between Phase 5 and 6, but the retreat in the number of links post-GFC was not as drastic as during the period after the Asian crisis.

- Pakistan (see Figure 2.12)
  Pakistan represents an isolated node in the first phase of the sample, more connected with its near-neighbour India than others. In Phase 2 it recorded a large increase in the number of direct links, surprisingly mainly in out-degrees, before contracting again in the post-Asian crisis (Phase 3). Pakistan remained a node with relatively small degrees throughout the rest of the sample, although links with India were again evident in Phase 6.

- Philippines (see Figure 2.13)
  The Philippines is relatively isolated in Phase 1, with links to Singapore and Indonesia as external bridges, but not to major European or the US markets. In the Asian crisis, Phase 2, the Philippines was clearly affected by the crisis (contagion) from Malaysia and

Thailand, and its links with Indonesia were broken. In Phase 3, like most of Asia, the Philippines was largely an isolated market. However, in Phase 4, in the build-up to the GFC, links with Asia increased, particularly with other ASEAN countries (although not Malaysia which isolated itself), including direct relationships with France, the US and UK as international major markets. This continued through Phases 5 and 6, when it did not record a decline in the total number of connections post-GFC.

- Singapore (see Figure 2.14)

  The Singaporean node is remarkable for its consistent connection with both Asian markets and developed markets throughout the sample phases, connecting with the US directly in all but Phase 2. Interestingly, Singapore provided a link between countries as diverse as the Philippines, Sri Lanka and China in the first phase, but in the Asian crisis phase, direct links to Singapore declined, with only a link to Indonesia in terms of Asian markets. Unlike Hong Kong, it was not directly connected to several of the main crisis markets such as Thailand and South Korea during this period. As with many Asian markets, the number of direct links to Singapore shrank during Phase 3, and expanded in Phase 4, providing a conduit to Japan for other Asian markets. During the GFC (Phase 5), the most evident connection for Singapore was with Hong Kong. This may indicate that Asian markets were able to avoid being drawn into the GFC, as markets in other regions (Singapore's figure for Phase 5 was comparable), representing that these two bridge markets were acted in a similar way. In Phase 6, Singapore was directly connected to developed international markets in all regions of the world. Reflecting the analysis of other countries, it no longer acted as a bridge node for other Asian markets. Each Asian market in Phase 6 had their own direct links to major global financial markets.

- South Korea (see Figure 2.15)

  Prior to the Asian crisis, South Korea was a protected market with fixed exchange rates. As the Phase 1 diagram indicates, it had relatively little direct connection to external markets. Interestingly, unlike other markets, South Korea showed evidence of a direct relationship with Japan. During the Asian crisis, Phase 2, South Korea was part of the main set of markets affected, and reforms–including floating the currency and opening capital markets–led to a substantial change in the functioning of Korean capital markets. The road to a fuller integration into the network was visually evident in the figures for Phase 3 – 6 when linkages continued to grow. By Phase 6, South Korea was connected to major markets in Asia and non-Asia directly. In this case, the forced liberalisation of the 1998 crisis seemed to hasten the road of being directly interlinked compared with markets such as Taiwan. This could be regarded as an (incredibly expensive) advantage of having crisis in the home market.

- Sri Lanka (see Figure 2.16)

  Surprisingly, for a relatively small Asian market, Sri Lanka had a relatively high number of first-degree connections in the early phases. During the Asian financial crisis (Phase 2) it decoupled from Asia directly, so links between Asian turmoil and Sri Lanka were transmitted via pathways to the US, including ASEAN markets (particularly Singapore, Thailand and Indonesia). Between the two crisis periods, Sri Lanka was an isolated node with few connections. This likely reflects the uncertainty associated with the political context and civil war this time. After the civil crisis settled, and during the GFC, there were more direct links from Sri Lanka to other Asian markets. However, by the end of the sample, there was little evidence that it was connected to major financial markets other than by rather convoluted paths.Sri Lanka may be a case in which directed strategy to build links with a bridge market, such as India or ASEAN markets, may be extremely helpful in building market presence globally.

- Taiwan (see Figure 2.17)

  Taiwan was an isolated market at the beginning of the sample. However, its first-degree connectedness expanded steadily over the sample. Although the number of links with Taiwan increased during each crisis period, the number of links did not materially reduce afterwards. This suggests that markets that are peripheral to crisis events, and are developing market structures, can independently continue to progress without being disrupted by the chaos around them. By Phase 3 Taiwan was connected to the ASEAN markets of Thailand, Singapore and Malaysia, allowing it to use these as direct bridges to the rest of the world. By Phase 4, these links extended to India and directly to the UK. From Phase 5 onwards, Taiwan did not seem to need these secondary level links as much, as it established direct links with many of the world's largest markets, including the US and France, and in Phase 6, China and Japan.

- Thailand (see Figure 2.18)

  In Phase 1 Thailand was directly connected to very few international markets, and most connections to major markets were bridged through Hong Kong or Indonesia. There were no direct links to markets such as Japan or Singapore. During the Asian crisis represented in Phase 2, there was an increase in the number of links. However, considering Thailand regarded by many to be at the absolute center of the Asian crisis the first-degree connectedness was remarkably low. While the Thai market directly affected the UK and Canada, there is no evidence of direct statistically significant links to either Japan or the US. Links with ASEAN markets increased, as did links to other Asian crisis markets such as the Philippines. In Phase 3, this increased connectedness was retained, but the markets involved changed somewhat. There were connections to Singapore, Thailand and Taiwan in the Asian region, but connections to developed markets seemed to involve smaller markets (avoiding the US, UK and Germany). During Phase 4 direct links involving Thailand contracted considerably, likely reflecting the political turmoil of this period, which focused the country on internal events and possibly led to reduced desire of foreign investors to be involved in Thai markets. During the GFC, Phase 5, Thailand resumed the level of connectedness observed in the previous (Asian) crisis, connecting with other ASEAN markets, Hong Kong and India, and the major markets of the US and UK. In Phase 6, direct connections of Thailand to the rest of the world were seemingly more established, and there was less connection with other ASEAN markets than previously, except where major trading links remained (e.g. Indonesia). Thailand now connects directly via its financial market network with major markets in the US, Asia and Europe.

2.5 Chapter summary

This chapter investigated whether financial networks change over time. Network diagrams improve the transparency of financial interrelationships and provide a more compelling picture of the complexity of these relationships, and the potential length and plethora of pathways between nodes, than simple tables of correlation analysis ever can. The unweighted network filters for non-statistically significant connections; thus, potentially spuriously large connections are omitted from the weighted network. Using the combined DY and Granger causality approach, our findings show increasing interconnectedness in financial markets. These interconnections became even stronger during crisis events. Interconnectedness is channeled through shocks that propagate in the financial system, thereby, threatening economic stability. Our findings also suggest the increasing involvement of the Asian markets in the global context. Our results show the dominant role of the Chinese market in more recent periods, indicating its rapid involvement in the global market especially through trade.

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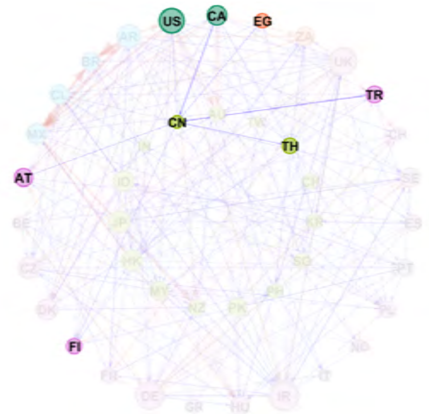

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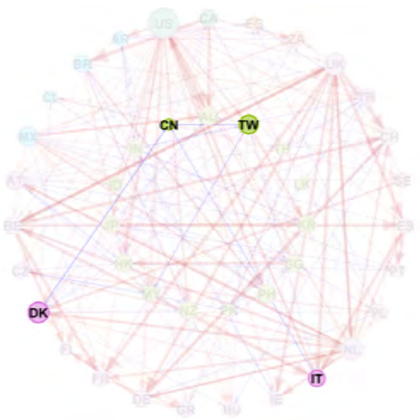
(c) Phase 3



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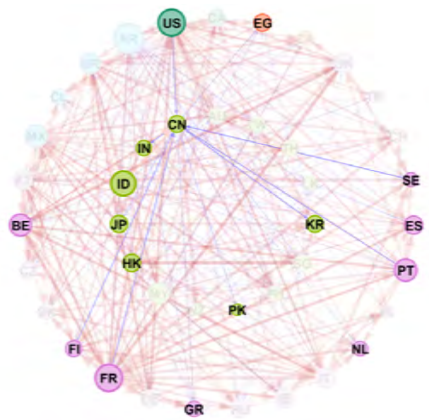

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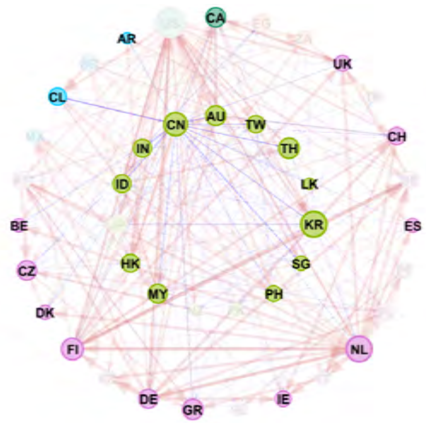
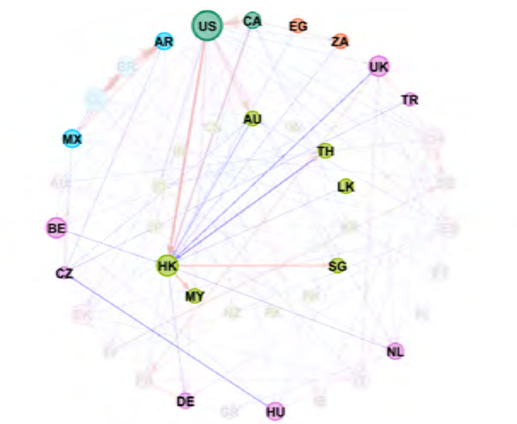


(f) Phase 6

Figure 2.6: Weighted networks for China



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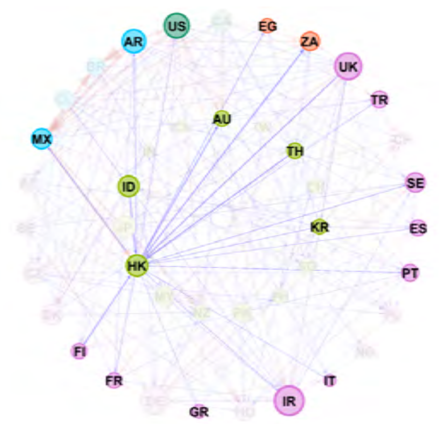

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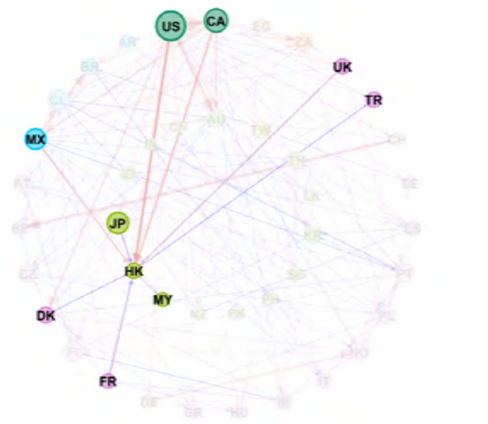

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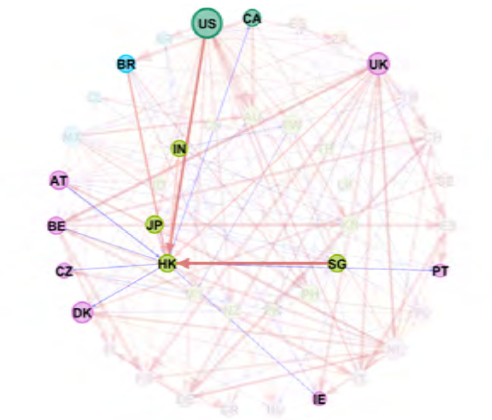

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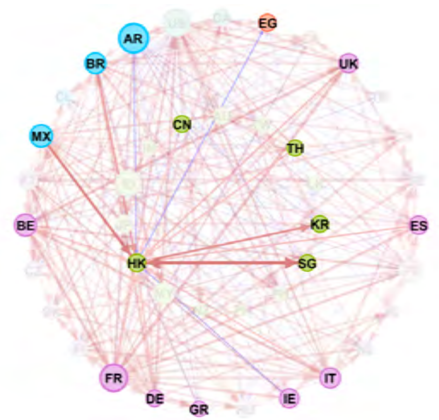

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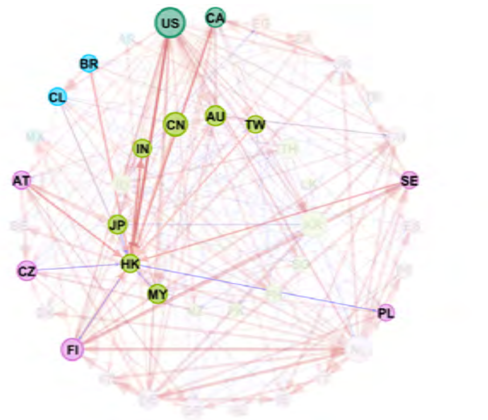
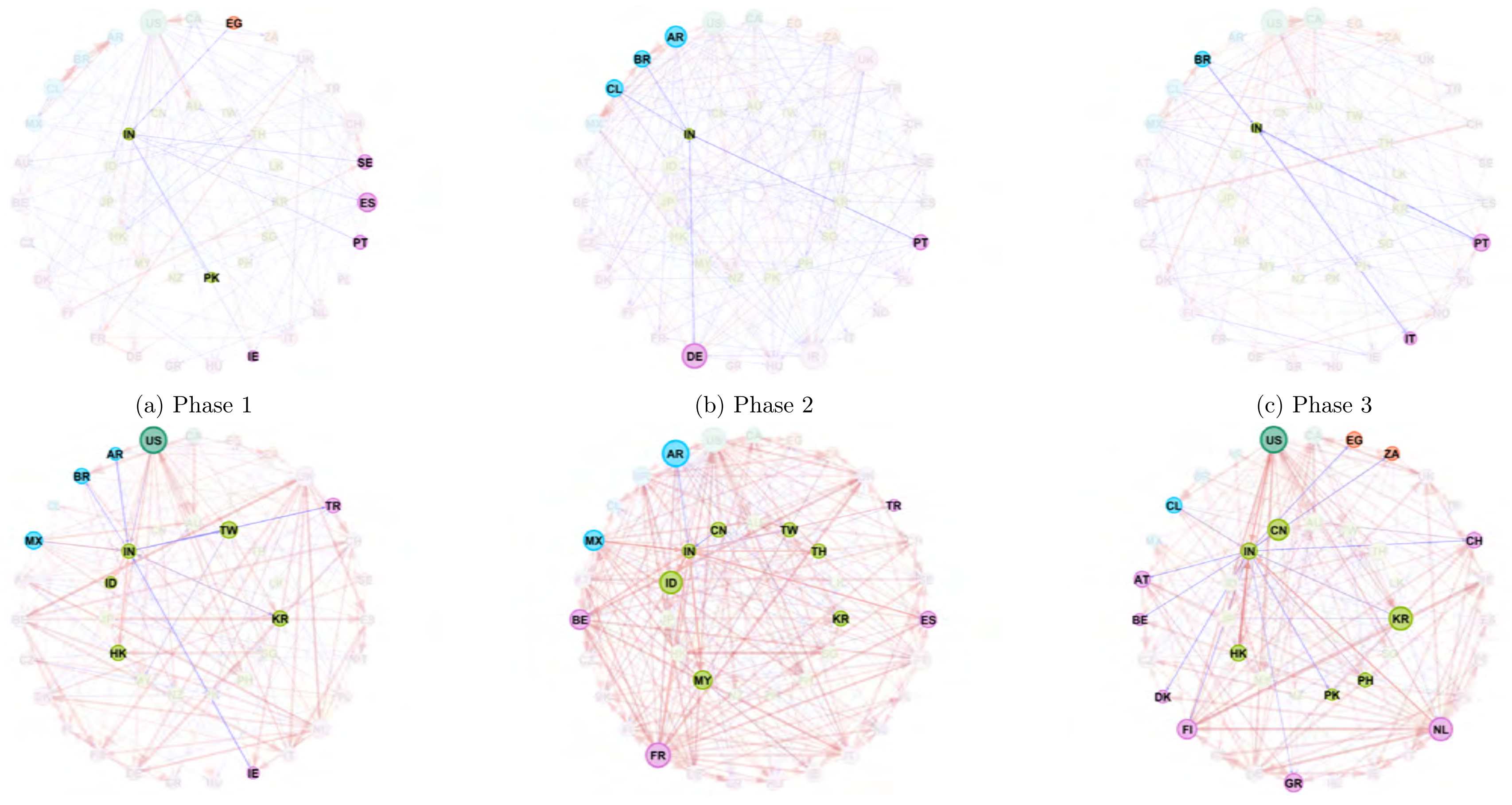


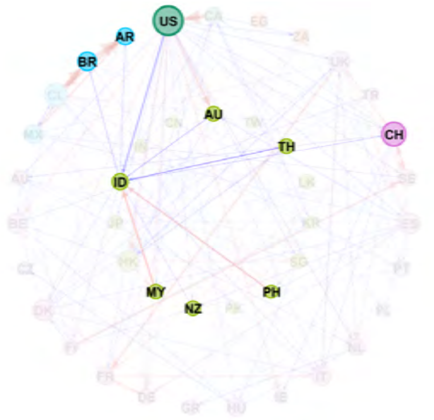
(f) Phase 6

Figure 2.7: Weighted networks for Hong Kong



(a) Phase 1
(b) Phase 2
(c) Phase 3
(d) Phase 4
(e) Phase 5
(f) Phase 6

Figure 2.8: Weighted networks for India



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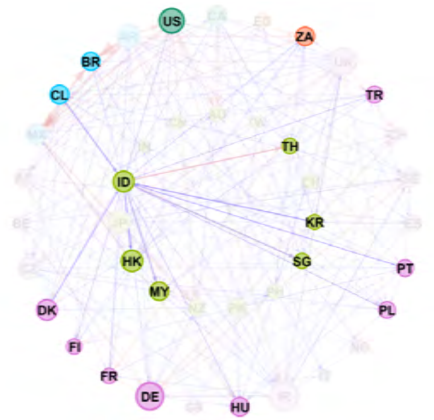

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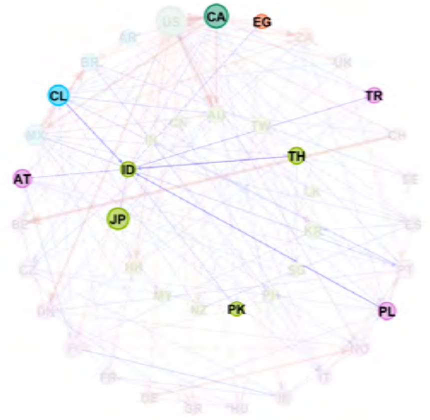

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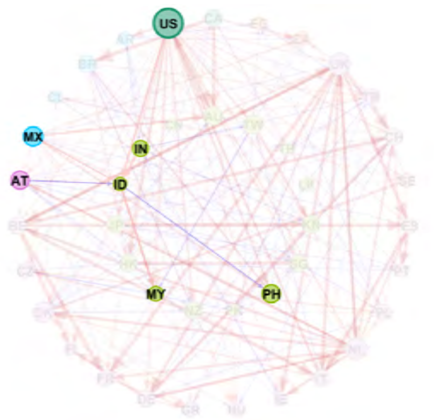

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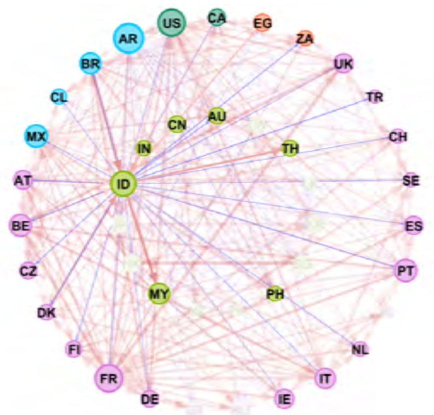

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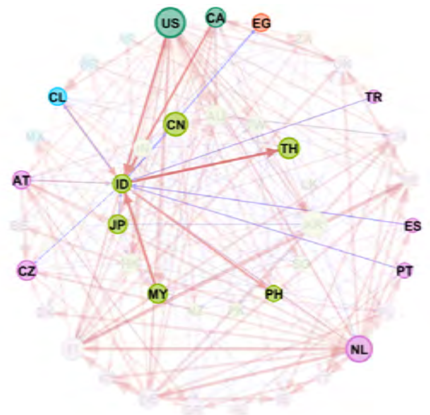
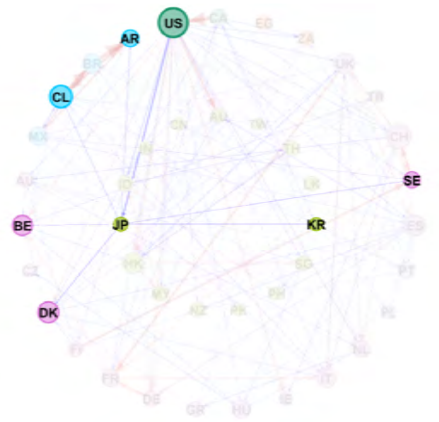


(f) Phase 6

Figure 2.9: Weighted networks for Indonesia



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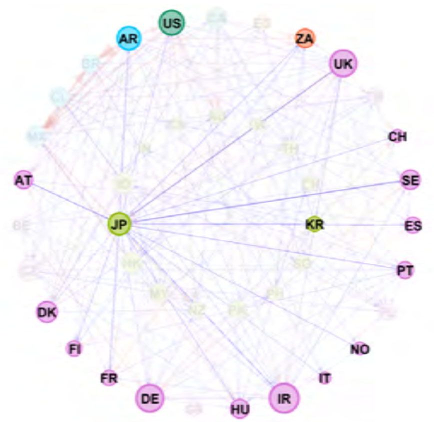

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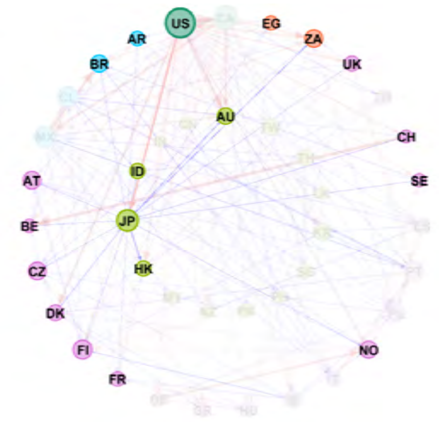

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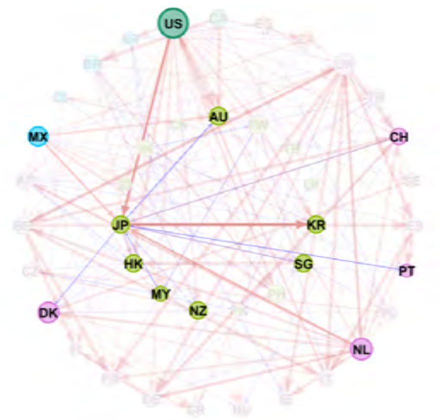

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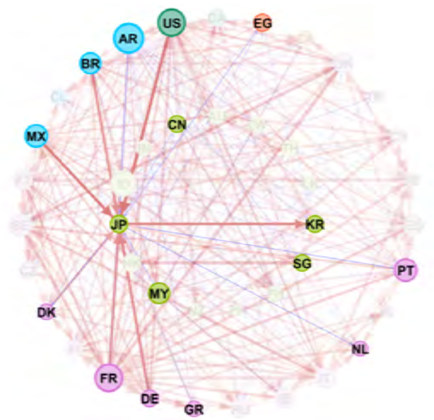

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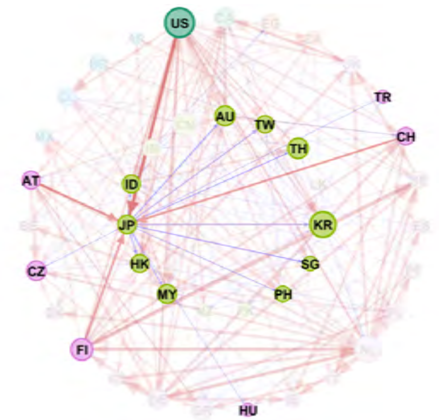


(f) Phase 6

Figure 2.10: Weighted networks for Japan

(a) Phase 1

(b) Phase 2

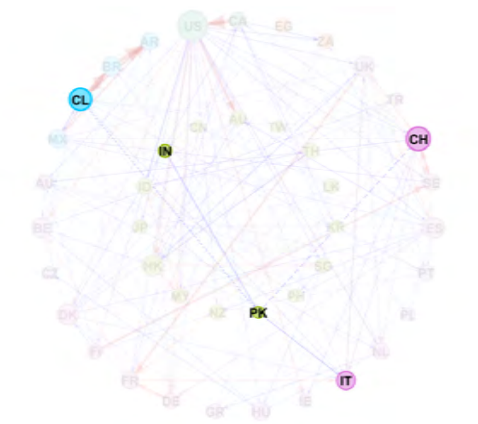
(c) Phase 3

(d) Phase 4

(e) Phase 5

(f) Phase 6

Figure 2.11: Weighted networks for Malaysia



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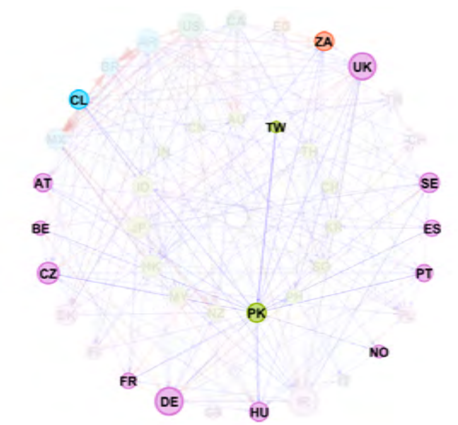

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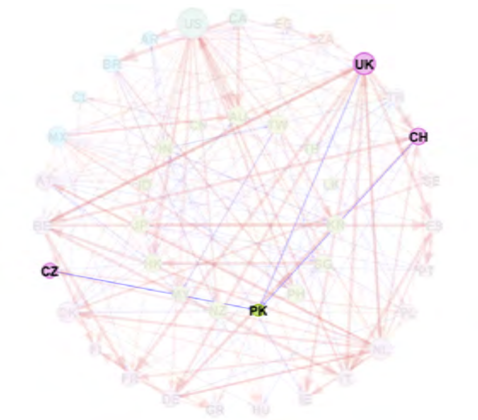

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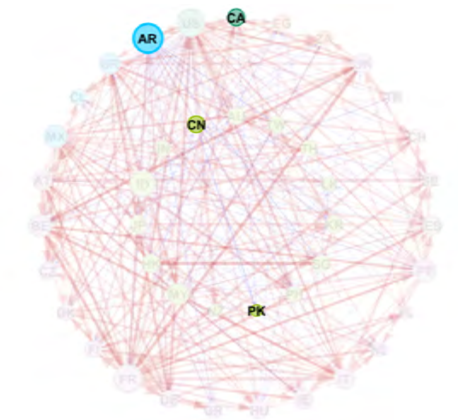

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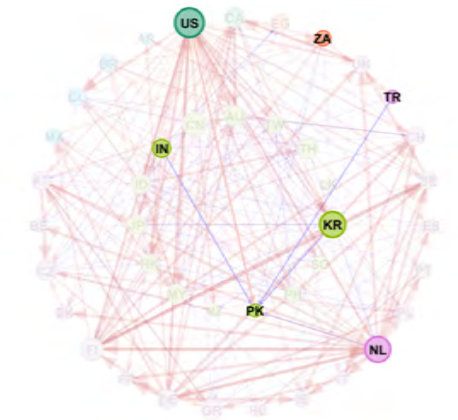
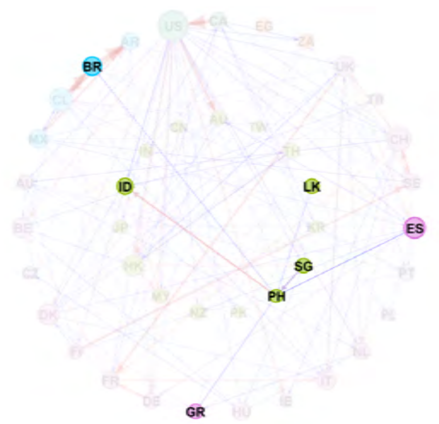


(f) Phase 6

Figure 2.12: Weighted networks for Pakistan



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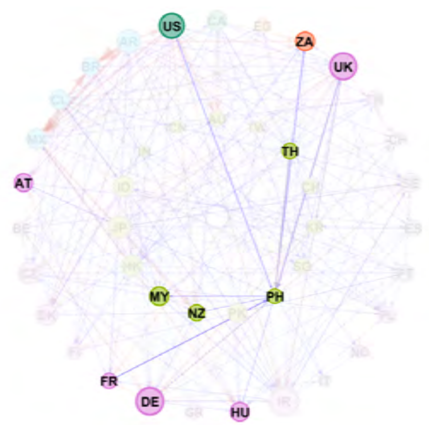

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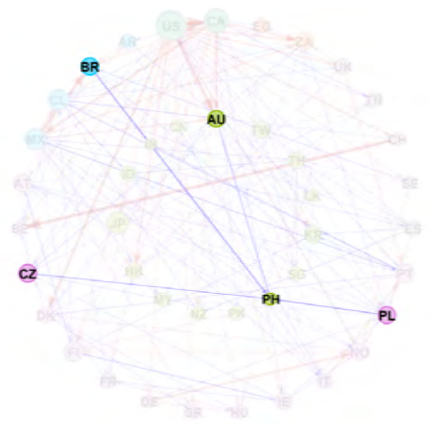

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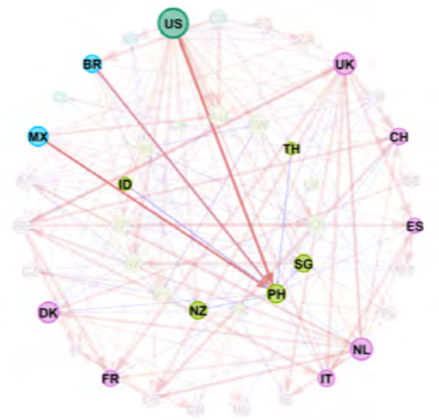

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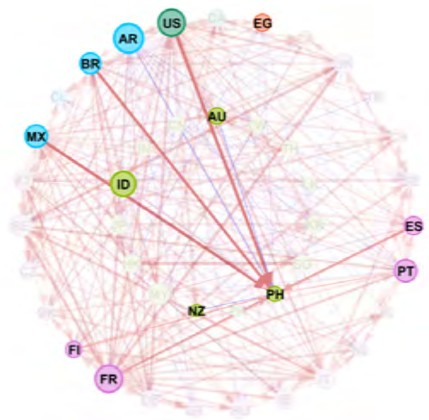

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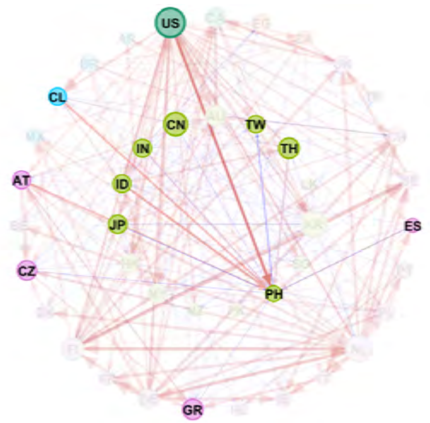
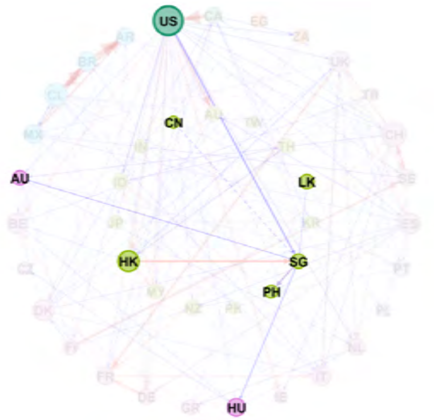


(f) Phase 6

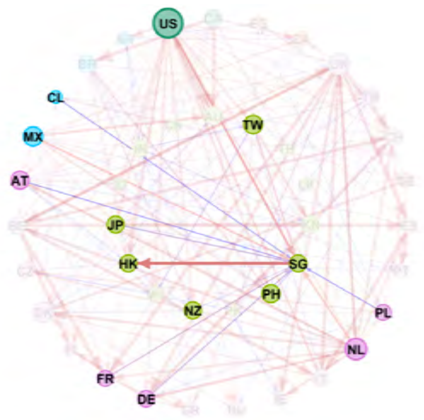
Figure 2.13: Weighted networks for Philippines



(a) Phase 1

(b) Phase 2

(c) Phase 3



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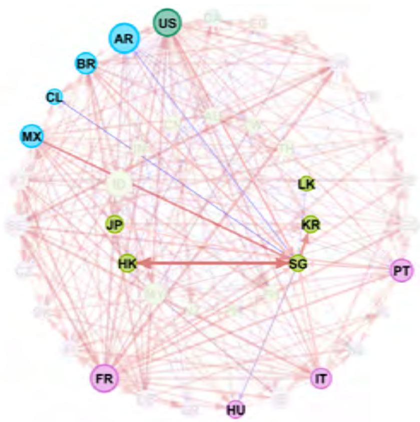

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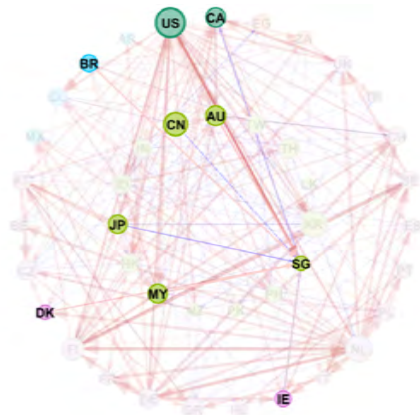
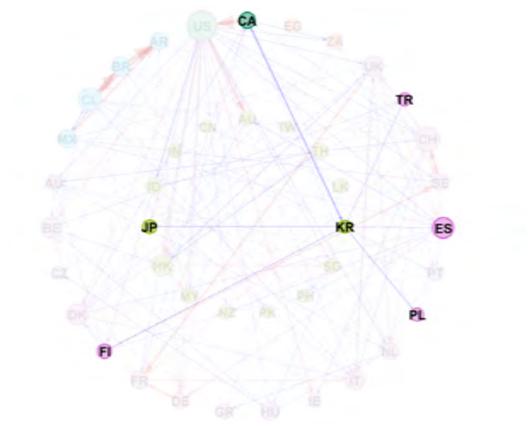
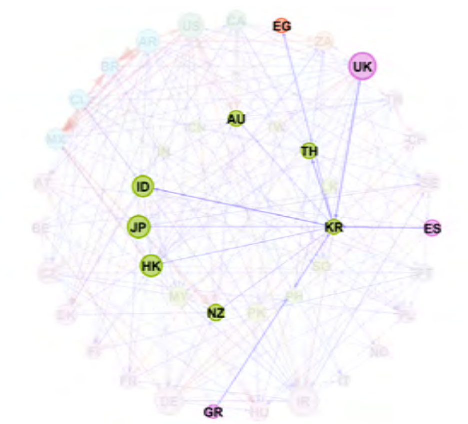


(f) Phase 6

Figure 2.14: Weighted networks for Singapore



(a) Phase 1



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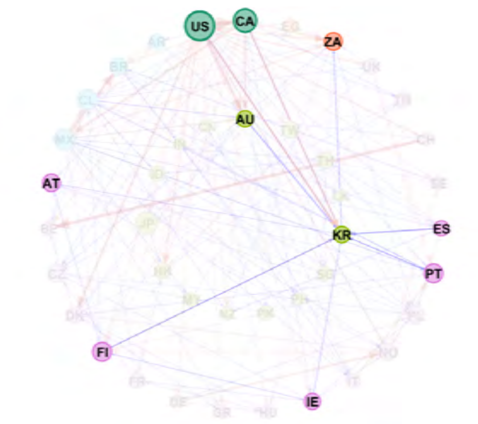

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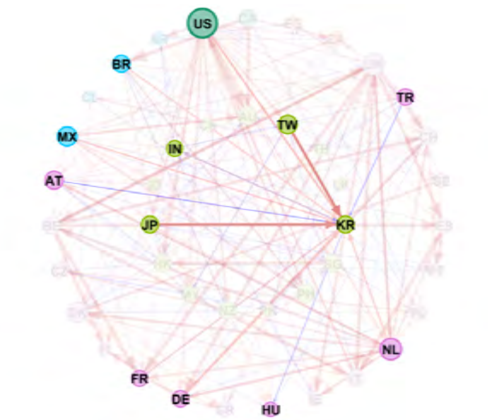

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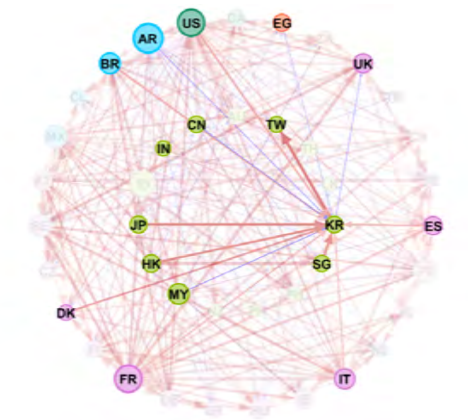

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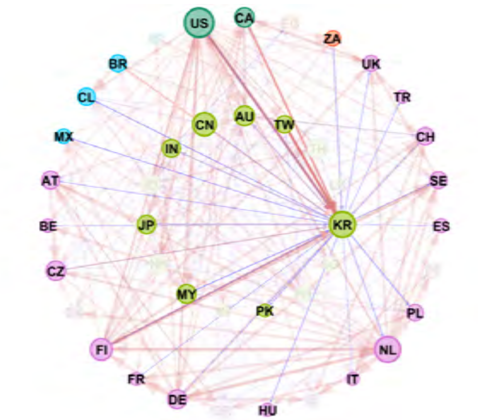
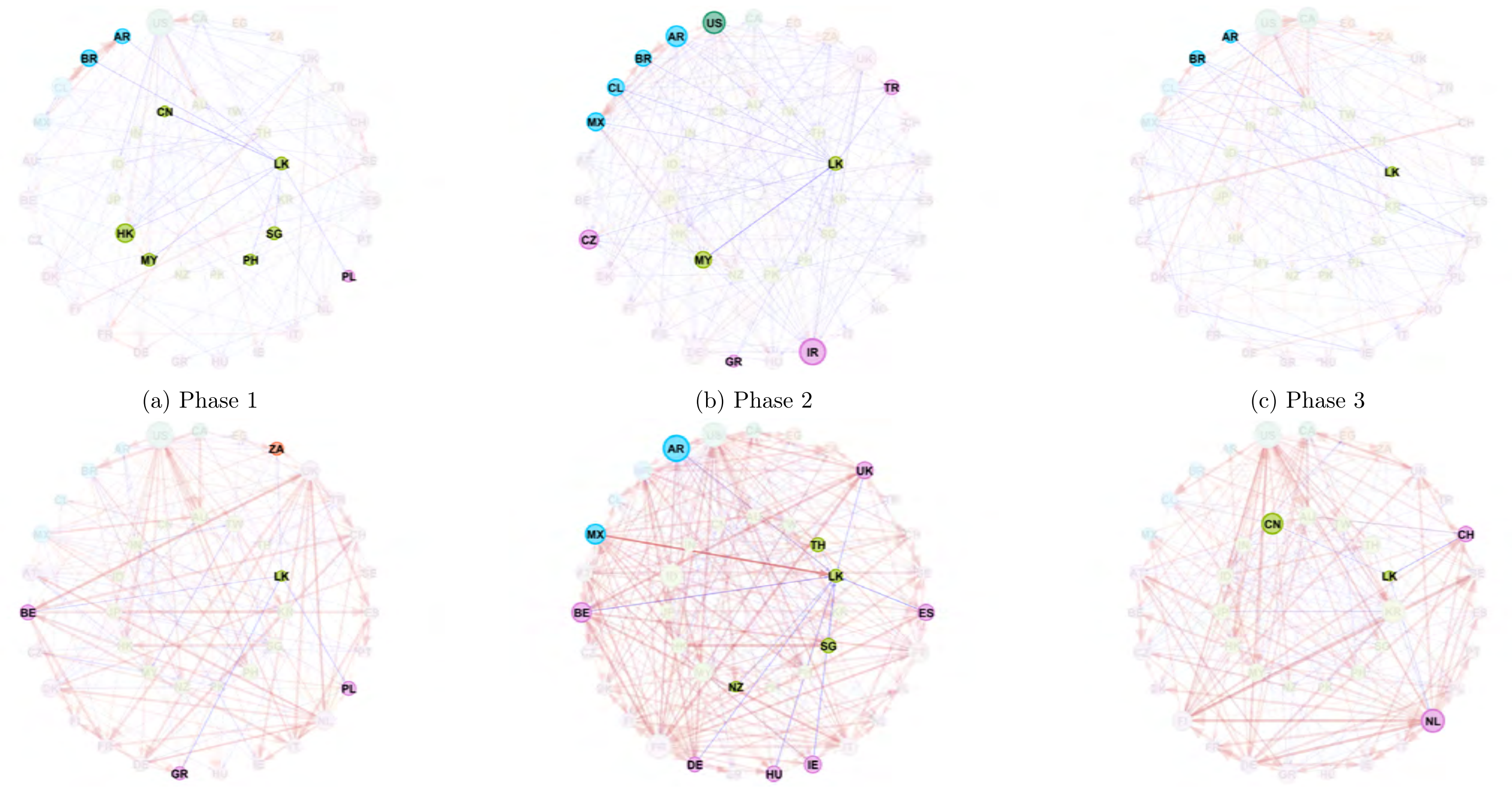


(f) Phase 6

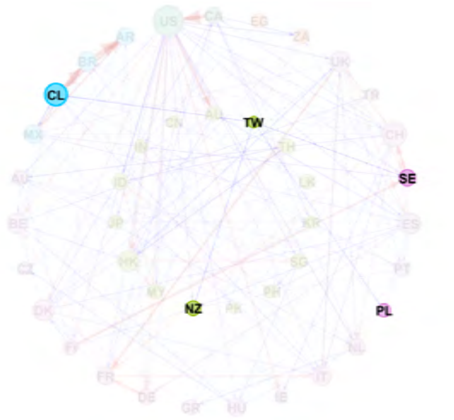
Figure 2.15: Weighted networks for South Korea



(a) Phase 1 (b) Phase 2 (c) Phase 3

(d) Phase 4 (e) Phase 5 (f) Phase 6

Figure 2.16: Weighted networks for Sri Lanka



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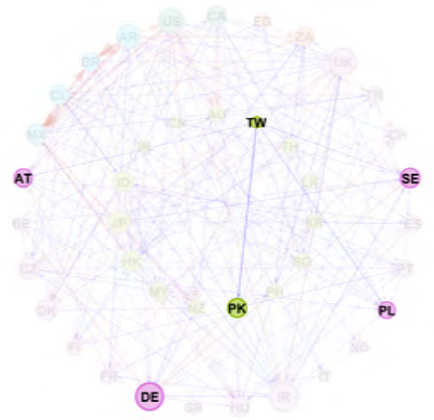

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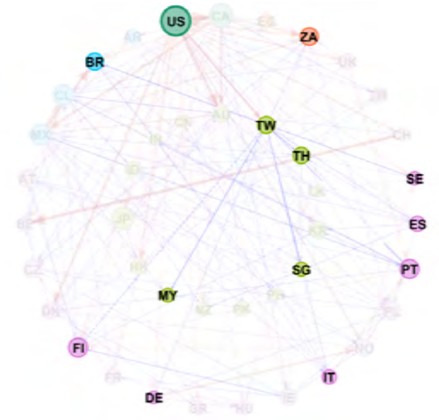

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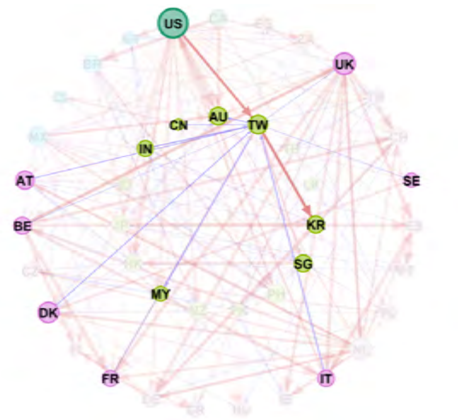

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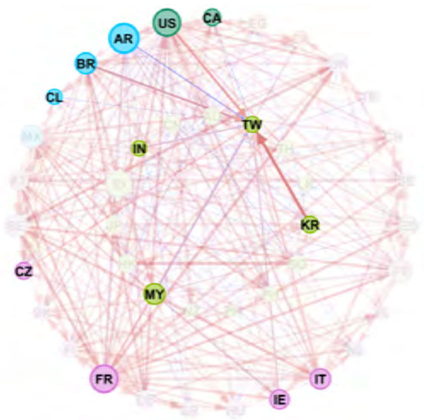

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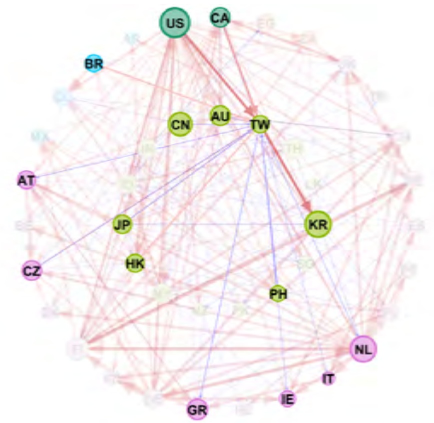

(f) Phase 6

Figure 2.17: Weighted networks for Taiwan

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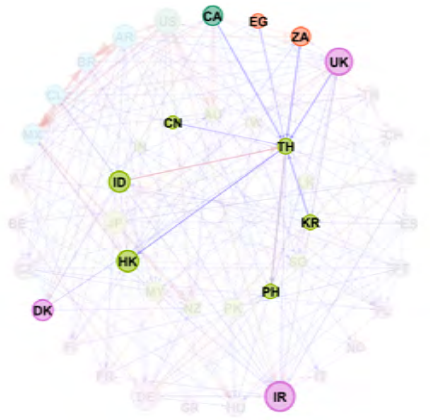

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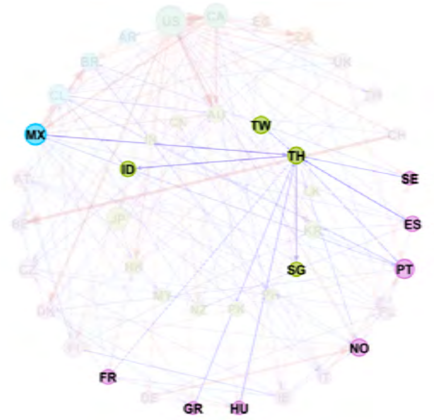

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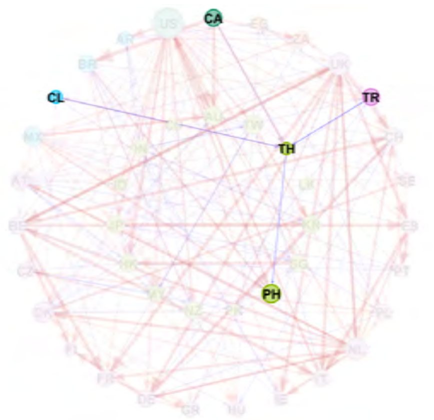

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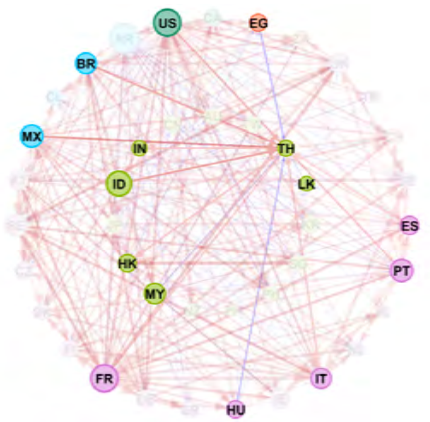

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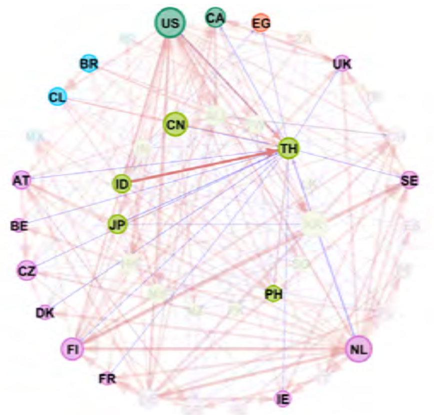


(f) Phase 6

Figure 2.18: Weighted networks for Thailand

This chapter affirmed findings of increased growth of interconnectedness between global markets and the involvement of the Asian markets. Findings indicate that this interconnectedness through cross-border activities became one of the channels of shock propagation in the financial system, posing a threat to the stability of the financial system. These findings motivated us to investigate network exposure in the financial system. This is achieved in Chapter 3 through investigation of the magnitude of network intensity. Specifically, network intensity parameter monitors the network exposure among different markets. Thus, Chapter 3 aims to investigate whether the network intensity parameter contributes either by increasing or decreasing network exposure. This would help in monitoring the financial system with the aim of promoting financial stability.

3 Dynamic effects of network exposure on equity markets

Abstract

Until recently, there has been a growing research focusing on how to predict systemic risks to minimise the recurrence of financial crises, while the importance of understanding how network exposure contributes to the spread of financial distress in the financial system has been largely underestimated. This chapter focuses on how network exposure contributes to both shock absorption and shocks spread. We utilised data from 45 economies and our findings showed that both network intensity and interconnections in the financial system have an effect on network exposure. We also demonstrated how to estimate network intensity in the financial system. Our results clearly indicate that an increased network intensity parameter is associated to the period when the financial system is under stress.

Keywords: Financial markets, financial networks, financial stability.

JEL classifications: G15, G10, G01, C21

3.1 Literature review

Recent studies have shown that a major contributor to the transmission of shocks during crisis such as the GFC $(2007 - 2009)$ was not only the institution size, but also the institution interconnectedness. Different interpretations of interconnectedness have resulted in the development of various measurement methods. All these measures aim to assess the role and impact of interconnectedness during financial distress.

Recent findings indicate that interconnectedness acts as a channel through which shocks and losses spread to other financial institutions (Glasserman and Young, 2015, 2016). Other findings show that interconnectedness acts as a 'double edge' by being able to absorb shocks up to certain point and also transmitting them to the financial system after a given threshold is reached (Acemoglu et al., 2015; Cohen-Cole et al., 2012; Gai and Kapadia, 2010; Tonzer, 2015).

Gai and Kapadia (2010) suggested that an increase in connectivity may lower the chance of contagion, but conditional on a default by a given node, an increase in interconnectedness may trigger defaults to other nodes, making the financial system more sensitive to defaults.

With increasing growth in the cross-border financial activities, interconnectedness poses threats to the financial system via increased vulnerability to shocks spreading globally. Minoiu and Sharma (2014) supported the fact that a high degree of interconnectedness triggered the breakdown of financial system during the 2007−2009 GFC. This implies that the more interconnected an institution, the higher the likelihood of risk amplification to the entire system threatening the stability of the economy.

Markose et al. (2012) referred to institutions that are 'too interconnected' as 'super-spreaders' of shocks in the financial system. This means that interconnectedness of financial institutions tends to spread shocks extensively across links, causing instability in the financial system. Gai and Kapadia (2010) showed that degree of interconnectedness has an impact on contagion by acting as a channel through which contagion spreads and shocks amplify. Greater interconnectedness aids in lowering the likelihood of contagion but increases shocks transmission when the financial system experiences difficulties.[1] Using spatial modeling, Tonzer (2015) assessed whether cross-border linkages have any impact on the stability of interconnected institutions. Though interconnectedness is beneficial in stable conditions, Tonzer (2015) showed that interconnection of financial institution to foreign entities provided a channel for propagating shocks when the system experienced difficulties.

Assessing interconnectedness in financial institutions could serve as an early warning indicator for distress in financial systems. Econometric measures based on Granger causality and principal components analysis proposed by Billio et al. (2012) measure interconnectedness. These measures show that an increase in links in a financial institution before a crisis signal an early warning. In addition, Minoiu et al. (2015) focused on determining whether interconnectedness in financial institution is a possible source of systemic risk that could serve as an early warning of crisis. Their findings suggested that interconnectedness has early warning indicator properties for a crisis. Diebold and Yilmaz (2009, 2012) proposed new measures of interconnectedness by measuring risk and management in financial institutions based on variance decomposition. Their results showed that global financial interconnectedness is time-varying, implying that network exposure within financial institutions varies over time.

Minoiu et al. (2015) showed that an increase in linkages within a country and a decrease in

[1] See Acemoglu et al. (2015), Gai and Kapadia (2010) and Glasserman and Young (2015) for more details.

cross-border linkages are associated with a high chance of financial crisis. This is consistent with the results of Peltonen et al. (2019) which indicated that more interbank linkages increase the chance of banking crises. The increase in cross-border transactions led to more interactions and relationships between different markets, leading to the formation of international 'robust-yet-fragile' financial networks. A financial network is 'robust-yet-fragile' when it serves as a shock absorber (promoting financial stability) up to a certain point, beyond which it amplifies shocks (leading to financial instability) in the whole financial system. While financial markets benefit through the formation of more robust and stronger interconnections beyond a certain point, they also create potential channels of shock transmission.

Several studies have explored roles that financial networks play in good and bad periods. The first strand of literature relates interconnectedness to risk diversification, cross-border investment opportunities and availability of different financial products in the market. A financial network is robust when it absorbs shocks, enhancing the stability and health of a financial system (Allen and Gale, 2000). Having more interconnections implies more risk-sharing and diversification, so shocks hitting the network will be shared among the various interconnected institutions building a resilient financial system (Glasserman and Young, 2016). This mechanism is supported by Vitali et al. (2016), who found that an increase in interconnections makes the financial system more resilient and increases shock diversification. Other studies show that formation of these interlinkages helps absorb shocks to a certain point before contributing to their spread (Acemoglu et al., 2015; Cohen-Cole et al., 2012; Gai and Kapadia, 2010; Tonzer, 2015). Kubelec and Sá (2012) argued that financial interconnectedness increases due to countries becoming more open, therefore causing the entire network to collapse. While Gai and Kapadia (2010) determined that stronger connectivity in the financial sector would improve absorption of shocks, they also suggested that conditional on the default of an institution, an increase in network connectivity propagates shocks from one institution to others.

The second strand of literature focuses on how interconnectedness enhances the channels through which shocks spread and intensify to the broader financial system (Battiston and Caldarelli, 2013; Glasserman and Young, 2015, 2016). That is, financial networks tend to be fragile when they amplify shocks rather than contain them. This may destabilise the entire financial system by increasing systemic risk, leading to financial instability. Many studies show the extent to which interconnectedness could have a negative effect on financial stability. For instance, Battiston and Caldarelli (2013) demonstrated that although individual institutions benefit from increased interlinkages, this could be a channel through which contagion and distress spread to the entire financial system. Battiston et al. (2012) found that an increase in financial interconnections increased credit exposure which increases systemic risk. Amini et al. (2016) argued that institutions with more interconnections contribute more to financial instability. Further, Acemoglu et al. (2015) stated that more interconnections can make the financial system more fragile due to increased shock propagation when shocks are either large or coincidental. These findings are supported by Markose et al. (2012), who referred to institutions that are 'too interconnected' as 'super-spreaders' of shocks. Minoiu and Reyes (2013) analysed the global banking network using 184 countries andreported that connectivity in the banking network tends to increase particularly when the market is under stress. This aligns with the findings of Glasserman and Young (2015), which asserted that interconnectedness among different markets were key contributors to the GFC of $2007 - 2009$. Yellen (2013) regarded interconnectedness as a financial stability concern after the occurrence of the global crisis while Sun and Chan-Lau (2017) argued that interconnectedness was the source of systemic risk.

The third strand of literature shows that specific institutions or markets play a key role in spreading shocks in the network. For instance, by investigating the patterns of international trade and financial integration, Schiavo et al. (2010) demonstrated a cause of the global crisis was shocks spreading from advanced economies to other markets, leading to network-wide distress. Kubelec and Sá (2012) found the US and UK to be the key players in the global financial network, with high interconnections compared to the rest of the world.

3.2 Spatial econometric concept

Introduction of spatial econometric techniques into financial application can be useful in modelling spillovers. The spatial econometric technique has been used recently in finance. For example, Eder and Keiler (2015) used it to model contagion risk among financial institutions; Fernandez (2011) employed it to measure risk premium propagation among firms; Asgharian et al. (2013) used it to investigate stock market co-movements while Catania and Billé (2017) applied it to advancements in score-driven models typically used in time series econometrics.

Spatial dependence parameter (network intensity parameter) captures the strength of the spatial dependent units; thus, it is a key component in investigating the structure of the spatial autoregressive process. Network intensity parameter falls within the range of 0 and 1, where 0 (1) is the minimum (maximum) estimate. A robust-yet-fragile financial system is associated with high (greater than 0 and approaching 1) network intensity. Financial systems benefit from high network intensity through risk-sharing and diversification. Conversely, increasing intensity beyond certain limits will increase the rate at which shocks propagate, leading to financial instability (Eder and Keiler, 2015). As a consequence, the financial system benefits from relative high network intensity (especially when there is no shock hitting the system), which allows for effective absorption of shocks rather than their amplification them to the entire system (Affinito and Pozzolo, 2017). Restricting network intensity parameters may improve stability leading to a more robust financial system (Gofman, 2017).

In addition, since estimation of network intensity depends on the connection matrix, the structure of the connection matrix will have an impact on the estimation of network intensity. Let $d \in [\underline{d}, \overline{d}]$ be the degree of network connectivity, where $\underline{d}$ and $\overline{d}$ are the minimum and maximum degree of connectivity respectively; then, a robust-yet-fragile network is associated with degree of connectivity close to $\overline{d}$. The network is robust in the sense that the risk-sharing and diversification are higher in the absence of large shocks and fragile when large shocks hit the network. High connectivity with shocks hitting the financial system imply more shocks being propagated in the network causing a fragile financial system (Glasserman and Young, 2015).

Consider a full or complete network with equivalent row-normalised weighted connection matrix, an example represented as:

$$W = \begin{pmatrix} 0 & 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0 & 0.25 & 0.25 & 0.25 \\ 0.00 & 0.50 & 0 & 0.00 & 0.50 \\ 0.25 & 0.25 & 0.25 & 0 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 & 0 \end{pmatrix}$$

A shock hitting the above network will be proportionally shared among the nodes in the network depending on the weights of the edges. The shock will either be equally shared or proportionally shared across the entire system depending on the size of the shock. Thus, a robust network exists when shocks are equally distributed to all institutions since the network is more resilient to small shocks (Hüser, 2015). Conversely, when weights are beyond a certain threshold, the risk-sharing effect is endangered by larger shocks being amplified in the financial system rather than being contained. This implies that shocks will affect nodes that are strongly interconnected.

Generally, financial institutions benefit from high connectivity in the absence of shocks, while high connectivity can lead to financial instability when large shocks hit the system. This argument is supported by various studies. For example, Haldane (2009) asserted that high connectivity in the financial system leads to greater risk-sharing and diversification; above certain connectivity thresholds, it will propagate shocks to the entire system. In addition, Vitali et al. (2016) argued that high connectivity beyond certain threshold leads not only to large systemic events, but also to more frequent occurrence of distress events. Acemoglu et al. (2015) also found that highly connected institutions are more resilient to small shocks that pose a high chance of contagion in the presence of large shocks. This is also supported by Silva et al. (2016), who identified a high potential for a default to be triggered, especially in a dense interconnected network since risk-sharing effects vanish when large shocks hit this network. Schiavo et al. (2010) suggested that the structure of the connection determines how the financial system responds to shocks.

Estimates of network intensity are dependent on the interaction of the endogenous spatial lag (Wy); thus, increasing interactions (a denser weighting matrix) leads to greater amplification of shocks rather than sharing shocks across these networks. This is supported by various studies. For example, using European CDS spread data, Blasques et al. (2016) showed that high time-varying spatial coefficients are associated with credit riskiness, which leads to fragility and potential collapse of financial system. Battiston et al. (2012) found that financial systems can be more resilient when the financial accelerator is low; when it is at a maximum, adverse effects are inflicted via spreading shocks. This suggests that when shocks hit the financial system, a high network intensity estimate signifies a higher probability that the financial system will be fragile (Vitali et al., 2016).

3.3 Motivation and hypotheses development

Financial integration is a process through which either financial markets, countries or regions become interconnected in different ways. This process includes cross-border lending and borrowing and is an important phenomenon in financial markets. Increasing integration is often associated with a more complex financial sector. Financial integration is beneficial to markets in terms of efficient capital allocation, higher investment and growth opportunities and risk-sharing. Risk-sharing improves the resilience of the global financial system (González-Páramo, 2010) . [2]

Financial integration also serves to spread shocks to the entire financial system. According to Schiavo et al. (2010), it is through integration that advanced economies become more interconnected with other markets, thereby spreading shocks to these markets. This leads to global

[2] See González-Páramo (2010) for more details on the benefit of financial integration in the global financial system.

distress and increased cross-border exposure threatening financial system stability. Hüser (2015) showed that an increase in the integration of the interbank network poses an increased risk of contagion, and as a consequence increases systemic risk. Asgharian et al. (2013) argued that cause of the Asian crisis was trade integration (measured by cross-border flows of imports and exports) between Asian countries, especially those emanating from Thailand and spreading rapidly to its neighbours (Indonesia, Malaysia and even Korea). In this context, we consider financial integration a contributory factor to increased network intensity. As countries engage in cross-border activities, financial integration expands potentially making financial markets more volatile.

Based on these motivation and related literature, we outline four hypotheses:

Hypothesis 1: Network intensity increases during periods of stress. This hypothesis tests whether network intensity estimate changes over time. It will determine whether it tends to increase or decrease when the market is under stress. We would expect network intensity to increase when shocks hit the network.

Hypothesis 2: Degree of connectivity affects estimation of network intensity. This aims to investigate whether greater interconnectedness among different markets influences estimation of network intensity parameter. This will provide an insight into how the connection matrix makes the financial network robust-yet-fragile.

Hypothesis 3: Financial integration affects the estimation of network intensity. This tests whether financial integration can explain why network intensity increases or decreases during different periods. With increasing cross-border activities, markets have become more integrated forming a possible channel through which shocks can spread in financial systems.

Hypothesis 4: Advanced economies have a greater impact in spreading shocks. This tests whether developed economies have a greater impact in the estimation of network intensity. This test is in line with Schiavo et al. (2010), who found that advanced economies were the key spreaders of shocks during the GFC.

3.4 Financial network and exposure to common factors

We will now consider the impact of exposure to common factors in financial networks. This will involve examination of how the structural model (which incorporates both systematic and idiosyncratic shocks) behaves in the presence of network exposure.

The starting point will focus on the structural model, capturing exposures to common factors as considered in Billio et al. (2015). According to Sharpe (1964) and Lintner (1965), the traditional capital asset pricing model (CAPM) is given by:

$$r_{it} - r_{ft} = \alpha_{it} + \beta_{it}(r_{mt} - r_{ft}) + \varepsilon_{it} \tag{3.1}$$

where r_{it} is the return on stock i at time t, r_{mt} is the market return at time t, r_{ft} is the risk-free rate and ε_{it} is a vector capturing the idiosyncratic shocks of stock i at time t. α_{it} and β_{it} are the parameters of the model.

The traditional CAPM model can be extended to the Fama–French three-factor linear model. Considering the pricing perspective, the Fama-French three-factor for a set of risk asset returns, r_{it} at time t is given by:

$$r_{it} - r_{ft} = \alpha_{it} + \beta_{it}(r_{mt} - r_{ft}) + h_{it}HML_{it} + s_{it}SMB_{it} + \varepsilon_{it} \tag{3.2}$$

where HML is the book-to-market factor of stock i at time t, SMB_{it} is the size factor of stock i at time t. h_{it} and s_{it} are additional parameters of the model; ε_{it} is a vector capturing the idiosyncratic shocks of stock i at time t.

The main focus of this approach is on both network exposures (endogenous) and exposures to common factors (structural exposure, which is exogenous). Equation (3.2) can be rewritten in a structural form as:

$$S(r_{it} - \mathbb{E}[r_{it}]) = \beta_M r_{it}^M + \beta_{HML} r_{it}^{HML} + \beta_{SMB} r_{it}^{SMB} + \eta_{it} \tag{3.3}$$

$$r_{it} - \mathbb{E}[r_{it}] = S^{-1}(\beta_M r_{it}^M + \beta_{HML} r_{it}^{HML} + \beta_{SMB} r_{it}^{SMB} + \eta_{it}) \tag{3.4}$$

The spatial matrix S in Equation (3.4) captures the contemporaneous relations associated with interconnections between different assets, while η_t is the structural idiosyncratic risk at time t.

Our aim is to construct a structural model that contains contemporaneous relationships driven by links across assets, andsystematic and idiosyncratic shocks. Thus, the spatial matrix S can be parametrised as $S = I_n - \rho W$, where I_n is $n \times n$ identity matrix, $|\rho| < 1$ is the spatial dependence parameter (network intensity parameter) indicating the strength of the network exposure. It monitors the network impact while W represents relationships across assets.[3]

[3]See Anselin (1988) for more details on spatial econometrics. For simplicity, we refer to ρ as the network intensity parameter.

Equation (3.4) into a spatial autoregressive framework (SAR) as:

$$(I_n - \rho W)(r_{it} - \mathbb{E}[r_t]) = \beta_M r_{it}^M + \beta_{HML} r_{it}^{HML} + \beta_{SMB} r_{it}^{SMB} + \eta_{it} \tag{3.5}$$

$$r_{it} - \mathbb{E}[r_{it}] = (I_n - \rho W)^{-1}(\beta_M r_{it}^M + \beta_{HML} r_{it}^{HML} + \beta_{SMB} r_{it}^{SMB} + \eta_{it}) \tag{3.6}$$

If we let $\beta_M r_{it}^M + \beta_{HML} r_{it}^{HML} + \beta_{SMB} r_{it}^{SMB} = Z$, using a geometric series expansion to the first degree[4], the above model can be represented as:

$$r_{it} - \mathbb{E}[r_{it}] = \underbrace{Z}_{\text{i}} + \underbrace{\eta_{it}}_{\text{ii}} + \underbrace{\sum_{j=1}^{\infty} \rho^j W^j Z}_{\text{iii}} + \underbrace{\sum_{j=1}^{\infty} \rho^j W^j \eta_{it}}_{\text{iv}} \tag{3.7}$$

where

i. structural exposure to common factors

ii. structural impact to idiosyncratic component

iii. network exposure to common factors

iv. network impact to idiosyncratic component

Equation (5.6) captures the impact of exposures (both structural and network exposures) of both systematic and idiosyncratic shocks. Therefore, we conclude that both idiosyncratic and systematic components are influenced by the presence of interconnections across assets/institutions.

3.5 Dataset and effect of network exposure

This section introduces the different datasets that form our subsequent empirical studies in this chapter. We worked with daily return data, r_{it} as in Chapter 2. We also used the liability, market value and 90 days treasury bill (T-Bill) rates data. Other datasets that include foreign exchange (FX), interest rate (IR), S&P 500 volatility index - US (VIX), Euro STOXX 50 volatility index - Europe (VSTOXX) and trade were also considered in the second part of the analysis.

The sample period considered is January 1999 – December 2017 because our focus is to observe the dynamics of the network exposure in the twenty-first century. By taking advantage of the

[4] By geometric expansion, we have $(I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + ...$, where ρW represent the influence of neighbours on each unit while $\rho^2 W^2$ second neighbourhood influences each unit and so on.

long horizon with a large number of observations (4,956), we subdivided the sample into four phases, as represented in Table 3.1: Phase 1 is the pre-crisis (1 January 1999 – 14 September 2008) period, Phase 2 is the GFC (15 September 2008 – 31 March 2010) period, Phase 3 is the European debt crisis (EDC) (1 October 2010 – 21 November 2013) and phase three is the most recent period (22 November 2014 – 29 December 2017). We followed Dungey et al. (2015) and Dungey and Renault (2018) when choosing these dates.

Table 3.1: Phases of the sample

Phase	Period	Representing	Number of observations
All phases	01.01.1999 – 29.12.2017	Entire period	4,956
Phase 1	01.01.1999 – 14.09.2008	Pre-crisis	2,531
Phase 2	15.09.2008 – 31.03.2010	Global financial crisis	403
Phase 3	01.04.2010 – 21.11.2013	European debt crisis	951
Phase 4	22.11.2013 – 29.12.2017	Recent period	1,071

We used the BIS database to obtain liabilities data to construct the weighting matrix. The BIS bilateral locational banking statistics provided a comprehensive cross-border data set of international banking transactions. This included aggregate international cross-border claims and liabilities of a set of both reporting and non-reporting countries. We use cross-border liabilities of reporting countries data, measured on a quarterly basis from $1999Q1$ – $2017Q4$ to construct the connection matrix (the weighting matrix is obtained using the combined Granger causality and DY approach). Each country is represented by direct liability towards all the other countries in all financial sectors (central banks, banks, non-bank financial institutions and non-financial sectors). We considered 45 (mature and emerging markets) countries in our sample (see Table 3.2), for which the data were complete and reliable. We also use different specifications of the connection matrix in our empirical analysis. Particularly, we randomly generated sparse (fewer interconnections) and denser (more interconnections) matrices for the 45 markets in our sample.[5]

Figure 3.1 displays the average cross-border liability flow, measured in US billion dollars, for the countries in our sample. Liability defined as what a country or company owes to others (including loans, bonds and other debts), plays a significant role in propagating shocks in the financial system. Having unsecured lending and borrowing could increase cross-border liability within the financial system. There was a change in the average liability between the

[5]Sparse connection matrix will be used to investigate the effect of network exposures with decreased interconnectedness while denser connection matrix will be used to investigate the effect of network exposure with increased interconnectedness.

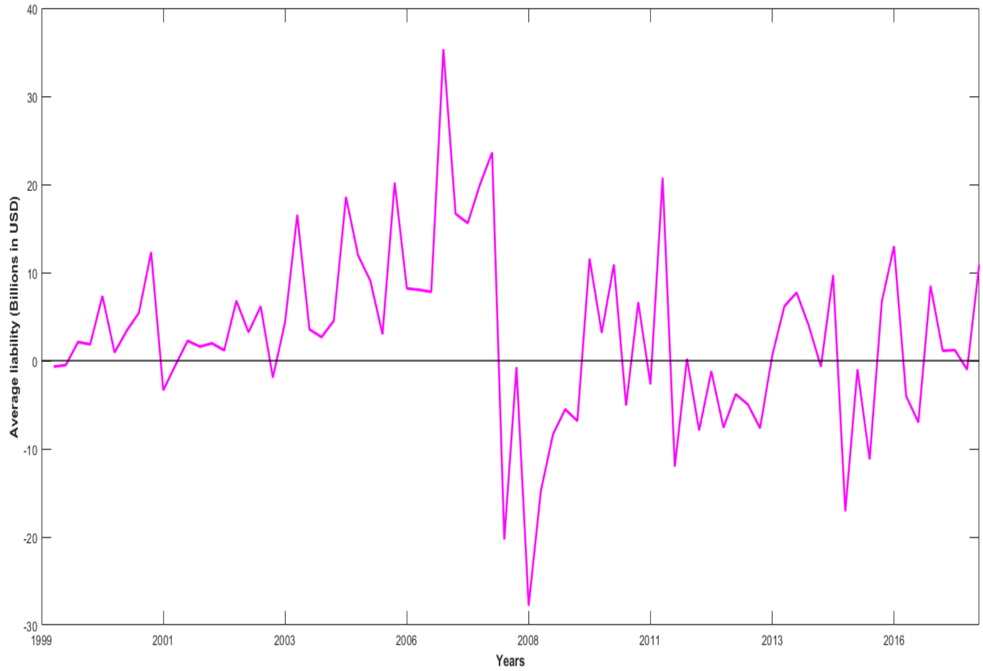


Figure 3.1: Average liability for all countries. The figure displays average liability over time. It reports the average liability of all countries in our sample is 1999Q1 and 2017Q4.

entire period of our sample. As shown in Figure 3.1, the average liability drastically changed during crises, implying that on average, countries in our sample paid more than required by a liability. This may be a contributory factor to the collapse of the financial system, because the failure of these countries to pay liabilities could lead to defaults for their counter-parties. Therefore, liability within countries serves as a major contributory factor to crises. The higher the liability, the greater the chance of system exposure to distress. These findings concur with those of Gai and Kapadia (2010), who found that liability from defaulting banks led to the spread of contagion, which in turn increased the vulnerability of interconnected institutions.

3.5.1 Effect of financial network to common factor model

This subsection investigates whether network exposure affects common factors. This enable greater understanding of the importance of financial networks in both spreading and absorbing financial shocks in the system. Our investigation focuses on the individual countries in our sample. Following Billio et al. (2015), we estimated both systematic and idiosyncratic components in the structural model. Our analysis relied on estimating these parameters because the Fama-French factors available in Kenneth French's data library were limited to few countries. Since the idiosyncratic component is unobservable and model-dependent, we used indirect estimation proposed by Campbell et al. (2001) to estimate it.

Estimating beta and idiosyncratic volatilities

To estimate idiosyncratic volatility for an individual stock in our sample, we assumed the return of each country i to be driven by a common factor and country-specific shock ε_{it}. To be precise, we followed Sharpe (1964) and Lintner (1965), who assumed a single factor return generating process and estimated the market model using Equation (3.1).

In this analysis, we computed the excess returns of individual countries as the log return on the global market index (r_{mt}) minus absolute change of 90 days' T-Bill rates (r_{ft}), which we considered the risk-free rate. The 90 days' T-Bill rates and market value data were obtained from Thompson Reuter's Datastream for January 1999 – December 2017.

The return on the global market index (r_{mt}) was computed as the value of weighted excess return of each country over the 90 days T-Bill rates r_{ft} of each country:

$$r_{mt} = \sum_{i=1}^{n} \omega_{it} * r_{it} \tag{3.8}$$

where ω_{it} is the ratio of country's i market value to the total market value of the entire market m in time t and n is the total number of countries.

The beta and residual estimates for each market were obtained by running the regression for each market index in the sample using Equation (3.1).

Following Bali and Cakici (2008), we estimated country-specific idiosyncratic volatility as the standard deviation of the residuals of each individual country given by:

$$IVOL_{it} = \sqrt{var(\varepsilon_{it})} \tag{3.9}$$

Effect of financial network on betas

The beta estimate for each country was estimated by running separate regressions. Table 3.2 displays the structural betas for individual countries in our sample. We estimated betas using Equation (3.1) for all phases categorised in Table 3.1. Our results clearly show that beta coefficients are different in all phases. In most countries, the structural betas were lower in the pre-crisis period, while increased in the GFC with the exception of some emerging markets (Indonesia, Malaysia, Philippines, Singapore, Sri Lanka and Egypt) in which estimates decreased

Table 3.2: Structural betas for countries in our sample

Country	All phases	Phase 1	Phase 2	Phase 3	Phase 4
Austria	0.9090	0.8274	0.9694	1.0169	0.9924
Belgium	0.0422	0.0134	0.8190	0.9975	0.9809
Czech Republic	0.5767	0.5701	0.8952	0.2423	0.3125
Denmark	0.0271	0.0145	0.9037	0.1605	0.5133
Finland	0.5594	0.5234	0.9620	0.5400	0.2193
France	0.0352	0.0676	0.9956	1.0077	0.9762
Germany	0.8195	0.5882	0.9779	1.0063	0.9054
Greece	0.0033	0.0032	0.0024	0.0570	0.0083
Hungary	0.6966	0.6444	0.8784	0.7639	0.3745
Ireland	0.3212	0.5090	0.0875	0.7248	0.9697
Italy	0.1926	0.0663	0.9905	0.9991	0.9333
Netherlands	0.8997	0.9320	0.8402	0.8932	0.9464
Norway	0.8838	0.7685	0.9929	0.9766	0.8878
Poland	0.0510	0.0316	0.9387	0.9882	0.9883
Portugal	0.9515	0.8766	0.9958	0.9775	0.9806
Romania	0.3757	0.3440	1.0007	0.9377	0.9911
Spain	0.9295	0.8406	0.9951	0.9459	0.9805
Sweden	0.1073	0.0308	0.9594	0.9977	0.9584
Switzerland	0.1837	0.0420	0.9967	0.9978	0.9968
Turkey	0.1006	0.1005	0.9740	0.9856	0.9654
United Kingdom	0.4765	0.1825	0.9918	0.9810	0.9833
Argentina	0.4963	0.2596	0.6725	0.9745	0.9940
Brazil	0.7767	0.5681	0.9534	0.7994	0.8971
Chile	0.9786	0.9900	1.0264	0.9822	0.8356
Mexico	0.7463	0.7059	0.9603	0.7001	0.9993
Canada	0.8965	0.9078	0.6805	0.9878	0.9823
United States	0.2102	0.0383	0.9776	1.0006	0.9968
Australia	0.4424	0.0911	0.8300	0.9899	0.9881
China	0.0302	0.0040	0.8010	1.0001	0.9122
India	0.7825	0.6903	0.9681	0.9860	1.0012
Indonesia	0.8583	0.8606	0.7730	0.9007	0.8730
Japan	0.0373	0.0076	0.8250	0.8125	0.9451
Hong Kong	0.0195	0.0167	0.9617	0.3539	0.8560
Malaysia	0.8413	0.8380	0.7939	0.9454	0.9828
New Zealand	0.0448	0.0055	0.9888	0.9819	0.9933
Pakistan	0.0033	0.0025	0.1978	0.8878	0.9124
Philippines	0.6169	0.7677	0.0608	0.9821	0.9436
Singapore	0.9806	0.9819	0.8075	0.8190	0.8837
South Korea	0.0004	0.0002	0.7882	0.7543	0.7782
Sri Lanka	0.8996	-0.0014	-0.0256	0.9792	0.9869
Thailand	0.2956	0.2913	0.9771	0.1056	0.9502
Taiwan	0.2038	0.1772	0.5884	0.8109	0.6233
South Africa	0.9806	0.9791	0.9834	0.9785	0.9839
Egypt	0.8001	0.7772	0.2363	0.9202	0.9857
Israel	0.0816	0.0744	0.9789	1.0065	0.9684

The period covered in the sample is 1 January 1999 to 31 December 2017. All coefficients are at a 5% level of significance.

during the global financial crisis period. The structural betas remain high in Phase 3, associated with the European debt crisis. Country-specific betas changed with the introduction of many factors. For instance, using Fama–French three-factor model might result in different estimates. Since our main focus was the effect of network exposure on structural betas, we did not focus on discussing each country's specific betas.

Using beta coefficients obtained from the regression model, we investigated how they changed with the increase in network exposure. First, we examined the effect of the connection matrix (W) on the structural beta. Figure 3.2a displays how the structural beta ($\bar{\beta}_i$) changed with the interaction of the connection matrix, given by:

$$\beta_i^* = \bar{\beta}_i + \sum_{i=1}^{n} W \bar{\beta}_i \tag{3.10}$$

where β_i^* is the new (augmented) beta obtained from the interaction with the connection matrix while $\bar{\beta}_i$ is the country-specific structural beta. The results show that the structural beta changes with the interaction with the connection matrix. The connection matrix is based on liability linkages obtained using the combined Granger causality and DY measure (see Chapter 2). This suggests that the increased interconnection between various market participants leads to change in the structural beta of a given country. The results also revealed the role of the weighting matrix in spreading shocks in a financial system. For example, the connection matrix increased the values of structural betas by more than 50% for countries whose beta values were small. Countries with low betas included Greece, Philippines and Poland. The size of the augmented betas varied depending on the strength of the connections a country has with others. In Figure 3.2a, we noted that beta values of countries (including Denmark, Greece, Sri Lanka Malaysia and the Philippines) tend to be 0 but are greatly influenced by the weighting matrix. The beta values increased depending on the level of shock one country receives from others. These results depict the role of interconnections in spreading risk. This observation is consistent with Glasserman and Young (2016), who showed that countries with high connectivity tend to suffer more when shocks hit the financial system.

For countries (including Greece, Sri Lanka and the Philippines) with lower beta estimates due to stronger links with other countries, we observed that the structural beta was amplified. This implies that these countries are strongly affected by other countries, leading to amplification of shocks.

It is important to understand whether using a different weighting matrix has a different impact

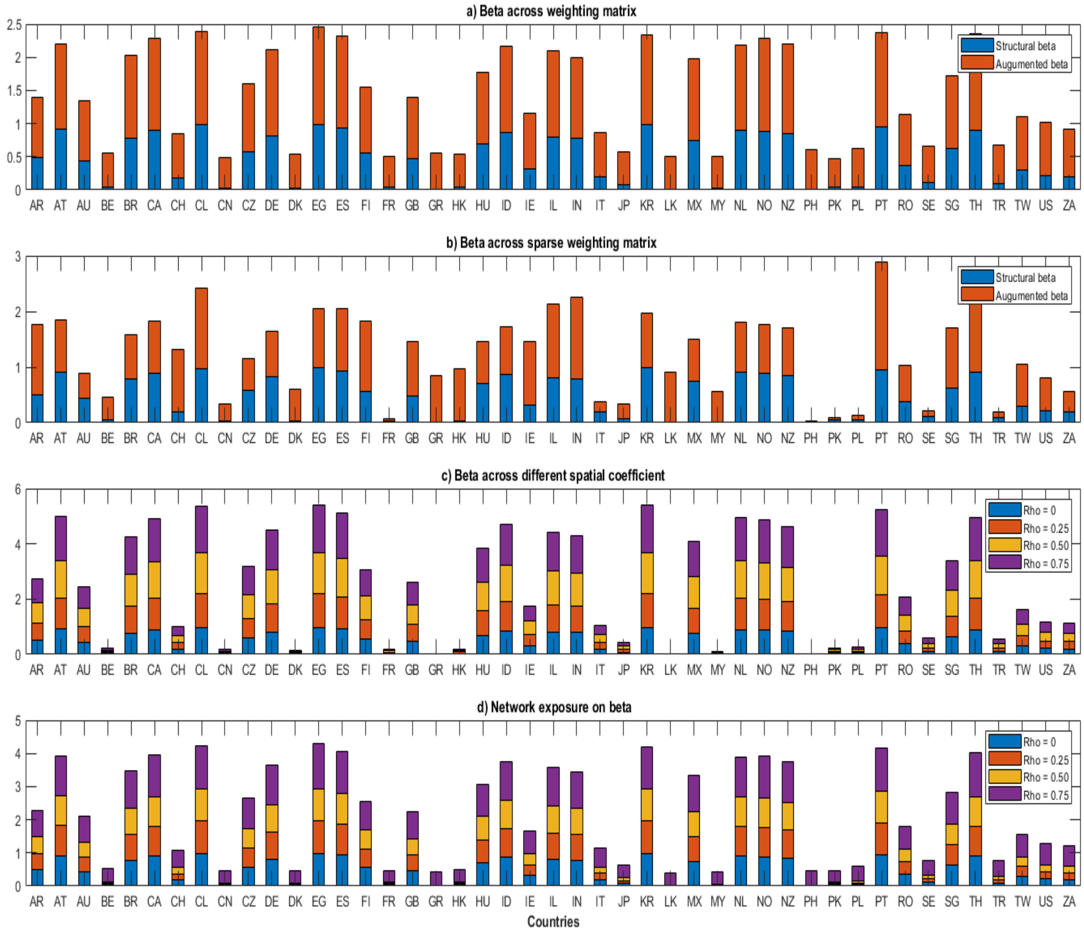


Figure 3.2: Structural betas for all the phases under different scenarios. The figures exhibit how the structural beta for all phases changed under different scenarios. We used country' abbreviations from BIS. Figure 3.2a displays changes in betas with and without the presence of the connection matrix. This was obtained by multiplying the betas with the corresponding liability weighted matrix. Figure 3.2b shows how betas changed using sparse weighting matrix. Figure 3.2c shows how betas changed across different network intensity parameters. Figure 3.2d shows the effect of network exposure on betas. The period covered in the sample is 1 January 1999 – 31 December 2017.

on structural betas. Figure 3.2b shows how betas changed using a sparse matrix.[6] We randomly generated a sparse matrix. From the results, we noted that the contribution of the weighting matrix changed depending on the strength of connections between countries. This is depicted using orange bars in Figures 3.2a and 3.2b. For example, the Philippines had stronger links in Figure 3.2a, leading to greater change in exposure, while in Figure 3.2b, it had weak links, leading to a smaller change in structural betas.

The impact of the different network intensity parameters on the structural betas can be estimated as:

$$\beta_i^{**} = \bar{\beta}_i + \sum_{i=1}^{n} \rho \bar{\beta}_i \tag{3.11}$$

where β_i^{**} is the new beta obtained from the interaction with the different network intensity parameters.

Figure 3.2c shows how structural betas changed across the different network intensity parameters (we assumed network intensity parameters to take quartiles values [i.e. 0.25, 0.5 and 0.75]). It is clear from these that structural betas tend to increase across different network intensity parameters. This is an indicator that as the network intensity increases, the level of risk in the financial system also tends to increase. Unlike the connection matrix, whose effect is severe to all countries with stronger connections including countries whose beta values are small, the network intensity parameters have more influence on the countries whose beta values are large. Countries with small values of beta (Greece, Sri Lanka and the Philippines) are less affected by network intensity parameters. Conversely, countries with high beta estimates (e.g. South Korea) are more affected by larger network intensity parameters. This explains the role of network intensity parameters in spreading and reducing shocks. Our finding indicate that network intensity parameters have a greater impact in spreading risk than absorbing it.

Next, we investigated the effects of network exposure on structural betas. This involved combining the connection matrix and network intensity parameters. This is because both coefficients have a great impact on betas. We used the following equation to gauge the role of network exposure on structural betas:

$$\beta_i^{***} = \bar{\beta}_i + \sum_{i=1}^{n} \rho W \bar{\beta}_i \tag{3.12}$$

[6] We can define sparse matrix as a connection matrix with few interconnected institutions/assets.

where β_i^{***} is the new beta obtained from the interaction with the changing network exposure. Figure 3.2d shows how the structural betas change across the changing network exposure. These results show that both the weighting matrix and the network intensity parameters have effects on the structural beta.

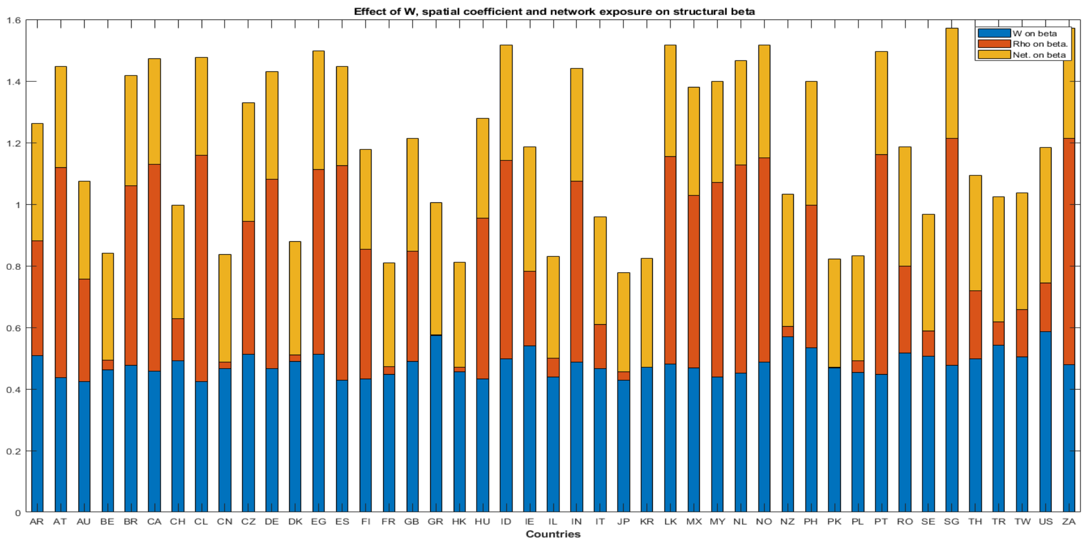


Figure 3.3: Change in structural betas due to network exposures. The figure reports contribution of connection matrix, network intensity parameters and network exposures on structural betas. Blue represents % change of betas due to the connection matrix, orange due to network intensity coefficient and yellow due to the network exposures. The period covered in the sample is 1 January 1999 – 31 December 2017.

To obtain a clear insight into how structural beta changed, we calculated the percentage change in betas in β_i^{*}, β_i^{**} and β_i^{***}. Figure 3.3 summarises the contribution of connection matrix, network intensity parameters and network exposure to structural betas. The height of the bar represents the percentage change of betas. These results revealed stronger connections between markets increases network exposure. This is consistent with Silva et al. (2016) who found that high connectivity triggers a greater probability of default in the financial system. It also shows that network intensity parameter has an amplifying effect on shocks. It is clear from the bar size that both the weighing matrix and the network intensity parameters have different effects. Although the contribution of the connection matrix is similar, it varies depending on the strength and number of the connections. Thus, our main finding from Figure 3.3 is that both network intensity parameters and connection matrix are key ingredients in either increasing or decreasing network exposure.

Network exposure to common factors

To investigate the effect of network exposure on common factors, we used slope coefficient betas as the systematic risk of specific country's market portfolios. This is useful to examine the effect of network exposure on both systematic and idiosyncratic volatility. Bali and Cakici (2010) used beta coefficients as the systematic risk of a country's market portfolio to determine whether country-specific risk are priced into the intertemporal capital asset pricing model (ICAPM). They found that country-specific risks are significantly priced into the ICAPM framework.

Table 3.3 reports country-specific idiosyncratic volatility in all sample periods, estimated in Equation (3.9). As noted by Hueng and Yau (2013), these estimates may vary depending on the data used because they are model-dependent. Notably, the country-specific idiosyncratic volatility of emerging markets as greater than those of developed economies is consistent with the findings of Bali and Cakici (2008, 2010) and Hueng and Yau (2013). We also observed, on average, that Turkey had high idiosyncratic volatility in the full sample period and also in Phase 1. These results are consistent with Bali and Cakici (2010) and Hueng and Yau (2013), who determined that Turkey had a higher estimate than other countries in their sample. Interestingly, most countries had greater idiosyncratic estimates in the crisis period. This could be explained by higher uncertainty in the market during the GFC.

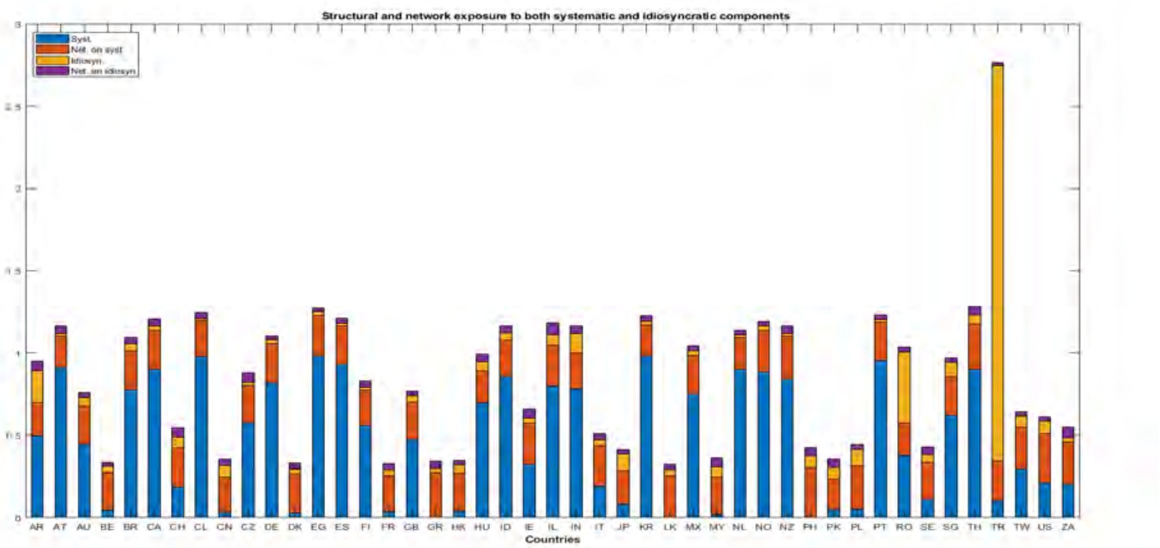


Figure 3.4: Network exposures on systematic and idiosyncratic shocks in the entire period. The figure reports both the structural and network contribution to systematic risk and idiosyncratic volatilities for entire period. The period covered in the sample is 1 January 1999 – 31 December 2017.

Therefore, we will not discuss country-specific idiosyncratic volatilities because our aim is to

Table 3.3: Estimates of idiosyncratic volatilities

Country	All phases	Phase 1	Phase 2	Phase 3	Phase 4
Austria	0.0179	0.0185	0.0275	0.0151	0.0110
Belgium	0.0359	0.0281	0.0324	0.0114	0.0098
Czech Republic	0.0201	0.0235	0.0273	0.0131	0.0083
Denmark	0.0280	0.0279	0.0266	0.0148	0.0127
Finland	0.0180	0.0198	0.0225	0.0158	0.0110
France	0.0352	0.0288	0.0217	0.0145	0.0110
Germany	0.0219	0.0234	0.0225	0.0128	0.0146
Greece	0.0219	0.0552	0.0224	0.0214	0.0240
Hungary	0.0559	0.0701	0.0643	0.0201	0.0156
Ireland	0.0296	0.0261	0.0441	0.0259	0.0115
Italy	0.0352	0.0283	0.0237	0.0180	0.0156
Netherlands	0.0176	0.0141	0.0332	0.0219	0.0108
Norway	0.0201	0.0221	0.0284	0.0123	0.0115
Poland	0.0983	0.1125	0.0285	0.0155	0.0131
Portugal	0.0147	0.0142	0.0168	0.0166	0.0124
Romania	0.4326	0.5782	0.0620	0.0239	0.0084
Spain	0.0177	0.0174	0.0212	0.0211	0.0119
Sweden	0.0493	0.0356	0.0238	0.0131	0.0157
Switzerland	0.0651	0.0404	0.0184	0.0104	0.0102
Turkey	2.4059	3.3873	0.0321	0.0169	0.0205
United Kingdom	0.0429	0.0336	0.0190	0.0134	0.0110
Argentina	0.1950	0.1980	0.0595	0.0290	0.0417
Brazil	0.0450	0.0491	0.0562	0.0265	0.0179
Chile	0.0122	0.0106	0.0118	0.0116	0.0143
Mexico	0.0283	0.0366	0.0217	0.0143	0.0089
Canada	0.0219	0.0150	0.0541	0.0107	0.0098
United States	0.0734	0.0410	0.0416	0.0121	0.0081
Australia	0.0525	0.0312	0.0602	0.0138	0.0089
China	0.0672	0.0398	0.0363	0.0155	0.0222
India	0.1183	0.1525	0.0767	0.0234	0.0087
Indonesia	0.0418	0.0546	0.0392	0.0180	0.0148
Israel	0.0980	0.1307	0.0194	0.0116	0.0068
Japan	0.0487	0.0324	0.0358	0.0380	0.0151
Hong Kong	0.0572	0.0686	0.0252	0.0128	0.0106
Malaysia	0.0149	0.0173	0.0253	0.0066	0.0055
New Zealand	0.0696	0.0345	0.0235	0.0177	0.0110
Pakistan	0.0714	0.0851	0.0702	0.0216	0.0136
Philippines	0.0854	0.0844	0.0737	0.0208	0.0158
Singapore	0.0227	0.0295	0.0224	0.0087	0.0093
South Korea	0.0334	0.0367	0.0359	0.0141	0.0092
Sri Lanka	0.0562	0.0125	0.0132	0.0521	0.0201
Thailand	0.0627	0.0685	0.0300	0.0463	0.0131
Taiwan	0.0250	0.0315	0.0241	0.0115	0.0081
South Africa	0.0216	0.0216	0.0275	0.0243	0.0162
Egypt	0.0632	0.0534	0.0877	0.0409	0.0245

The table reports the idiosyncratic volatilities for all countries in all phases. The period covered in the sample is 1 January 1999 – 31 December 2017.

determine the role of network exposure on both systematic and idiosyncratic components. By assuming the first order neighbourhood in Equation (5.6), we investigated the effect of network exposure on the structural model. We used the network intensity parameter to capture the strength of the network exposure (network intensity). This coefficient lies between 0 and 1, where close to 0 implies lower network intensity and close to 1 signifies higher network intensity. The existence of network exposure is captured by the weighting matrix which was row-normalised. The weighting matrix takes the values between 0 and 1 as representing exposure from other markets, where values close to 0 imply less exposure, while close to 1 implies high exposure. We used the weighting matrix constructed from combined Granger causality and DY approach by using the cross-border liabilities. Based on simple continuity, we assumed that the network intensity parameters exert a similar effect on each country. To be precise, we assume this network intensity parameter to be 0.5, which is related to the mean estimate obtained in Section 3.7. Other studies, including Blasques et al. (2016), found the estimate to be higher (approximately 0.7). Figure 3.4 shows how the structural model responds to network exposure across the entire sample period. The blue bar represents the structural systematic component, and the yellow bar is the idiosyncratic component. The orange bar is the absolute contribution of network exposure to change in the systematic component while the purple bar is the absolute contribution of network exposure to change in the idiosyncratic component.

Turkey, Romania and Argentina had greater values of idiosyncratic volatility than other economies with smaller estimates. We observed that the systematic component was predominant in most economies compared to the idiosyncratic volatility. The effect of network exposure on systematic component was higher (represented by the size of the orange bars in Figure 3.4) than on idiosyncratic component, with the exception of Turkey, Argentina and Romania.

Figure 3.5 show the contribution of network exposure on the structural model in different periods. On average, the idiosyncratic volatility of Turkey was still dominant in Phase 1 but reduced in all other phases. We can relate Turkey's high idiosyncratic volatility to the banking crisis that led to capital flight and recession in the economy at the end of 2000. This demonstrates that Turkey's banking crisis was largely idiosyncratic even though it could have been triggered by other external factors. Higher idiosyncratic volatility also explains the ability of Turkey's investors (who are mostly foreign) to diversify their portfolios. Turkey's idiosyncratic volatility seemed to diminish in Phase 2. Surprisingly, we expected it to increase due to the GFC. This may have happened due to Turkey's restructure of its financial system after the banking crisis in 2001.

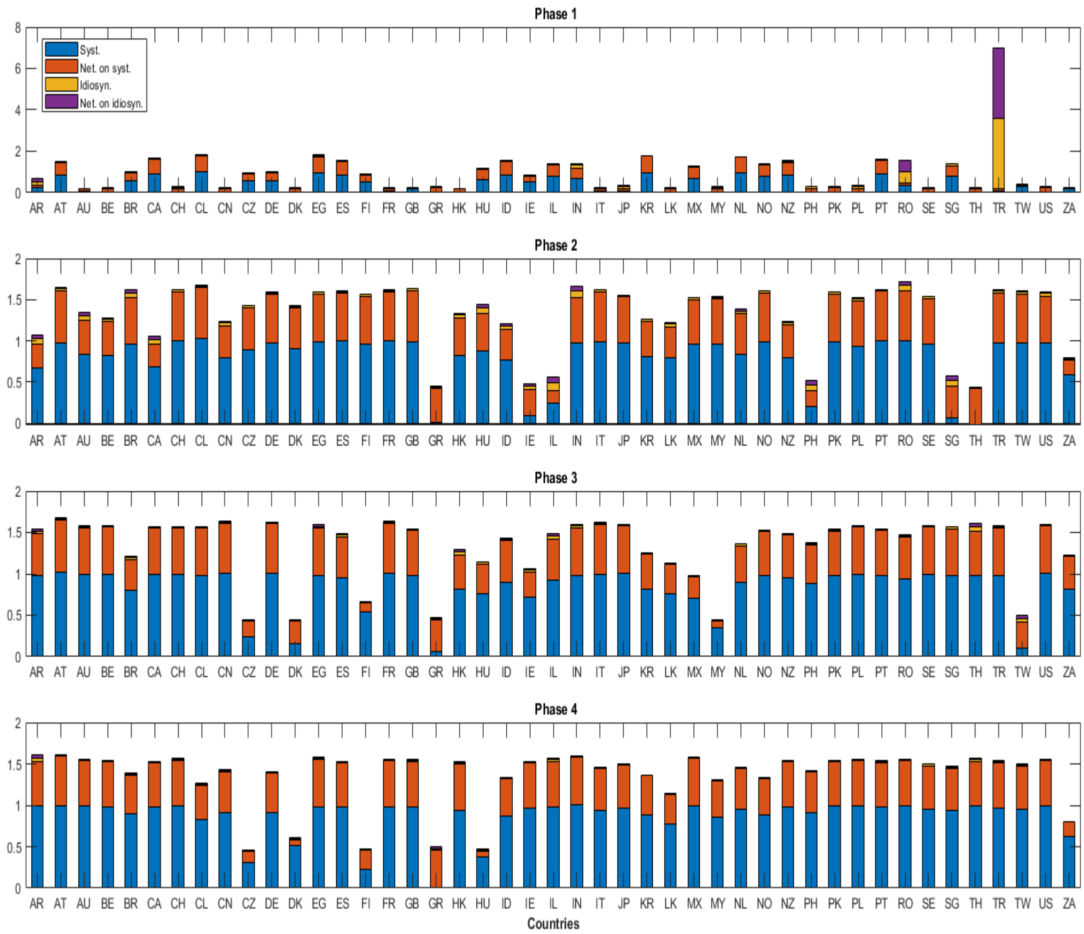


Figure 3.5: Network exposures on systematic and idiosyncratic shocks in all the phases. The figures show the contribution of network exposure to both systematic and idiosyncratic volatility in each phase. The period covered in the sample is 1 January 1999 – 31 December 2017.

The results in Phase 1 for all other countries shows that the network contribution to the idiosyncratic component is almost irrelevant. A possible suggestion is that the network exposure has a diversifying effect on the idiosyncratic component. The network contribution to the systematic component was large; thus, it has an amplifying effect on the systematic component. The results in all other phases indicate that network exposure has a greater impact on the systematic component and less impact on idiosyncratic volatility. These results support the notion that network exposure contributes to spreading and diversifying risks.

In general, our contribution highlights the distinction between the spreading and sharing of sharing. From Figure 3.5, it can be observed that the presence of network exposure increases systematic risk and reduces idiosyncratic risk. Institutions with increased unsecured borrowing and lending have a higher chance of receiving and spreading shocks to other institutions. Figure 3.5 also reveals the changing nature of interconnections in the different phases. This is

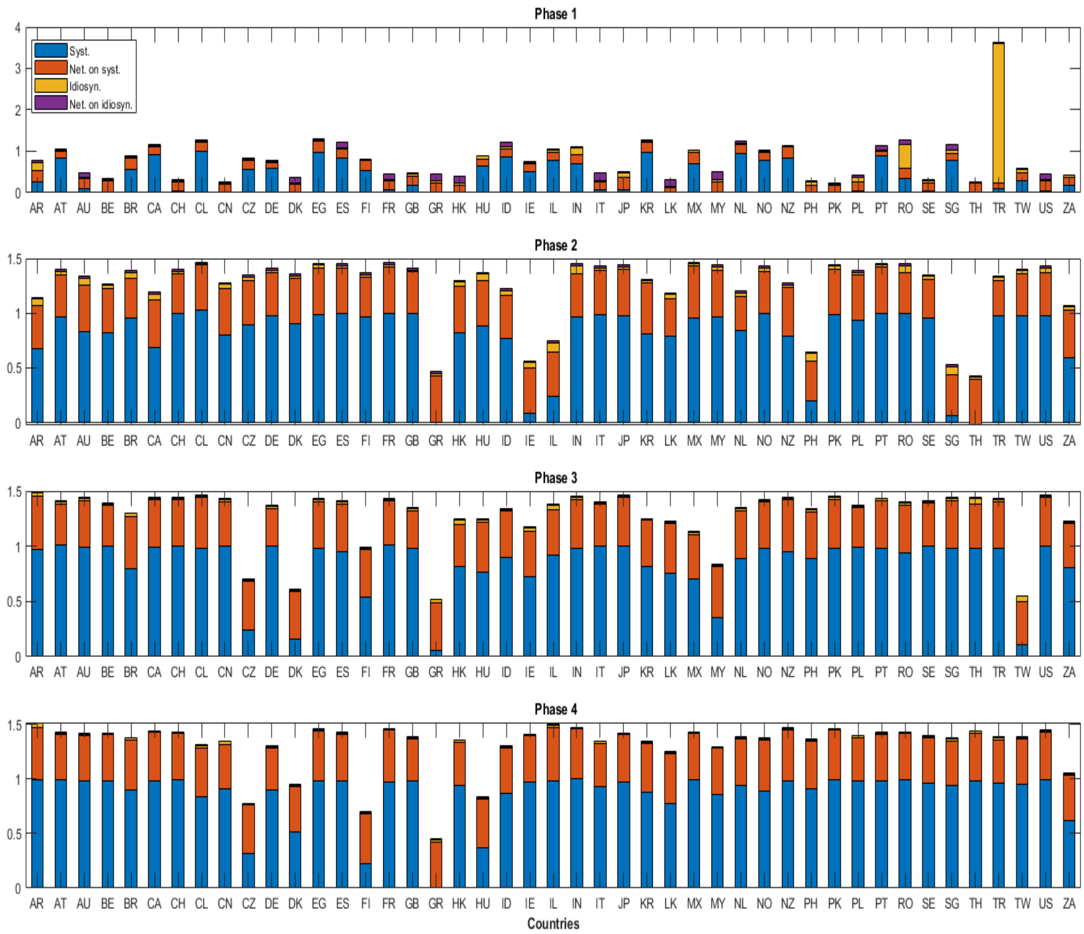


Figure 3.6: Effect of network exposures with decreased interconnectedness. The figures show how the contribution of network exposure to both systematic and idiosyncratic volatility changed with reduced interconnections between markets. This involved using a sparse weighting matrix. The period covered in the sample is 1 January 1999 – 31 December 2017.

because we used a constant network intensity parameter while changing the connection matrix. Billio et al. (2015) reported similar results in which the presence of network effect increased the systematic component and decreased the idiosyncratic component. With the increase in network intensity parameters (from 0.5 to 0.75), the financial system became more vulnerable to shocks and benefited more from diversification. If the network intensity parameter is decreased from 0.5 to 0.25, there will be a decrease in shock spreading and a reduced diversification effect. These results are consistent with recent studies that showed that the presence of interconnection increases vulnerability in the financial system while also helping to diversify risks.[7] The results also indicate that network exposure had greater impact in Phases 2, 3 and 4 than Phase 1. This is attributable to the GFC in Phase 2, EDC in Phase 3 and Chinese market crash in

[7]See Acemoglu et al. (2015); Gai and Kapadia (2010); Tonzer (2015).

Phase 4.

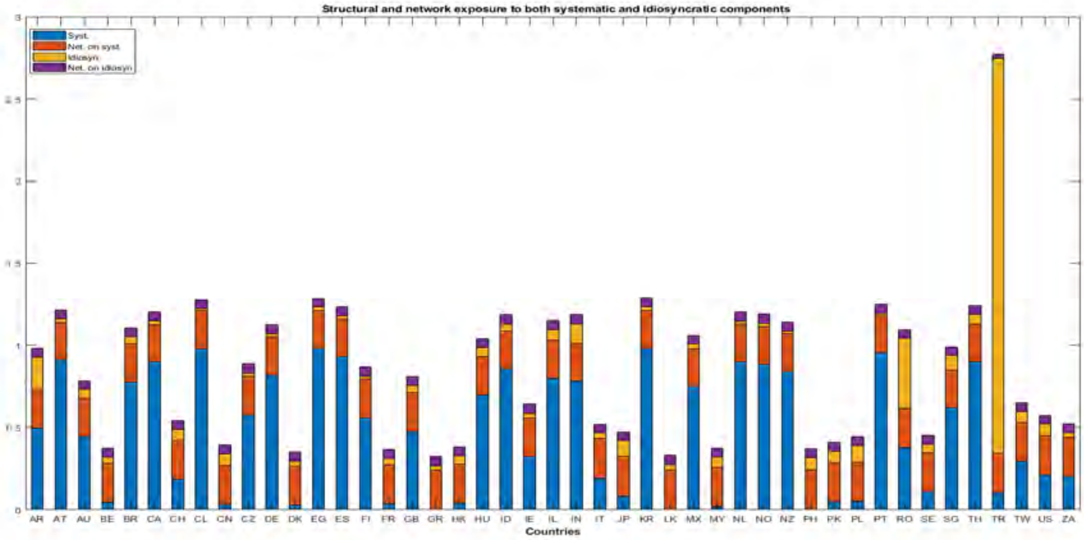


Figure 3.7: Effect of network exposures with increased interconnectedness. The figure shows how the contribution of network exposure to both systematic and idiosyncratic volatility changed with increased interconnections between markets. This involved using a denser connection matrix. The period covered in the sample is 1 January 1999 – 31 December 2017.

We also investigated the effect of network connectivity on the structural model. For our case, we used a sparse matrix to determine whether a decrease in network connectivity increased or decreased network exposure. We randomly generated the sparse matrix. As shown in Figure 3.6, fewer interconnections in the financial system led to a reduction in the size of the bars. This suggests that having fewer interconnections reduces the magnitude of the spread of absorption of shocks .

We also used dense matrix to determine its effect on the structural model. Figure 3.7 shows the contribution of using denser weighting matrix in all sample periods. This weighting matrix was based on trade linkages. Trade linkages are denser because countries are more interlinked through bilateral trade. This figure shows that more interconnection in the financial system increases the systematic risk and reduces the idiosyncratic component. This implies that using a denser weighting matrix increases the network exposure and amplify shocks as well as diversify some shocks. Overall, our approach shows that an increase in network exposure significantly increases systematic shocks through risk spreading, and reduces idiosyncratic risk through diversification. Further, these results signify that a large degree of connectivity does not necessarily dampen risk exposure, but amplifies shocks in the financial system. This is consistent with Amini et al. (2016), who affirmed that an increase in network connection may lead to systemic instability.

3.6 Optimal value of the network intensity parameter

The next question to address is the estimation of the network intensity parameter (ρ), which captures the strength of the network exposure. This coefficient is also important, as it plays a key role in monitoring network exposure (Section 3.5). Different estimation methods have been proposed to estimate network intensity parameter, including ordinary least squares (OLS), maximum likelihood estimation (MLE), method of moments (MoM), two-stage least squares (2SLS) and the generalised method of moments (GMM).

3.6.1 Static network intensity parameter

This subsection introduces spatial autoregressive (SAR) model to measure network intensity parameter. We began by considering a simple first-order (pure) SAR model, where 'pure' refers to the absence of exogenous regressors (X_n) as proposed by Anselin (1988) and is defined as:

$$y = \rho W y + \varepsilon \tag{3.13}$$

where n is the number of observations, $y = (y_1, y_2, ..., y_n)'$ is a vector of observations on the dependent variable, W is $n \times n$ exogenous connection matrices, ρ is a scalar representing the network intensity coefficient and $\varepsilon = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_n)'$ as a vector of residuals assumed to be independent and identically distributed.

By rearranging Equation (3.13), the error term yields:

$$\varepsilon = y - \rho W y \tag{3.14}$$

LeSage and Pace (2009) described the vector Wy as spatial lag representing a linear combination of the neighbouring values to each observation. This was supported by Lee (2007), who showed that the influence in the neighbouring asset is due to spatial effects.

Our first estimate of ρ is based on OLS. However, the OLS estimate of ρ is considered biased and inconsistent. Following Anselin (1988), the OLS estimate of ρ is denoted by $\hat{p}$ and given by,

$$\hat{p} = (y'W'Wy)^{-1} y'W'y \tag{3.15}$$

An estimate of ρ is unbiased if $E(\hat{p}) = p$. We prove below that $E(\hat{p}) = p$.

$$\begin{aligned} E(\hat{p}) &= E\left[(y'W'Wy)^{-1}y'W'(\rho Wy + \varepsilon)\right] \\ &= \rho + E\left[(y'W'Wy)^{-1}y'W'\varepsilon\right] \end{aligned} \tag{3.16}$$

Therefore, the OLS estimate is biased since the second term in Equation (3.16) does not equal 0, $E(\hat{p}) \neq p$. To show that the OLS estimate is inconsistent, Anselin (1988) demonstrated that the probability limit ($plim$) for the term $y'W'\varepsilon$ is not 0 except in trivial cases when $\varepsilon = 0$.[8] Since the OLS estimate is biased and inconsistent, we had to consider alternatives to estimate the network intensity parameter.

We first considered the MLE method because of its simplicity. According to LeSage and Pace (2009), the MLE for ρ requires identification of the value of the SAR coefficient that maximises the likelihood function, given by:

$$\begin{aligned} L(\sigma^2;\varepsilon) &= \frac{1}{2\Pi\sigma^{2(n/2)}} exp\{-\frac{1}{2\sigma^2}(y-\rho Wy)'(y-\rho Wy)\} \\ L(y|\rho,\sigma^2) &= \frac{1}{2\Pi\sigma^{2(n/2)}}(J) exp\{-\frac{1}{2\sigma^2}(y-\rho Wy)'(y-\rho Wy)\} \end{aligned} \tag{3.17}$$

The Jacobian function can be obtained through the differentiation of Equation (3.14) with respect to the dependent variable y yielding:

$$J = \frac{\partial \varepsilon}{\partial y} = |I_n - \rho W| \tag{3.18}$$

where I_n is $n \times n$ identity matrix. Substituting Equation (3.18) for Equation (3.17) gives:

$$L(y|\rho,\sigma^2) = \frac{1}{2\Pi\sigma^{2(n/2)}}|I_n - \rho W| exp\{-\frac{1}{2\sigma^2}(y-\rho Wy)'(y-\rho Wy)\} \tag{3.19}$$

Lee (2002) asserted that deriving the eigenvalue (λ) of the connection matrix W simplifies the computation problem. The natural logarithm of Equation (3.19) is:

$$\begin{aligned} \ln L &= -\frac{n}{2}\ln(2\Pi\sigma^2) + \ln|I_n - \rho W| - \frac{1}{2\sigma^2}(y-\rho Wy)'(y-\rho Wy) \\ &= -\frac{n}{2}\ln(2\Pi) - \frac{n}{2}\ln(\sigma^2) + \ln|I_n - \rho W| - \frac{1}{2\sigma^2}(y-\rho Wy)'(y-\rho Wy) \end{aligned} \tag{3.20}$$

The natural logarithm can be further restructured by eliminating the residual parameter, σ^2.

[8] Anselin (1988) shows that $plimN^{-1}(y'W'\varepsilon) = plimN^{-1}\varepsilon'W(I-pW)^{-1}\varepsilon$.

This is achieved by substituting with the error term, given by:

$$\hat{\sigma}^2 = \frac{1}{n}(y - \rho W y)'(y - \rho W y) \tag{3.21}$$

This yields to:

$$\ln L = -\frac{n}{2}\ln(2\Pi) - \frac{n}{2}\ln(y - \rho W y)'(y - \rho W y) + \ln|I_n - \rho W| \tag{3.22}$$

The parameter space of ρ requires that the determinants of $I_n - \rho W$ to be strictly positive. A univariate optimisation problem can be used to maximise the above expression with respect to ρ. This implies that the optimal search of ρ estimates take feasible values within the range:

$$1/\lambda_{min} < \rho > 1/\lambda_{max} \tag{3.23}$$

where λ_{min} is the minimum eigenvalue of the standardized matrix W while λ_{max} is the largest eigenvalue of the same matrix.

Equation (3.13) can be extended to investigate how network intensity changes with the presence of exogenous variables. The mixed-SAR model (see LeSage and Pace (2009)) can be written as:

$$\begin{aligned} & y = \rho W y + \beta X + \varepsilon \\ & \varepsilon \sim N(0, \sigma^2 I_n) \end{aligned} \tag{3.24}$$

where $X = (X_1, X_2, ..., X_n)$ a vector ($n \times k$, and where k is the number of variables) of observations on the exogenous variables having $\beta = (\beta_1, \beta_2, ..., \beta_k)$ coefficients.

Rewriting Equation (3.24) repeatedly yields:

$$\begin{aligned} y &= \rho W y + \beta X + \varepsilon \\ &= \rho W y(\rho W y + \beta X + \varepsilon) + \beta X + \varepsilon \\ &= \rho W y(\rho W y(\rho W y + \beta X + \varepsilon) + \beta X + \varepsilon) + \beta X + \varepsilon \\ &= \sum_{n=1}^{\infty}[\rho W]^n(\beta X + \varepsilon) \end{aligned} \tag{3.25}$$

Equation (3.25) clearly shows the effect of the weighting matrix in spreading shocks from one entity to the other until it diminishes leading to a steady-state.

Equation (3.24) can also be written in a more compact way as:

$$(I - \rho W)y = \beta X + \varepsilon \tag{3.26}$$

which provides a structure to the contemporaneous relationship based on the spatial proximity in association with the SAR model. Thus, the model includes contemporaneous relationships, driven by interconnections across different assets (markets), exogenous regressors and asset (market) specific shocks. Equation (4.4.2) is conveniently expressed in compact because our focus is to estimate the network intensity parameter, ρ which captures the endogenous effect of network exposure.

The general idea is to first construct a univariate optimisation problem for the parameter ρ. Following Anselin (1988) and LeSage and Pace (2009), this was done by maximising the full likelihood function of the dependent variable with respect to the unknown parameters. This is given by:

$$L(y|\rho, \beta, \sigma^2) = \frac{1}{2\Pi\sigma^{2(n/2)}}|I_n - \rho W|exp\{-\frac{1}{2\sigma^2}(y - \rho Wy - X\beta)'(y - \rho Wy - X\beta)\} \tag{3.27}$$

The natural logarithm function in Equation (3.27) can be specified as:

$$\begin{aligned} \ln L &= -\frac{n}{2}\ln(2\Pi\sigma^2) + \ln|I_n - \rho W| - \frac{1}{2\sigma^2}e'e \\ &= -\frac{n}{2}\ln(2\Pi) - \frac{n}{2}\ln(\sigma^2) + \ln|I_n - \rho W| - \frac{1}{2\sigma^2}e'e \\ &\text{where} \\ &\quad e = (y - \rho Wy - X\beta) \\ &\quad \rho \in (\min(\omega)^{-1}, \max(\omega)^{-1}) \end{aligned} \tag{3.28}$$

where ω is the eigenvalue constructed from matrix W. The value of ρ is assumed to be bounded between 0 and 1. Next, we estimated each parameter in Equation (3.28). This was done by solving the first-order derivatives of equation (3.28) with respect to the individual parameters.

- **Estimate of β**

By differentiating Equation (3.28) with respect to β. We obtained:

$$\begin{aligned}
\frac{\partial ln(L)}{\partial\beta} &= 0 \\
\frac{\partial ln(L)}{\partial\beta} &= \frac{\partial\Big(\frac{1}{2\sigma^2}(y-\rho Wy-X\beta)'(y-\rho Wy-X\beta)\Big)}{\partial\beta} \\
0 &= \frac{\partial\Big(\frac{1}{2\sigma^2}(y-\rho Wy-X\beta)'(y-\rho Wy-X\beta)\Big)}{\partial\beta} \\
0 &= \frac{1}{2\sigma^2}(X'(y-\rho Wy)-X'X\beta) \\
\beta &= (X'X)^{-1}X'(I_n-\rho W)y
\end{aligned} \tag{3.29}$$

From Equation (3.29), the estimate of β is:

$$\hat{\beta} = (X'X)^{-1}X'(I_n-\rho W)y \tag{3.30}$$

For simplicity, this can be written as:

$$\hat{\beta} = (X'X)^{-1}X'y-\rho(X'X)^{-1}X'Wy \tag{3.31}$$

- **Estimate of σ^2**

  We differentiated Equation (3.28) with respect to σ^2 to yield:

$$\begin{aligned}
\frac{\partial ln(L)}{\partial\sigma^2} &= 0 \\
\frac{\partial ln(L)}{\partial\sigma^2} &= \frac{\partial\Big(-\frac{n}{2}\ln(\sigma^2)+\frac{1}{2\sigma^2}(y-\rho Wy-X\beta)'(y-\rho Wy-X\beta)\Big)}{\partial\sigma^2} \\
0 &= -\frac{n}{2\sigma^2}+\frac{1}{2(\sigma^2)^2}(y-\rho Wy-X\beta)'(y-\rho Wy-X\beta) \\
0 &= -n+\frac{1}{\sigma^2}(y-\rho Wy-X\beta)'(y-\rho Wy-X\beta) \\
\sigma^2 &= \frac{(y-\rho Wy-X\beta)'(y-\rho Wy-X\beta)}{n}
\end{aligned} \tag{3.32}$$

Thus, the estimate of σ^2 is given by:

$$\hat{\sigma^2} = \frac{(y-\rho Wy-X\beta)'(y-\rho Wy-X\beta)}{n} \tag{3.33}$$

- **Estimate of ρ**

Unlike β and σ^2, which have closed form solutions, ρ needs to be estimated using optimisation problem that maximises Equation (3.28) with respect to ρ. By replacing estimates of β and σ^2 in Equation (3.28) and letting $\hat{\delta}_0 = (X'X)^{-1}X'y$, $\hat{\delta}_d = (X'X)^{-1}X'Wy$ in Equation (3.31), we have:

$$y = X\hat{\delta}_0 + \hat{e}_0 \quad \text{and} \quad Wy = X\hat{\delta}_d + \hat{e}_d \tag{3.34}$$

which can be estimated by OLS. Thus, Equation (3.31) can be rewritten as:

$$\begin{aligned} \hat{\beta} &= (X'X)^{-1}X'y - \rho(X'X)^{-1}X'Wy \\ &= \hat{\delta}_0 - \rho\hat{\delta}_d \end{aligned} \tag{3.35}$$

The error term from Equation (3.34) can be given by: $\hat{e}_0 = y - X\hat{\delta}_0$ and $\hat{e}_d = Wy - X\hat{\delta}_d$. Substituting to σ^2 yields

$$\sigma^2 = \frac{(e_0 - \rho e_d)'(e_0 - \rho e_d)}{n} \tag{3.36}$$

Using the results of β and σ^2, Equation (3.28) becomes:

$$\begin{aligned} \ln L &= -\frac{n}{2}\ln(2\Pi) - \frac{n}{2}\ln\left(\frac{(e_0 - \rho e_d)'(e_0 - \rho e_d)}{n}\right) + \ln|I_n - \rho W| - \frac{1}{2} \\ &= -\frac{n}{2}\ln(2\Pi) - \frac{n}{2}\ln\Big((e_0 - \rho e_d)'(e_0 - \rho e_d)\Big) - \frac{n}{2}\ln(n) + \ln|I_n - \rho W| - \frac{1}{2} \end{aligned}$$

which can be written as:

$$\begin{aligned} &= c - \frac{n}{2}\ln\Big((e_0 - \rho e_d)'(e_0 - \rho e_d)\Big) + \ln|I_n - \rho W| \\ c &= -\frac{n}{2}\ln(2\Pi) - \frac{n}{2}\ln(n) - \frac{1}{2} \end{aligned} \tag{3.37}$$

Thus, to obtain the estimates of ρ, we need to simplify the log-likelihood with respect to the scalar ρ and optimise the following equation:

$$\begin{pmatrix} f(\rho_1) \\ f(\rho_n) \\ \vdots \\ f(\rho_r) \end{pmatrix} = \begin{pmatrix} c - \frac{n}{2}\ln\Big((e_0 - \rho_1 e_d)'(e_0 - \rho_1 e_d)\Big) + \ln|I_n - \rho_1 W| \\ c - \frac{n}{2}\ln\Big((e_0 - \rho_2 e_d)'(e_0 - \rho_2 e_d)\Big) + \ln|I_n - \rho_2 W| \\ \vdots \\ c - \frac{n}{2}\ln\Big((e_0 - \rho_r e_d)'(e_0 - \rho_r e_d)\Big) + \ln|I_n - \rho_r W| \end{pmatrix} \tag{3.38}$$

3.6.2 Dynamic network intensity parameter

The static SAR model specified in Equation (3.24) can be further extended to a dynamic SAR. This allows estimation of a time-varying network intensity parameter (ρ_t). This is useful in understanding how the spatial parameter changes over time. As pointed out by Blasques et al. (2016), time-varying network intensity parameters indicate how the spillover changes over time. We considered the case when we have constant volatility.

A time-varying SAR model with constant disturbances is defined as:

$$\begin{aligned} y_t &= \rho_t W y_t + \beta X_t + \varepsilon_t \\ \varepsilon_t &\sim N(0, \Sigma), \quad t = 1, 2, ..., T \end{aligned} \tag{3.39}$$

Where Σ is constant over time.

Assuming constant disturbances allowed us to investigate how the spatial parameter changes over a specific point in time. This is an important aspect of examining financial systems in which the volatility of returns is known to vary considerably between non-crisis and crisis periods (Blasques et al., 2016; Catania and Billé, 2017). The diagonal elements represent the time-conditional variances of the cross-sectional independent innovation at any given point in time. We imposed diagonality assumption as the standard constant conditional correlation (CCC) and dynamic conditional correlation (DCC) model proposed by Engle (2002).

The generalised log-likelihood function of the constant (Lc_t) variance models became:

$$\begin{aligned} &\ln Lc_t = -\frac{n}{2}\ln(2\Pi) - \frac{n}{2}\ln(\Sigma) + \sum_{t=1}^{T}\ln|I_n - \rho_t W| - \frac{1}{2}e_t'\Sigma^{-1}e_t \\ &\text{where} \\ &\qquad e_t = (y_t - \rho_t W y_t - X_t\beta) \\ &\qquad \rho_t \in (\min(\omega)^{-1}, \max(\omega)^{-1}) \end{aligned} \tag{3.40}$$

Allowing for time-varying variance in the shocks led to the following:

$$\begin{aligned} & y_t = \rho_t W y_t + \beta X_t + \varepsilon_t \\ \text{where} & \\ & \varepsilon_t \sim N(0, \Sigma_t), \quad t = 1, 2, ..., T \\ & \Sigma_t \sim diag(\sigma_1^2, \sigma_2^2, \cdots, \sigma_t^2) \end{aligned} \tag{3.41}$$

The generalised log-likelihood function of the time-varying (Lv_t) variance models became:

$$\begin{aligned} & \ln Lv_t = -\frac{n}{2}\ln(2\Pi) - \frac{n}{2}\ln(\Sigma_t) + \sum_{t=1}^{T} \ln|I_n - \rho_t W| - \frac{1}{2}e_t'\Sigma_t^{-1}e_t \\ & \text{where} \\ & \qquad e_t = (y_t - \rho_t W y_t - X_t\beta) \\ & \qquad \rho_t \in (\min(\omega)^{-1}, \max(\omega)^{-1}) \end{aligned} \tag{3.42}$$

3.7 Empirical analysis

We used the MLE method to estimate the values of ρ using the same data as in Section 3.5. MLE is preferred over OLS because of the limitations of OLS as discussed in Section 3.6.1. Despite the known limitations of OLS in estimating ρ, Elhorst (2010) stated that the OLS estimate of ρ could serve as a guide of the expected true value. The initial OLS estimate of ρ for our data was 0.5327. Therefore, it is expected that the optimal value of the estimate of ρ will be within this range. Next, we estimated ρ using the MLE method discussed in Section 3.6.1 and allowed the search to be within the range $1/\lambda_{min} - 1/\lambda_{max}$. The y vector is the average return of each country in our sample over the entire sample period, while we constrained W to lie within the interval {0,1} through the process of row standardisation; using the row-normalised contiguity matrix of weights ensures that each row of the matrix sums to unity. The row-normalised matrix represents the portion of total liability that the source country/institution shares among its target nodes. We used the same connection matrix as discussed in Section 3.5.

By estimating static network intensity parameter using a pure SAR model (Equation 3.20), we ensured consistency with the extant spatial literature (Asgharian et al., 2013; Fernandez, 2011). The static network intensity parameter (which captures the endogenous effect of network exposure) is estimated at each phase. We began the estimation by excluding additional explanatory variables. Table 3.4 contains the static network intensity estimates with their corresponding standard errors in parentheses. The estimate for the whole sample was 0.5072 with a small standard error of 0.0043. This is close enough to the estimate obtained using OLS (0.5327) and represents the potential impact of the parameter on the entire network. Comparing estimates in the different phases, the network intensity parameter was higher in Phase 2 (0.6134). From Figure 3.8, we observed a more than 30% increase in the estimate from Phase 1 to 2. It only increased by 16% in Phase 3 which is approximately half the increase reported for Phase 2.

Table 3.4: Network intensity estimates and their robust standard errors

	All Phases	**Phase 1**	**Phase 2**	**Phase 3**	**Phase 4**
Whole sample	0.5072	0.4727	0.6134	0.5495	0.5110
	(0.0043)	(0.0059)	(0.0142)	(0.0099)	(0.0091)
Advanced	0.5292	0.5014	0.5919	0.5664	0.5378
	(0.0042)	(0.0059)	(0.0144)	(0.0097)	(0.0089)
Emerging	0.3125	0.2804	0.4232	0.3379	0.3236
	(0.0040)	(0.0054)	(0.0147)	(0.0095)	(0.0084)
Europe	0.5281	0.5018	0.6196	0.5651	0.5232
	(0.0043)	(0.0059)	(0.0147)	(0.0099)	(0.0092)
All America	0.3497	0.3327	0.4447	0.3758	0.3321
	(0.0040)	(0.0056)	(0.0149)	(0.0098)	(0.0081)
Asia	0.3515	0.3132	0.4466	0.4068	0.3569
	(0.0041)	(0.0055)	(0.0148)	(0.0097)	(0.0084)

The table reports the estimated network intensity and their robust standard errors in parentheses for the static SAR model. The period covered in the sample is 1 January 1999 – 31 December 2017.

From the static network intensity results in Table 3.4 and Figure 3.8, it is evident that network intensity increased drastically in Phase 2 (corresponding to the GFC), followed by in phase 3 (associated with the EDC) compared to the other two phases. This is consistent with the finding of Blasques et al. (2016), who used the CDS data of big players in Europe to show that network intensity is higher when the financial system is under stress, suggesting higher spillover in the financial system. Our results also reveal that the GFC, which is associated with large network intensity, had a severe impact on the entire financial system compared to the EDC. The GFC spread throughout the entire network while the EDC severely affected only European countries.

Overall, we can conclude that increases in network intensity estimate could be associated with periods when the financial system is under stress. This is in line with Hypothesis 1, which states that higher network intensity could be associated with crises. For instance, higher estimates in

Phase 2 corresponded to GFC; in Phase 3, they could be associated with the EDC. Finally,in Phase 4, they could correspond to the Chinese market crash of 2015 (Alter and Beyer, 2014; Black et al., 2016; Yu et al., 2017).

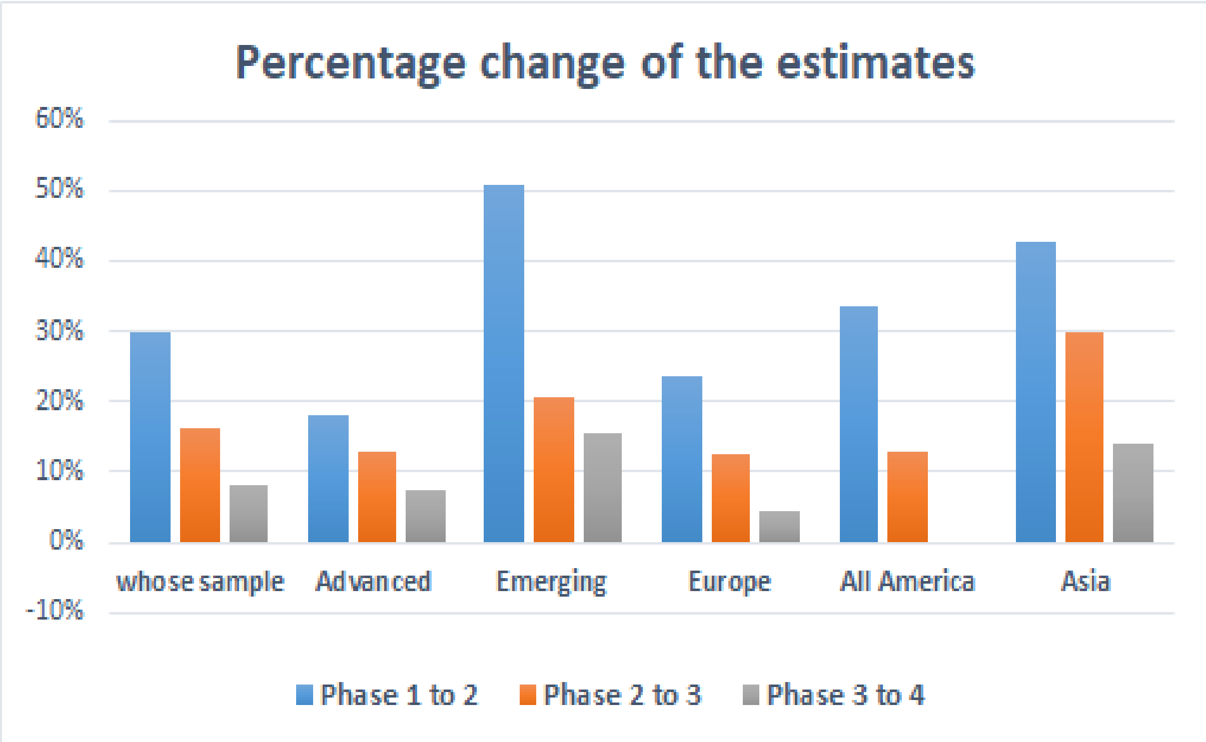


Figure 3.8: Change in network intensity estimates in subsequent phases. The figure reports the percentage change of network intensity estimates in the subsequent phases. The entire period covered in the sample is 1 January 1999 – 31 December 2017.

The increase in the estimate during times of stress could have an economic effect. Large network intensity estimates are assumed to signify higher propagation strength of a shock to the entire system. This is because of high interconnectedness, which increases network exposure, and thus, may increase fragility in the financial system (Minoiu and Reyes, 2013). We can relate this to the findings of Tonzer (2015) and argue that high network intensity is associated with increased cross-border exposures.[9] Our findings are also similar to those of Cao et al. (2017), who found that cross-border linkages tend to increase during crises. This could be a signal of greater propagation of shock when institutions are under distress.

To capture the dynamics of the network intensity parameter, we conducted an estimation using a 251-day (one-year horizon) rolling window. We investigated how network intensity changed over time. A one-year period is assumed to be adequate to capture any significant change in economies. Before estimating the parameter, it would be interesting to determine if

[9]Tonzer (2015) argued that the foreign exposure during the GFC increased in the banking sector, leading to risk spreading through the interconnected links in the financial system.

the estimates differed using a constant initial value of ρ and a changing initial value of ρ at each point in time (the initial value will be used as the starting values in search of the real values in our optimisation problem). To proxy the initial changing values of ρ, we assumed the pattern of the network intensity parameter to be same as those used by Blasques et al. (2016).[10] Specifically, we assumed the following: constant ($\rho_t = 0.5$), sine ($\rho_t = 0.5 + 0.4 * cos(2\pi t/200)$, fast sine ($\rho_t = 0.5 + 0.4 * cos(2\pi t/20)$ and step ($\rho_t = 0.9 - 0.5 * (k > 500)$). We estimate the network intensity parameters by both excluding and including the additional explanatory regressors.

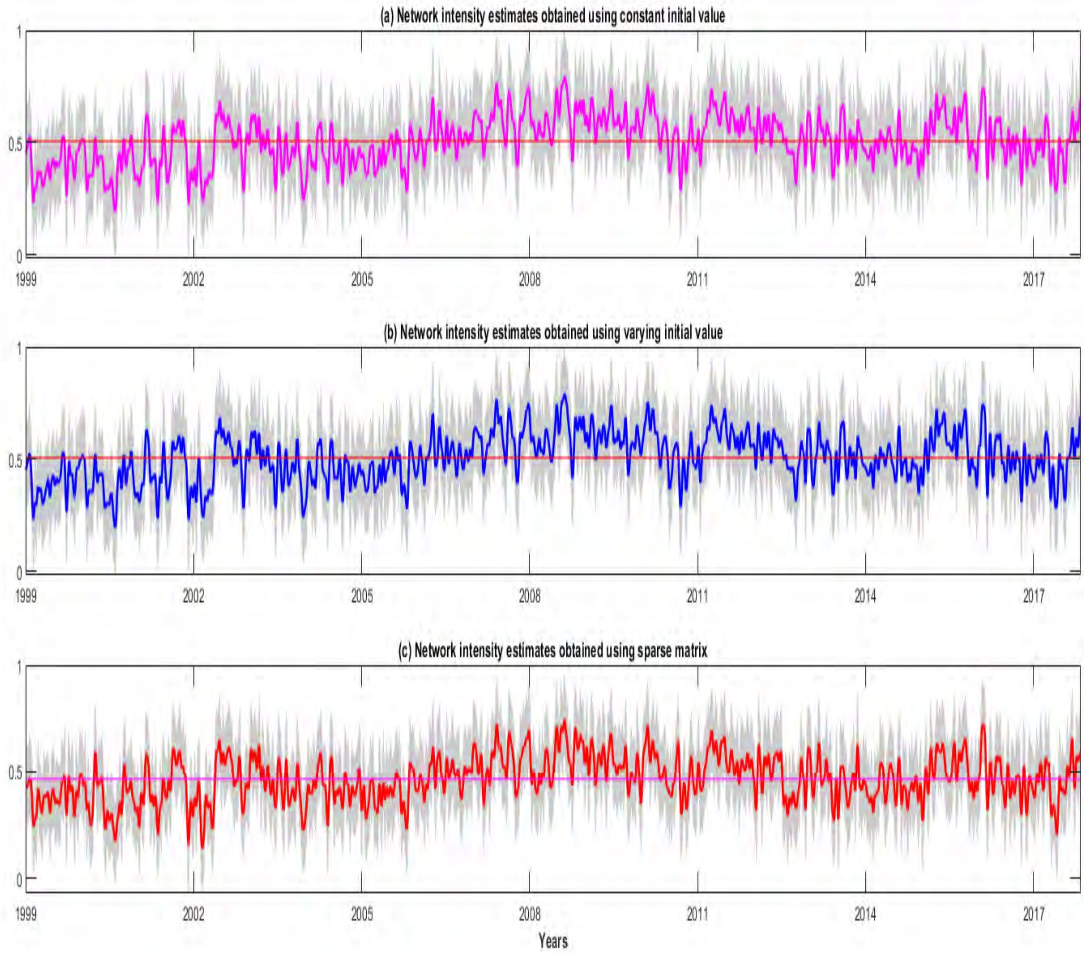


Figure 3.9: Network intensity estimates for the entire period. The figures display the network effect for the whole sample period without regressors. The light areas are the 95% confident intervals with the horizontal line representing average estimate in the whole period. Figure 3.9a presents the dynamic estimates obtained with an assumption of constant ($\rho = 0.5$) initial value while Figure 3.9b displays the estimates obtained using changing initial value (it follows $\rho_t = 0.5 + 0.4 * cos(2\pi t/200)$). Figure 3.9c presents network intensity estimates using sparse matrix. The period covered in the sample is 1 January 1999 – 31 December 2017.

[10]See Appendix A.2.4 for more details on the patterns of the network intensity parameter.

The evolution of the network intensity parameter for the whole sample with the 95% confidence intervals are presented in Figures 3.9a to 3.9c. In terms of whether using the different initialisation of ρ within the range of 0 and 1 leads to different estimates, our results indicate that dynamic network intensity estimates are identical when using any specification of ρ within (0,1). Next, we investigated whether using varying initial values of ρ would result in different estimates of the network intensity coefficient. The results in Figures 3.9a and 3.9b show that both initialisations of ρ produce similar plots. The implication here is that dynamic network intensity estimates does not necessarily depend on the initial value of ρ.

Figures 3.9a and 3.9b clearly show that the network intensity parameter changes over time. This is consistent with other studies, such as Forbes and Rigobon (2002), who stated that spillover is time variant. We also observed that estimates oscillated between 0.2 and 0.8, which signifies a higher variation of propagation chance of shock hitting specific nodes in the network. There is a notable repetition of similar trends of network intensity estimates in that estimates were lower before a crisis and increased during the crisis. This is an indicator of higher propagation of shocks to the system. This finding supports Hypothesis 1, which associates high network intensity to periods of stress, which could be due to increased interconnectedness resulting in fragility of the entire financial system.

In general, higher network intensity estimates in Figures 3.9a and 3.9b coincide with past major events in the financial sector that include:

- the dot-com bubble in 2002
- the second war in Iraq in 2003
- the GFC between 2007 and 2009
- the EDC in May 2010
- the rapid fall of prices of gold in early 2013
- Chinese stock market turbulence in 2015.

These results imply that network intensity tends to increase during times of stress, which could be associated with an increase in interconnectedness in the financial system (Geraci and Gnabo, 2018). These findings are supported by Blasques et al. (2016) , who related high network intensity to increased spillover in the financial system. These findings are similar to Cao et al. (2017), who reported that cross-border linkages tend to increase during crisis periods. Conversely, larger network intensity–especially during times of stress–are associated with increased cross-border lending, which results in transmission of stronger shocks between markets. Previous research by Tonzer (2015) and Sun and Chan-Lau (2017) supports this reasoning. They found that foreign exposures play a significant role in spreading risk. This implies that countries are exposed more to more risks due to large exposure from trading partners. The high network intensity across markets signifies the strong exposure of a shock to the entire financial system (Forbes and Rigobon, 2002).

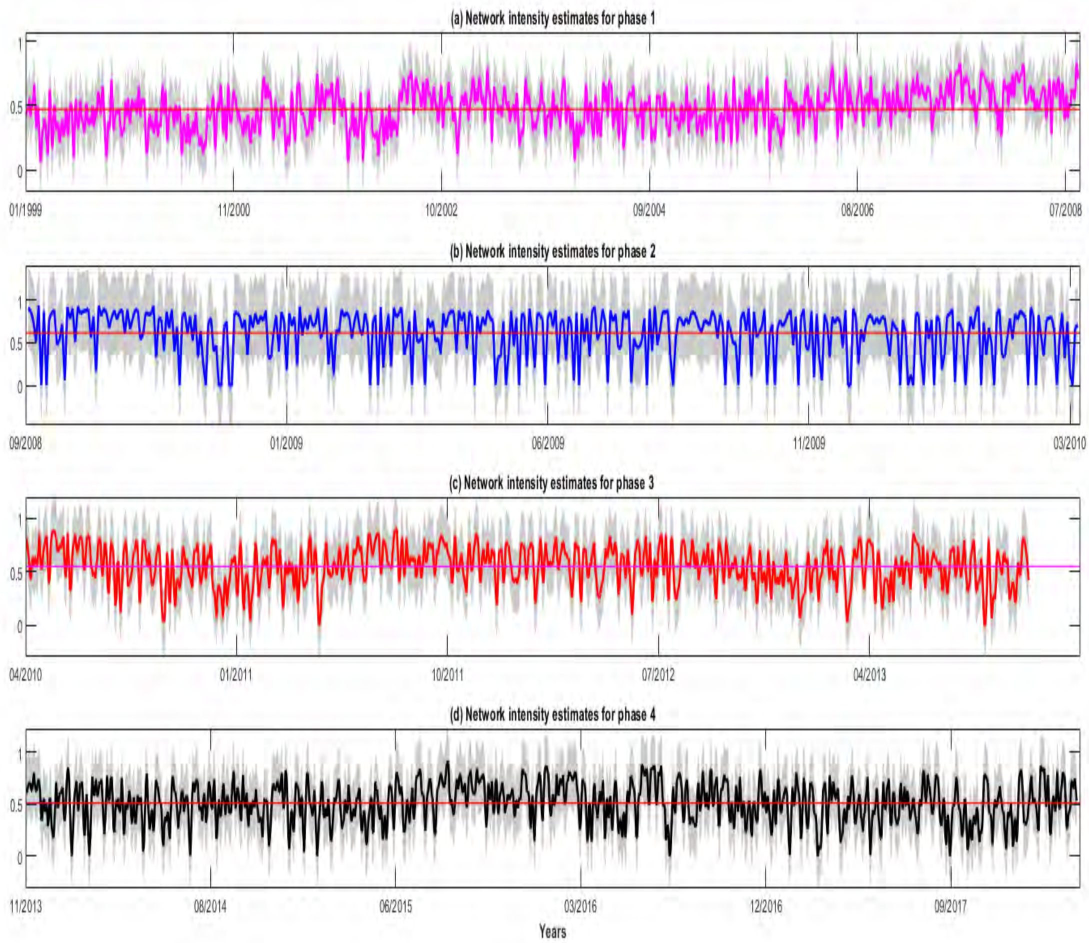


Figure 3.10: Network intensity estimates in different phases. The plots display the network effect for the whole sample period in each phase. The light areas are the 95% confident intervals while the horizontal line is the is the average estimate in the entire period. The period covered in the sample is 1 January 1999 – 31 December 2017.

To check Hypothesis 2, we used an alternative sparse matrix to estimate network intensity parameter. The sparse matrix provided us with an idea of how the degree of interconnection in a financial system affects estimation of network intensity parameter. We used a random sparse network matrix with the exception of main diagonal taking zeros. Figure 3.9c shows the dynamic estimates of the network intensity parameter obtained using sparse matrix with 95% confidence intervals. From this figure, we observed that network intensity estimates shift downwards when sparse weighting matrix is used. The dynamics of network intensity in Figure 3.9c differ from those in Figure 3.9a. The results also indicate that interconnectedness among financial markets changes the patterns of network intensity over time. A more stable economy with higher network connectivity would beneficial in shock absorption, leading to a more resilient financial system. The converse is also true. Further, these results imply that as the degree of connectivity increases (decreases), then network intensity parameter shifts upwards (downwards). As a result, the degree of interconnection plays a key role in the estimation of network intensity parameters. These findings are consistent with previous studies. For instance, Silva et al. (2016) found that shocks spread from highly interconnected networks, leading to financial distress in the entire financial system. This is also supported by Amini et al. (2016), who showed that a financial market with larger connections is associated with spreading shocks in the network, leading to financial instability. As Minoiu and Reyes (2013) described the financial network as volatile, we expect this to have an impact on the estimation of network intensity parameters.

To obtain a clearer picture of the evolution of network intensity, we obtained the values of the estimates at each phase. Figure 3.10 displays the dynamic network intensity coefficients at each phase. From these, we can draw a similar conclusion those drawn from the static estimates. On average, these estimates are lower in Phase 1 than in other phases, and increase in Phase 2. The network intensity parameter remains higher in Phase 3 (after the crisis and during the EDC). This suggests that network intensity tends to be higher when the market is under stress. Blasques et al. (2016), who used European CDS data, arrived at a similar conclusion.

3.7.1 Impact of exogenous factors on the estimation

Next, we investigated the marginal effects of the explanatory variables on the estimation of network intensity (Equation 3.27). The beta coefficient of the model represents the exogenous exposure to the common factors, while the network intensity parameter captures the endogenous effect of the network exposure in the model. All these external regressors are country-specific. They include volatility index, FX and IR. Volatility index captures the change in risk appetite, which gauges the overall market sentiment. It is measured using the implied volatility of the world index. We considered implied volatilities of two major stock indices, VIX and VSTOXX, because of the unavailability of individual country data.

Figure 3.11 shows the trend of the implied volatility of these stock indices. We used these two

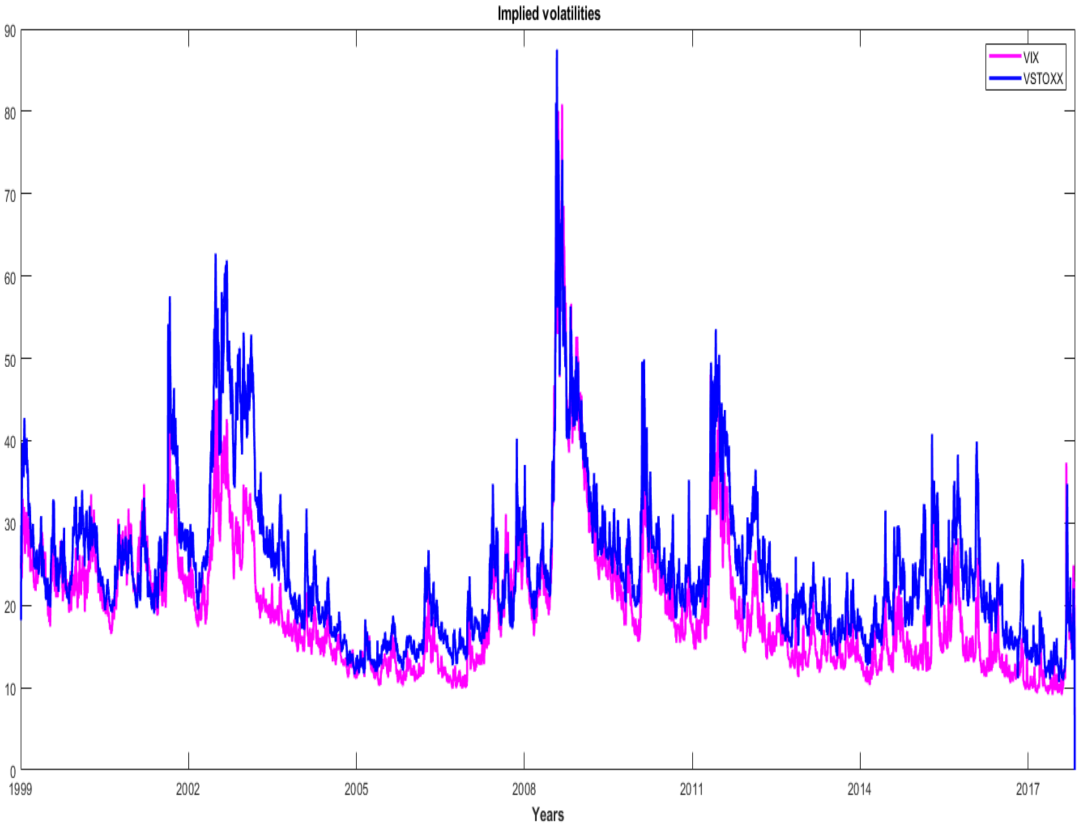


Figure 3.11: Volatility estimates. The figures display the implied volatilities for VIX and VSTOXX indices during the entire period. The period covered in the sample is 1 January 1999 – 31 December 2017.

major implied volatility indices to investigate the impact on network intensity estimation. It can be observed in the figures that the implied volatility depicts similar patterns. For example, during the GFC of $2007 - 2009$, the two indices reached their peak over the whole period. We also observed a comparable shift in the magnitude of volatility at different points in time. High spikes in the implied volatility were associated with periods when financial markets were under stress. For instance, the spikes in 2002 are associated with the dot-com bubble, those in 2003 are associated with war in Iraq (Degiannakis et al., 2018), $2007 - 2009$ spikes were associated with the GFC, 2010 spikes with the EDC, 2013 with the rapid fall of prices of gold and 2015 with turbulence in the Chinese stock market.

The country-specific regressors include IR and FX. Local market returns measured the growth of the economy of any country; this measures the stability of a country's economic outlook. IR affects the cost of borrowing; higher IRs are associated with increases in borrowing costs. In addition, IR measures financial integration because it reflects capital movement between countries (Asgharian et al., 2013). We used the absolute changes of 90 days' T-Bills as a proxy for IRs. FX involves trading currencies across the global market. This may affect international trade and capital flows, thereby affecting the economy. Research has found that sudden change in exchange rates have implications tfor the entire financial system (Flood and Garber, 1984; Krugman, 1979; Salant and Henderson, 1978). This fluctuation in exchange rate is associated with currency crisis (Frankel and Rose, 1996). Following the approach used in Asgharian et al. (2013), we used exchange rate volatility, which is computed as the standard deviation of daily log changes in bilateral exchange rates. All these variables are indicators of financial integration and thus may either directly or indirectly have an effect on estimating the network intensity parameter. Daily data for these explanatory variables were obtained from Thompson Reuters' Datastream. The sample consists of 45 countries and the period is January 1999 – December 2017; weekends were excluded.

Table 3.5: Comparison of network intensity estimates with and without regressors

	Base	**IR**	**FX**	**VIX**	**All regr.**	**VSTOXX**
Liability matrix						
Est. Par.	0.5149	0.5117	0.5166	0.1055	0.1933	0.0978
	(0.0042)	(0.0042)	(0.0042)	(0.0027)	(0.0039)	(0.0025)
Trade matrix						
Est. Par.	0.5698	0.5669	0.5718	0.1781	0.2000	0.1617
	(0.0041)	(0.0042)	(0.0041)	(0.0038)	(0.0040)	(0.0036)

The table reports the comparison in network intensity parameter with and without regressors. These estimates are obtained using a dynamic SAR model and they represent the mean values of the whole sample period. The estimates represent the average value of the estimate in the whole sample period. Base are the estimates obtained without including external regressors, All regr. are estimates obtained with inclusion of all other regressors, excluding the VSTOXX index. The other estimates are based on individual regressors.

The estimates shown in Table 3.5 represent the mean value of the network intensity parameter in the whole sample period. Both liability and trade weighting matrix were used to estimate the static network intensity parameter. These results show that the estimate is greater (0.5149) when additional regressors are excluded than when they are included (0.1933). This is an approximately 62% change (decrease) in the estimate when all additional regressors are included in the estimation. Therefore, the presence of explanatory variables has a discernible effect on the estimation of the network intensity parameter. This suggests that each additional regressor may have either positive or negative effects on the estimation. We observed that the introduction of each variable separately has an effect on network intensity estimate.

Although there is no significant difference between the network intensity estimates with and

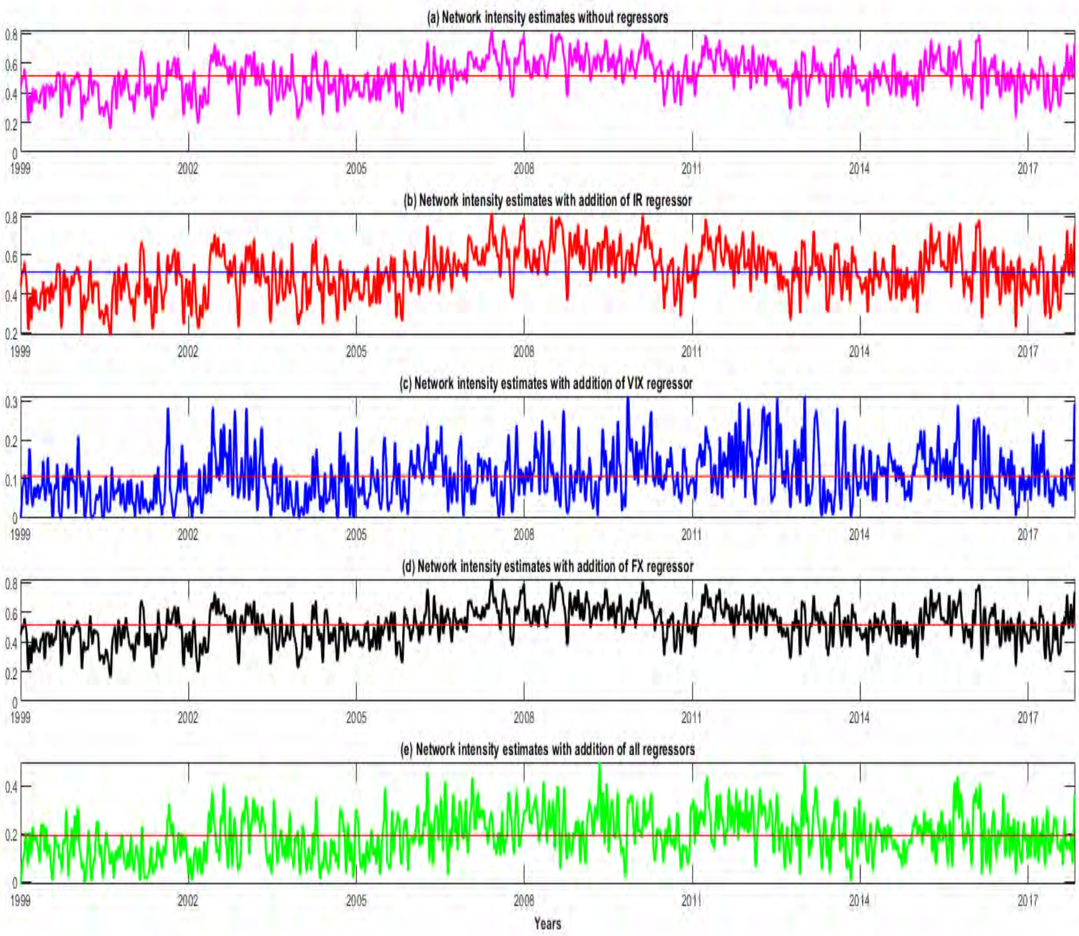


Figure 3.12: Network intensity estimates with and without regressors. The figures display network effect for the entire sample period with the addition of external regressors. The horizontal line is the average estimate in the entire period. Figure 3.12a displays network intensity estimates without external regressors. Figures 3.12b, 3.12c and 3.12d display network intensity estimates with IR, VIX and FX respectively being the external regressors. Figure 3.12e displays network intensity estimates with all external regressors.

without inclusion of IR and FX, it is worth discussing their impact on the estimation. IRs across countries may fluctuate due to the FX. Higher IR fluctuations may have a greater impact on network intensity estimates. This is because increases in IR volatility increases uncertainty, which create a channel through which shocks can spread in financial markets (Edwards et al., 1998). This may lead to an increase or decrease in network intensity parameter. Our results reveal that the IR fluctuations lead to decrease in network intensity of 0.6%. FX rates differ from country to country and this may affect the borrowing rates of each country (Bruno and Shin, 2014). A more volatile exchange rate increases currency risk premium, and thereby effecting financial market co-movements (Asgharian et al., 2013). This suggests that FX may have a greater impact on estimation. From the static results, we observed that, on average, the volatility in exchange rate leads to an increase in network intensity parameter of 0.3%.

Volatility (the amount of uncertainty regarding change in each stock market index) has a greater impact on network intensity estimation. As displayed in Figure 3.11, fluctuations in the implied volatility index, especially during periods of stress, cause shifts in network intensity. High fluctuations in volatility result, on average, in a decrease in network intensity parameter by approximately 80% in the case of VIX and 81% for VSTOXX. Both VIX and VSTOXX have almost similar effects on network intensity parameter. Based on these results, we conclude that implied volatility has a major impact on the estimation of the network intensity parameter and would have discernible effects on the financial system. This is supported by Antonakakis et al. (2013), who showed that implied volatility, for instance VIX, dampens returns, which could result in lower network estimates. Therefore, among the external regressors, the volatility of stock market index has a greater impact on the estimation of the network intensity parameter, resulting in a 62% decrease in the estimate.

Figure 3.12 shows dynamic network intensity parameter, including and excluding explanatory regressors. The estimates were obtained using the dynamic SAR model specification using a 251 rolling window size.

Figure 3.12a displays a time-varying trend of estimate without the external regressors. The horizontal line represents the average estimate of the whole sample period. Figures 3.12a, 3.12b and 3.12d display similar patterns, while Figures 3.12c and 3.12e show varying patterns. This is because while the IR and FX fluctuations either increased or decreased estimates, implied volatility (we used VIX as a proxy of implied volatility since VSTOXX provided almost identical results) of stock index had discernible effect on the estimation of network intensity parameter. Higher volatility changes the trend of network intensity estimates. These effects are clearly observed during the global crisis, for which the trends of Figures 3.12a and 3.12c of Figure 3.12 differ.

Although we can observed a similar trend in Figure 3.12 (which excluded the explanatory variables), reduction of the estimated values (previously presented in Table 3.5) can be observed. The estimates fluctuate between 0.3 and 0.75. This led to the same conclusion as previously discussed. The spikes in the estimates are associated with periods when the market was under stress. This is in line with Hypothesis 1. For example, the spike before 2002 is associated with the dot-com bubble, $2007 - 2009$ with the GFC, post-2010 with the European debt crisis and 2015 with the Chinese market crash.

We now introduce additional regressors to support Hypothesis 3. Our preliminary findings showed that external factors (integration measures) have an effect on estimation. This may suggest that the financial market is highly integrated in terms of cross-border activities.

As stated in Hypothesis 2, increased interconnectedness between different markets results in increased network intensity estimates. Let us relate the horizontal line (mean value) to the period of financial system stability (robust network intensity estimate) while periods when there are spikes above the line correspond when the financial system is under stress (fragile network intensity estimate). Figure 3.12 depict a robust-yet-fragile network intensity estimate. A robust-yet-fragile network would diversify small shocks, while propagating large shocks to the entire financial system, leading to distress (Acemoglu et al., 2015; Gai and Kapadia, 2010; Tonzer, 2015). Although the network intensity was robust-yet-fragile between 2002 and 2006 (as shown in Figure 3.12), the financial system benefited from risk-sharing effect. During the GFC, shocks were amplified in the financial system, causing financial instability.

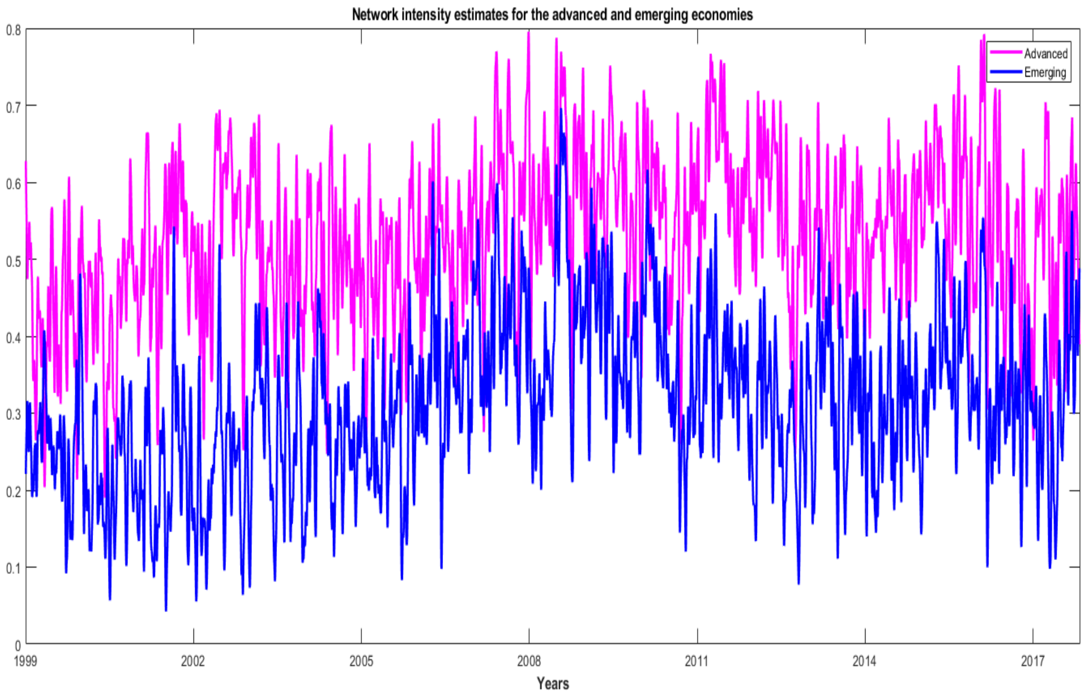


Figure 3.13: Network intensity estimates comparison for developed and emerging markets

3.7.2 Developed versus emerging markets

There is increasing involvement of emerging markets in enhancing financial growth and stability. Therefore, it is important to estimate the network intensity parameter for these markets and compare them with those of developed economies. The countries in our sample were classified as developed (54%) or emerging (46%) based on IMF 2017 classification.[11]

In Table 3.4, we observed that developed economies have higher network intensity estimates than emerging markets. This could be due to their high inter-linkage with other markets. Schiavo et al. (2010) stated that developed economies are more interconnected to the other countries, and thus, spread shocks to other economies. Although developed markets have higher estimates than the emerging markets, emerging markets experience high fluctuations in different periods (see Figure 3.8). We observed that emerging markets experienced more than a 50% change in the estimate in Phase 2. This implies that they are largely exposed to and affected by external shocks, originating from developed economies, especially in times of GFC (Aizenman et al., 2016a).

Figure 3.13 displays the dynamics of network intensity parameters for both developed and emerging markets. Figure 3.13 suggests that the dynamics of estimates for both economies differ. While the estimates of the developed markets are identical to those of the entire sample, estimates of emerging markets have different patterns. Emerging markets exhibit higher fluctuations than developed markets. This is in line with Hypothesis 4. From these results, it can be theorised that developed markets with stable economies tend to experience high network exposure, but less fluctuation. Conversely, network exposure for emerging economies varies more. Harvey (1995) suggested that this could be due to segmentation from global markets.

Our results concur with those of Aizenman et al. (2016a)–that developed markets have greater influence with higher network intensity than do emerging markets. This greater influence can be associated to developed economies being the key contributors to the GFC. That is, when a shock hit these economies through their network links, it had a greater effect on the entire economy. This finding is supported by Schiavo et al. (2010), who showed that one of the contributors of the GFC was shocks from developed markets spreading to other markets. Kubelec and Sá (2012) suggested that shocks from the US and UK (being big players in developed markets) propagated to the entire financial system during the global crisis. We identified developed economies as having many interconnections with other markets, making them more prone to risk in terms of spreading shocks to other markets. This is supported by Amini et al. (2016), who argued that institutions with large connections have a higher chance of affecting the stability of the entire system due to their link structures. Aizenman et al. (2016b) also argued that emerging markets were more resilient during and after the GFC. Thus, developed markets played a significant role in propagating shocks to the entire financial system. This is a clear indication that policy

[11] Most countries in our sample are developed economies.

makers should be more concerned when network intensity estimates are greater for developed markets.

Although emerging markets have lower network intensity estimates, they may also have the greatest influence in propagating shocks. We observed that emerging markets had having greater spikes especially when the market was under stress. This finding shows that emerging markets are not immune during the GFC. This suggests that emerging markets serve as hubs through which shocks from developed economies spread to the entire financial system. Aizenman et al. (2016a) also found that emerging markets were also exposed to external shocks during the GFC, especially to shocks originating in developed markets. These findings indicate that emerging markets increasingly play a role in the world economy by engaging in cross-border relationships with developed and emerging economies (Bekaert and Harvey, 2017).

In terms of integration, we observed that developed economies with high network intensity have more cross-border activities, making the estimate higher than those of emerging markets. These results suggest that developed economies that are more stable benefit from higher network intensity. However, in the presence of shocks, these economies might have a great impact on financial stability. These findings are similar to those of Chevallier et al. (2018), who showed that developed markets play a dominant role in propagating shocks to the entire system while emerging markets are becoming more integrated with other markets. This means they can transmit shocks to other economies. These results are also supported by Schiavo et al. (2010), who found that developed economies tend to be more integrated and more clustered, resulting in larger estimates of network intensity parameters.

Finally, developed economies network intensity estimates exhibit a robust-yet-fragile feature. The financial system could benefit more from risk-sharing and diversification when small shocks hit the system. There is also a danger of large shocks being amplified throughout in the entire system, making the financial system more susceptible to collapse.

Generally, the findings suggest that developed markets are dominant in terms of high propagation of shocks to other markets compared to emerging markets (Arnold et al., 2013). This could be a result of large cross-border transactions to other markets. Although emerging markets are less dominant, they still contribute to global propagation of shocks.

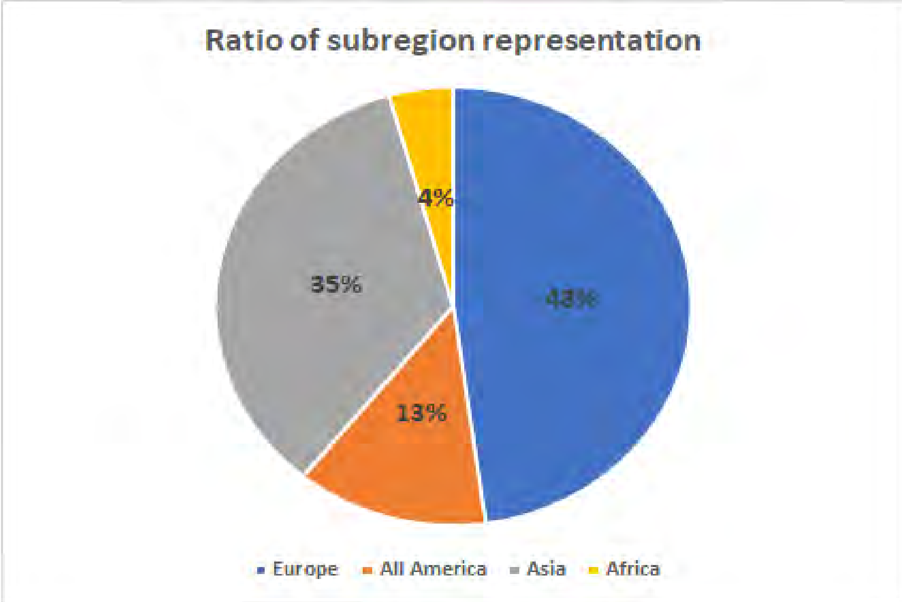


Figure 3.14: Ratio of the regional representation of the financial markets

3.7.3 Region specific network intensity

This section investigates the evolution of network intensity parameters in different regions. From Figure 3.14, all America (include both North and Latin America) represents 13% of the total sample, Asia represents 35% and Europe represents 48%. The liability weighting matrix for each region was obtained using the combined DY and Granger causality approach. These analyses aid in investigating the extent to which network intensity parameter differs among these regions. This is in line with Hypothesis 3. Hypothesis 3 aims to investigate whether regional integration has an impact on the estimation of network intensity parameters.

Network intensity estimates in Table 3.4 differ for each region. On average, America has the lowest (0.3497) estimate with low standard error than all other regions. The estimate is 31% lower than the original average estimate of 0.5072. The network intensity estimate of Asia is also lower (0.3515) than the original estimate, representing a 30% decrease. Europe has the highest estimate (0.5281) in the whole period, representing a 4% increase in estimate as compared from the original estimate. From Figure 3.8, these estimates changed (increased or decreased) from one phase to another. For instance, these estimates increased when moving from Phase 1 to Phase 2 by more than 24% in all regions. Asia experienced a significant increase in estimates (40% change). The estimates slightly changed (decreased) moving from Phase 2 to 3. They also changed (decreased) moving from Phase 3 to 4.

With the increasing development in the financial sector and globalisation, there has been a high degree of both regional and global integration, which may be depicted in the results (Chevallier

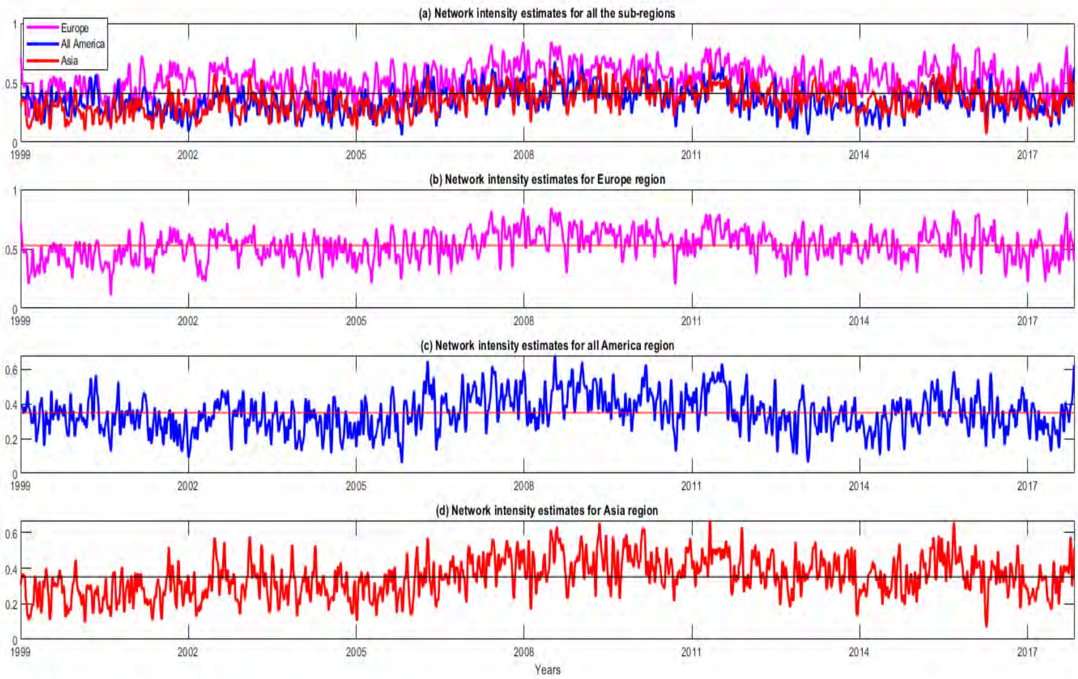


Figure 3.15: Network intensity estimates for each region

et al., 2018). The increase of cross-border transactions has led countries to become more interconnected, leading to increased financial integration between these markets. An increase in integration is be associated with increased network exposure, which tends to increase network intensity estimates (Hüser, 2015). Higher network intensity estimates in Europe signify greater integration in the European market.

Figure 3.15 shows the dynamic network estimates for each region. Figure 3.15a presents the network intensity estimates for all regions. The horizontal line is the average network intensity parameter in the whole sample. According to Figure 3.15a, Europe has higher estimates than other regions. The estimates for the European market fluctuated above the mean, while other regions, they fluctuated above and below the mean.

All America and Europe produced different patterns, suggesting that the two regions have different exposures. This could be due to different banking systems across regions, making cross-border banks from large countries (mostly the US) pose the 'too big to fail' problem. Propagation of shocks led to financial dislocation and tensions especially in the Euro areas (Belke and Gros, 2016). Additionally, network exposure for the US and Europe would differ because the equity returns of these markets react differently to shocks. Previous literature has shown that the US had problems in banking and sovereign debt, thereby establishing a diabolical loop (Chan-Lau et al., 2015; Dufrénot and Keddad, 2014).

For all America, we observed that network intensity estimates were higher at the beginning of the sample period and continued to decline until 2007, when the estimate fluctuate upwards. There were spikes in mid–2008, implying that propagation strength increased suddenly. The estimates fluctuated at around 0.4 before increasing to 0.6 in 2014. The presence of Latin American countries (Argentina, Brazil, Chile and Mexico) affected network intensity estimates. These emerging markets exhibited higher fluctuations in return over time.

For Europe, the opposite was true. Network intensity estimates were lower at the beginning of the sample period and then increased. Before 2012, there were spikes (the propagation strengths are higher) in network intensity estimates. They are associated with the onset of the EDC in 2010 (Mink and De Haan, 2013). The estimates then fluctuated in an increasing trend in 2012. This suggests that European markets became more interconnected, increasing their exposures in the financial system. The propagation strength was higher during crisis periods and remained higher during the sovereign debt crisis. This could indicate a larger impact of shock propagation, especially when a shock hits the financial system.

Conversely, the Asian region depicted a different pattern from other regions. There was a spike in 2002, and it remained higher until 2003 before dropping then fluctuates again. The estimate declined at the beginning of the crisis period before spiking in 2007. Thereafter, there is a declining trend of network intensity until hit its lowest point in 2014. The estimate remained low after 2013. These results are similar to the static estimates in Table 3.4. These results are consistent to those of Guimarães-Filho and Hong (2016) ,who argued that Asian markets are more exposed to shocks from other region, thereby increasing their exposure during crises.

Overall, the results from the regional network intensity show that exposures are high especially during crisis periods. This suggests that the fragility of the financial system tends to increase during time of stress (Sun and Chan-Lau, 2017). This leads to financial instability.

Our findings indicate the possibility that regional network intensity estimates have an implication for policies that affect economic growth and stability. A high network intensity estimate may imply higher propagation effects from shocks to the financial system, leading to financial instability (Sun and Chan-Lau, 2017). This aligns with Tonzer (2015), who showed that regional integration might be beneficial to stable economies. Therefore, by having higher network intensity, a region might benefit from diversification of shocks.

The estimates of network intensity using alternative weighting matrix are discussed in Appendix A.2.1. The comparison of MLE with other approaches is discussed in Appendix A.2.3.

3.8 Implication of empirical study

From our empirical results, we highlight why the network intensity estimate is important, especially to the financial system. We do so in an attempt to answer the questions posed in the following Sections 3.8.1 – 3.8.2.

3.8.1 Do high network intensity estimates signify spillover in the financial system?

The changing nature of network intensity parameters raises the question of whether high or low network intensity estimates are associated with return spillover in the markets. Transmission of shocks across the financial system through different channels is known to cause financial distress. This transmission of shocks can be a result of many factors, not limited to the increasing growth of cross-border activities in the financial system.

With increasing cross-border activities over recent years, there has been a tendency for increased exposures throughout the financial system. This is depicted from our results, in which we observed that the network exposure tends to increase when the financial system is under stress. This can signify a spillover in the financial system. Moreover, increasing interactions between different markets imply high exposure to these markets in terms of risk, thereby posing a threat to the stability of the financial system. Network intensity is also affected by financial integration through cross-border flows. This in itself creates a channel of increasing spillovers in the financial system.

In general, network intensity parameters capture the strength of exposure, which relates to spillovers. We conclude, based on our results, that network intensity evolves over time and during important events. When network intensity is high, it implies that spillover is increasing in the financial system. It is worth noting that with increasing cross-border financial activities, financial institutions have become more interconnected. This has resulted in high exposure of the financial system to shocks. These results confirm that a high network intensity parameter is associated with high interconnectedness in the financial system.

3.8.2 Does network intensity respond to different market conditions?

Ever changing market conditions have led to greater complexity in the financial sector. Recent studies have revealed increased co-movements of cross-border activities. This means that with favourable market conditions the financial market has become more integrated. A natural question to ask is whether the different market conditions increase the chance of vulnerability in the financial sector.

For example, FX volatility may have a positive influence on network intensity estimate. This is reflected in our results, in which we observed high network intensity corresponding to periods of high volatility in FX rates.

Implied volatility used to capture overall market riskiness is expected to have a positive influence on network intensity estimates. With increasing uncertainty in the market, financial sectors are at a higher risk of failure. Our results show the considerable impact of implied volatility on network intensity estimates. All this suggests that with changing market conditions, there is an increased possibility of high network intensity, and thus, a possibility of stress in the financial system.

3.9 Chapter summary

This chapter investigated the dynamics of the network intensity parameter that monitors network exposure. To be specific, this chapter produced two empirical findings. The first part examined the impact of network exposure on common factors. Our findings show that both the network intensity coefficient and interconnectedness increase exposure to common factors.

The second part aimed to estimate the network intensity coefficient. Interconnectedness was estimated using existing measures, such as Granger causality and the DY approach. Our initial aim was to estimate a static network intensity parameter. OLS and MLE approaches were used in the estimations. We also extended our work to estimate a dynamic network intensity parameter to determine whether a high network intensity is associated with period of extreme events. Our findings suggest that a high network intensity coefficient is associated with extreme events that are related to period of distress in the financial system. The size of the network intensity coefficient serves as an indicator of stress events and could be useful in monitoring the financial system, ultimately promoting financial stability.

This chapter highlighted the importance of network exposure by showing the extent to which financial systems are exposed to shocks from existing linkages. Caution must be taken to monitor these exposures to reduce the transmission impact of these shocks. Further research is required to investigate the evidence of spillover and contagion among financial markets. This motivates us to examine the transmission of shocks in Chapter 4. Chapter 4 focuses on investigating the changing vulnerability in financial systems, with emphasis on Asian markets.

4 Changing vulnerability among Asian markets: Contagion and spillovers

Abstract

The increasing involvement of the Asian market in the global context plays a fundamental role in spreading shocks across the financial system. This chapter examines the extent of vulnerability across Asian markets and the US by distinguishing between spillovers and contagion over January 2003 – December 2017. Spillovers are detected using generalised historical decomposition in a vector autoregressive model while contagion is detected using portfolio mimicking factor framework using moment conditions. The findings show evidence of distinct spillovers among Asian markets and the US. The transmission of spillovers is assessed to capture both the direction and strength of the spillovers. Spillovers are also distinguished by signs to assess the impact of the spillovers across different periods. Increased connections during crisis periods are evident as well as a general deepening of the global network. The findings also reveal strong evidence of contagion using the US as the mimicking factor. Our results show evidence of changing vulnerability among Asian markets and the rest of the world. These suggest that caution is needed when developing regulations or methods to create a stable financial system. These connections might result in reduced opportunities for emerging markets.

Keywords: Financial stability, networks, Asian markets, financial crises

JEL classifications: G15, C21, N25, G01

4.1 Literature review

Detecting evidence of the changing nature of transmission of shocks has generated a considerable body of literature over the last two decades. Many researchers have applied correlation-based tests (detecting the presence of contagion) to detect unexpected changes in transmission from Asian markets to international markets, where Asian markets are used as the source of contagious shocks. This is particularly true during the Asian financial crisis. The literature on this includes Forbes and Rigobon (2002), who used Hong Kong and China as the source of shocks to other markets in a bivariate correlation framework; Sander and Kleimeier (2003) searched for contagion within Asia and from Asia to other emerging markets using Granger causality tests. Baur and Schulze (2005) considered quantile regressions in a co-exceedance framework to detect shocks from Thailand and Hong Kong to other Asian and international markets. Finally, Baur and Fry (2009) used both cross-section and time-series identification to estimate the spread of contagion within Asian markets. Much of the literature on measuring contagion from the Asian financial crisis is reviewed in Dungey et al. (2005). Since then, new methods have emerged that have been tested on the dataset for the Asian financial crisis. These methods include; the generalised autoregressive conditional heteroskedasticity (GARCH) process (Dungey et al., 2015), dynamic conditional correlation (DCC) (Chiang et al., 2007), smooth transition, indices and other time-varying models (Kim et al., 2015) and copulas (Busetti and Harvey, 2010).

A smaller body of literature considers Asian markets in terms of how they were affected by shocks originating elsewhere. Examples include Hwang et al. (2013) and Kim et al. (2015) who considered the impact of the US financial crisis on emerging markets. Kim et al. (2015) also drew attention to the importance of examining this issue for interventions to protect Asian economies from crises emanating elsewhere. ADB (2017) investigated whether crises from other economies affect Asian economies. Beirne et al. (2010) considered local, regional and global effects for 41 emerging markets and concluded that significant spillovers from global effects cannot be rejected in Asian markets. Mobarek et al. (2016) used all possible pairings between 10 emerging and 10 developed markets, including seven Asian markets, in a DCC mixed-data sampling framework. They conclude that there are many different and time-varying relationships between them that will affect the efficacy of policy making. These multivariate approaches are typically based on equity market data and either consider particular subgroups of countries or bundle Asian markets together.

The increasing importance of Asian financial markets in the global economy especially China, has led to a growth in literature focusing on spillovers between financial markets in Asia and other markets, both regional and international. Spillovers are the normal flow of information and adjustment of portfolios between markets, although this does not imply that spillovers are static. Yilmaz (2010) produced a time-varying spillover index for East Asian markets. Spillovers do not capture the abrupt changes associated with stress caused by contagion. Rather, they evolve relatively slowly with increasing financial integration, trade relationships, and the normal course of business and expansion. The literature comparing these types of channels includes Van Rijckeghem and Weder (2001) and Dungey et al. (2018a). Given the growth in the size and relative importance of Asian markets, we believe that the relationships between Asian and global financial markets have changed since the start of the twenty-first century in response to changing cross-regional relationships and periods of financial stress experienced during crises.

This chapter investigates this changing vulnerability over time to investigate the evidence for contagion and the time evolution of spillovers from the global market affecting Asia and compare this evidence with regionally sourced influences. We differ from the existing literature that detects either contagion or spillover independently, by focusing on detecting contagion and spillover by considering the influence of Chinese and US markets. US markets have been used as a proxy for global conditions in existing studies, such as Chiang et al. (2007) and Kim et al. (2015). Dungey et al. (2015) compared the influences of China and the US. Kim et al. (2015) argued vigorously against including China as a source of spillovers and contagion in financial market integration studies because of a perceived lack of market freedom in determining observed outcomes. Arslanalp et al. (2016) examined the growing role of spillovers from China to other Asian financial markets. Yilmaz (2010) tested whether the inclusion of India and China is important for calculating a spillover index for the region; they found that the impact was evident only after 2002.

We implemented recently developed spillover and connectedness methods to detect and measure spillovers and contagion. The spillover method builds on the index developed by Diebold and Yilmaz (2009, 2014), which provides a summary measure of financial spillovers in a network of markets based on a forecast error variance decomposition of a vector autoregression (VAR) of returns data. The Diebold-Yilmaz (DY) connectedness index has attracted a great deal of attention in the literature as a means of determining building pressure in spillovers between markets. The index was applied in Diebold and Yilmaz (2009, 2012, 2014, 2015), Demirer et al. (2018) and Yilmaz (2010) among others. Dungey et al. (2018b) showed that by rearranging information in the same VAR structure it is possible to obtain information on the source of the spillovers affecting each market and the extent to which spillovers from one market affect others, and to distinguish these effects with signs. This makes it possible to distinguish whether the spillover is associated with either positive or negative shocks.

Identifying positive and negative spillover effects is important because it allows assessment of whether transmissions via spillovers amplify or dampen shocks originating in one market and affecting others. In general, links that amplify the transmission of bad shocks to other markets are undesirable during crises periods. We argue that these are the shocks policy makers should be most concerned about. To do this, it is important to be able to distinguish between amplifying shocks and dampening shocks. This means that when a shock from one market is dampened in its transmission, it contributes to the usually desirable outcome of reducing volatility in the recipient market. Dampening shocks lead to undesirable outcomes if paths that provide counter-balancing measures are inadvertently shut down. These counter-balancing measures aim to stop harmful transmission paths of shocks in the financial system. For this reason, we introduced a time-varying measure of both the size and direction of contributions of spillovers to the transmission of shocks between markets.

In the early literatures, such as Forbes and Rigobon (2002), contagion effects were considered to have negative impacts. The contagion effect introduced by Forbes and Rigobon (2002), as a one-sided test in asset returns among financial markets, is associated with statistically significant increases in correlation beyond what would be expected during normal conditions, even after controlling for increased market volatility. This increased volatility is regarded as undesirable because it can lead to flight to quality, leverage effects and a flight to home or a flight to familiarity. A flight to home and a flight to familiarity can be attributed to increased risk and uncertainty in both markets experiencing crisis and those associated with them (Giannetti and Laeven, 2015). Arguably, the most important empirical debate in the literature has been to distinguish periods of contagion from interdependence due to changes in volatility in periods of stress in the financial system. The literature originated largely from Forbes and Rigobon (2002).

An appealing way of testing for contagion is via changes in correlation between assets or markets. A correlation coefficient is a simple transformation of the links between two markets, scaled by their relative volatility (i.e. in the regression of $y_t = \beta x_t + \varepsilon_t$, where y and x are stochastic variables representing different stock market returns, β is the ordinary least square (OLS) estimate and ε_t residuals. The correlation coefficient is given by $\rho = \beta \sigma^x \sigma^{-y}$ where σ^x is the variance of x and σ^y the variance of y). A simple test of change in transmission between two sample periods is to test whether $\rho_1 = \rho_2$, which is essentially a proxy for the underlying test of $\beta_1 = \beta_2$ (where ρ_1 and ρ_2 are the correlation coefficients in the two periods, and β_1 and β_2 are the OLS estimates in the two periods.). Forbes and Rigobon (2002) asserted that there is a mechanical relationship between increased volatility and increases correlation coefficient between periods. They suggest a scaled version of the correlation coefficient to correct the test. Empirically, this vastly reduces the incidence of contagion identified between the uncorrected and corrected correlation tests. Hence, the Forbes and Rigobon (2002) correction has been shown to be overzealous and results in the under-detection of contagion. This is partly due to the need to accommodate the bounded nature of correlation coefficients in applying t-tests to the difference between them via a Fisher correction. Dungey and Zhumabekova (2001) examined the properties and Dungey et al. (2005) examined a correction. However, even this relies on unconditional variance estimates for distinct periods.

Two developments have provided some improvement for contagion detection. The first is the implementation of two-sided tests, in which contagion is associated with statistically significant increases in transmission links (correlation) between assets. Here, when there are no statistically significant changes, it is labelled interdependence; evidence of a statistically significant reduction in the transmission of shocks between assets (correlation) is labelled decoupling. Decoupling stems from literature, including Caporin et al. (2018), who showed that Portugal's and Greece's debt markets during the European debt crisis were less associated with movements in source markets than they were during normal times. Evidence of these effects is becoming more pronounced, particularly as studies of financial markets under stress consider a greater variety of potential links with the use of multivariate models and increased processing capacity for higher-order models.

The second development is the use of conditional variance to identify contagion effects, and thereby control for changes in the relative volatility of the assets under consideration. Contagion tests in the correlation form implicitly rely on the assumption that the relative contribution of idiosyncratic and market shocks remains the same for each asset during periods of stress and calm. Using a decomposition that takes advantage of the conditional variance of the assets, Dungey and Renault (2018) showed how the underlying test of changes in transmission (contagion) between markets can accommodate the potential for change in the idiosyncratic volatility for individual assets. This changes the results in a priori unpredictable direction compared with the unconditional test results.

This chapter uses the Dungey and Renault (2018) contagion tests and compares the outcomes with the traditional Forbes and Rigobon (2002) uncorrected and corrected tests. We also identify whether the tests are consistent with contagion, interdependence or decoupling, moving beyond the one-sided contagion test common in the correlation test literature. We consider three aspects of recent developments in the literature on modelling transmissions between markets during periods when turmoil appears and disappears in other markets. We contribute to the literature by investigating how vulnerability changes over time with specific emphasis on Asian markets. We focus on the impact of shock transmission on Asian markets and specifically incorporate the following:

i. modelling the time-varying contribution of spillovers for Asian markets during and after the GFC
ii. testing for abrupt changes in the transmissions of shocks to Asian markets consistent with contagion effects as volatility conditions change in global markets
iii. distinguishing between amplifying and dampening transmissions in spillover linkages, and between contagion, interdependence and decoupling.

4.2 Detecting contagion and spillovers

We begin by examining the time-varying nature of the contributions of shocks from the different sources over the sample period using an unconditional analysis to identify spillovers. We then consider the conditional relationships between markets during different periods in the sample. We use this to identify the extent of change in the propagation of shocks from source markets to target markets in different periods. These two approaches have several advantages over those in the literature. First, the effects of one market on another are signed. Through this approach, we are not only able to detect whether there is a significant transmission path of unusual shocks between markets, but we can also determine whether that transmission amplifies or dampens the effects on the recipient market. This aspect is not addressed in most studies that analyse shock transmissions (e.g. Billio et al., 2012; Diebold and Yilmaz, 2009, 2014) and contagion (Forbes and Rigobon, 2002). The extant literature primarily seeks evidence of significant links (and perhaps their direction) rather than the sign of those links. For policy and investment management purposes, however, the significance, direction and sign of the links are all relevant. Policy makers and investors want to know whether an event in a source market is likely to affect another market (via significance and direction) and whether that is likely to amplify or dampen volatility or returns (via sign) in the target market. We now introduce the two methodologies that enable us to assess these effects; generalised historical decomposition (GHD) methodology and contagion methodology. [1]

[1] Dungey et al. (2018b) provides further technical details on GHD, and see Dungey and Renault (2018) for more information on contagion methodology.

4.2.1 Spillovers using the generalised historical decomposition methodology

Consider n-dimensional random vectors of returns from different markets, r_t, which we consider are related to each other in the normal course of internationally linked financial markets. We applied standard VAR to the random vector which is expressed as:

$$r_t = \Phi_0 + \sum_{l=1}^{L} \Phi_l r_{t-l} + \varepsilon_t \tag{4.1}$$

where L is the number of lags[2], Φ_l and Φ_0 are parameters of the model and ε_t represents reduced form errors. There are many potential problems with modelling daily returns in this manner, including the issue of GARCH and non-normality. For example, Dungey et al. (2015) for discussion on the inclusion of GARCH into VAR representations. The problem is one of tractability–accounting for multivariate GARCH greatly reduces the tractability of the model and increases its numerical complexity for estimation. In keeping with the approach of Diebold and Yilmaz (2009, 2014), we push these issues aside for the purposes of computing the spillover and directional spillover indices proposed here.[3]

Spillovers are measured by the combined effects of shocks originating in one market and spreading to other markets. That is, they represent how effects flow from one market to another. In the DY approach, the spillover measure is achieved using the forecast error variance decomposition matrix from the VAR at a specified forecast horizon. They obtain a time-varying measure by using VARs estimated from rolling windows of data across the sample. Thus, the DY spillover index involves two ex-ante modelling choices: the forecast horizon and the size of the rolling window.

The GHD takes the estimated VAR in a slightly different organisational direction. Rather than focusing on the forecast error variance decomposition, it uses the moving average representation of the reduced form VAR(L) to recognise that at any point in time (t). The moving average representation of VAR(L) is represented as:

$$r_t = \theta(L)\varepsilon_t = \sum_{i=0}^{\infty} \theta_i \varepsilon_{t-i} \tag{4.2}$$

[2]The choice of L in the empirical section is based on Akaike information criteria (AIC). We used $L = 2$.

[3]Billio et al. (2012) took the alternative route of pre-filtering their data for GARCH properties before examining links between them. We did not follow this approach because we wanted to exploit how the relationships between the series move through periods of changing volatility.

where $\theta(L)$ is a matrix of the moving average in the lag operator L. For a particular period $(t+j)$, equation (4.2) may be decomposed into the sum of all the previous shocks in the system (See Fackler and McMillin, 1998). This is given as

$$r_{t+j} = \underbrace{\sum_{i=0}^{j-1} \theta_{t+j-i}\varepsilon_{t-i}}_{\text{i}} + \underbrace{\sum_{i=j}^{\infty} \theta_i \varepsilon_{t+j-i}}_{\text{ii}} \tag{4.3}$$

which represents the historical decomposition (HD_{t+j}). The decomposition of Equation (4.3) has two terms where:

i. represents the 'base projection' of r_{t+j} given the information available at time t

ii. represents the difference between the actual series and the base projection due to the structural innovations in the return variables subsequent to period t. Particularly, it depicts that the gap between the actual series and the base projection is the sum of the weighted contributions of the innovation to particular series under consideration(Dungey et al., 2019a).

The elements of $HD_{t,ij}$ show the dynamic properties of the network and represent the connectedness measure for i to j denoted by $c_{t,i\rightarrow j}$. Thus, it is possible to analyse the connectedness matrix $C_t = [HD_{t,ij}]$ with off-diagonal elements representing the pairwise directed connectedness. Letting $c_{t,j\rightarrow i}$ and $c_{t,i\rightarrow j}$ be in-degree and out-degree respectively (with $c_{t,j\rightarrow i} \neq c_{t,i\rightarrow j}$ not restricted to be identical), we can define the net-pairwise directed connectedness of i as $c_{t,i} = c_{t,j\rightarrow i} - c_{t,i\rightarrow j}$, which is not restricted to be positive.

Total directional connectedness from and to others is given by:

$$\begin{aligned} c_{t,i\leftarrow others} &= \sum_{i=1,j\neq i}^{n} HD_{t,ij} \\ c_{t,others\leftarrow i} &= \sum_{i=1,j\neq i}^{n} HD_{t,ij} \end{aligned} \tag{4.4}$$

Pairwise directional connectednesss for sample n is defined as:

$$c_{ij} = \frac{1}{n}\sum_{t=1}^{T} HD_{t,ij} \ \forall i \neq j \tag{4.5}$$

For the purposes of our spillover indices, this gives us the ability to propose the same form of the DY spillover index. However, it has the advantage of parameters θ_i not being restricted to being strictly positive, as is the case for the weights from the forecast error variance decomposition as given in Equation (4.2). Consequently, we can trace a spillover or vulnerability index over time using historical decomposition, and observe not only the contributions shocks from different markets to the system but also whether these shocks amplified or dampened the transmission from the source market. The disadvantage is that, our decomposition is sourced from an unconditional estimate of the system over the sample period. Thus, it does not directly capture problems that may be associated with changing underlying variance regimes in the data. This is a particularly a problem when comparing non-crisis and crisis periods. To manage this, we constructed sub-sample VARs for the same subsamples used in the contagion estimation. This is outlined in the following discussion on the contagion methodology so that the results are directly comparable across the two methods.

4.2.2 Contagion methodology

In a latent factor model representation of the relationship between markets we might postulate that each return is exposed to both a common factor ($f_{\omega,t}$) and an idiosyncratic factor ($f_{i,t}$) (or that it is in capital asset pricing model (CAPM) framework with a non-diversifiable and diversifiable risk). We are able to write that any individual return at time t, denoted $r_{i,t} \in r_t$

$$r_{i,t} = \beta_i f_{\omega,t} + f_{i,t} \tag{4.6}$$

where in matrix form, the system is represented by:

$$r_t = B f_{\omega,t} + F_t \tag{4.7}$$

and F_t is a diagonal matrix that represents the variances. In a CAPM framework, we invoked a market indicator or 'mimicking factor' to represent $f_{\omega,t}$. This is usually in the form of market return (often an index or an equally weighted index of constituent assets). That is, the usual formulation of Equation (4.6) will be:

$$r_{i,t} = \beta_i r_{o,t} + \mu_{i,t}, \;\; E[\mu_{i,t}] = 0, \;\; \mathrm{cov}[r_{o,t}, \mu_{i,t}] = 0 \tag{4.8}$$

where r_o is the asset return of possible source of contagion, r_i is the asset return of possible target of contagion, β_i is identified by the correlation between r_i and r_o, and the idiosyncratic factors are represented by the residuals in Equation (4.8).

The problem of identifying contagion arises when during different sample periods, we observed changes in the relationships between the variables, specifically changes in β_i and wanted to identify the source of those changes. Consider two periods defined as period of low and high volatility–for convenience we label them L (low volatility) and H (high volatility). In the simplest case we can observe that:

$$r_{i,L} = \beta_{i,L} r_{o,L} + \mu_{i,L},\ E[\mu_{i,L}] = 0,\ \text{cov}[r_{o,L}, \mu_{i,L}] = 0 \tag{4.9}$$

$$r_{i,H} = \beta_{i,H} r_{o,H} + \mu_{i,H},\ E[\mu_{i,H}] = 0,\ \text{cov}[r_{o,H}, \mu_{i,H}] = 0 \tag{4.10}$$

where $\beta_{i,L} \neq \beta_{i,H}$ and is identified by the correlation in low and high periods respectively. The debate is then about why these parameters (or corresponding matrices for a vector of returns) have changed. Initial arguments focused on changes in volatility contributing to changes in correlation and resulting in increased non-diversifiable risk during crises due to $\beta_H > \beta_L$. Forbes and Rigobon (2002) however, demonstrated the mechanical relationship between higher volatility and higher correlation parameters. They concluded that in most cases the increase in β_H in a period of high volatility was mainly due to the interdependence of markets, rather than contagion.

Consider for example the correlation between r_i and r_o in the low and high periods. We know that in the simple form, we are using the correlation coefficient $\rho_{i,L}$ (low period) and $\rho_{i,H}$ (high period) that can be expressed as:

$$\rho_{i,L} = \beta_{i,L} \frac{\sigma_{o,L}}{\sigma_{i,L}},\ \rho_{i,H} = \beta_{i,H} \frac{\sigma_{o,H}}{\sigma_{i,H}} \tag{4.11}$$

where $\sigma_{i,L}, \sigma_{o,L}, \sigma_{i,H}, \sigma_{o,H}$ are the volatility of returns in both the target and source markets (for both low and high periods), with a corresponding form for $\rho_{i,L}$ and $\rho_{i,H}$. Rearranging this so that parameters $\beta_{i,L}$ $\beta_{i,H}$ can be directly compared, we produced the Forbes and Rigobon (2002) result–if the increase in volatility in the source market from $\sigma_{o,L}$ to $\sigma_{o,H}$ is not exactly offset by the same rise in the volatility of the target market from $\sigma_{i,L}$ to $\sigma_{i,H}$ then the observed correlation must increase. That is, if an increase in volatility in the source market exceeds the change in volatility in the target market, we will necessarily observe $\rho_{i,H} > \rho_{i,L}$ in a way that is not consistent with contagion as an increase in the transmission of shocks in β_i between the two periods. This led Forbes and Rigobon to propose a scaling adjustment to test contagion based on correlation. They concluded that most contagion identified in this manner was because of changes in underlying volatility.

The Forbes–Rigobon (FR) adjustment has been shown to under-reject the null hypothesis of no contagion (Dungey et al., 2004). This is because the change in observed volatility in the target market has two potential sources. The first is the transmission of increased volatility from the source market–that is, the increase in σ_i. The other is due to potential changes in volatility in the idiosyncratic component (the diversifiable risk) which is associated with the asset, which we denote $\omega_i = \text{var}(\mu_i)$. Dungey and Renault (2018) provided the proof that the FR adjustment only works when idiosyncratic volatility in target markets is also unchanged between sample periods–that is, when $\omega_{i,L} = \omega_{i,H}$. Otherwise, the test on correlations will tend to over-accept the null of no contagion.

The clearest lesson from the literature on detecting contagion via changes in correlation coefficients is that although it is intuitively appealing, it is also fraught with hazard because of the number of implicit assumptions invoked. The clearest approach is to directly examine the changes in β_i between periods and, at the same time, be aware that these changes have several sources of volatility influence that must be distinguished.

Consider that Equation (4.9) and (5.1) are our approximation of Equation (4.8), where we approximate the common factor with our mimicking return, $r_{o,t}$ and that this can be represented as:

$$f_{\omega,t} = br_{o,t} + \upsilon_{o,t} \tag{4.12}$$

where $\text{var}(\upsilon_{o,t+1}) = \omega_o^2$ and the correlation between the idiosyncratic component of $f_{w,t}$ and of $r_{i,t}$ is denoted as:

$$\text{cov}(\mu_{i,t+1}, \mu_{o,t+1}) = \omega_{i,o} \tag{4.13}$$

Assuming the shocks to $f_{\omega,t}$ are independent, we find the unconditional variance of $f_{\omega,t}$ which is not identified. The return variance of $f_{\omega,t}$ can be extended by incorporating a constant component. This constant component represents the proportion of the factor variance explained by the mimicking return. That is:

$$\alpha = \frac{\text{var}(f_\omega)}{\text{var}(r_{o,t+1})} = \frac{\sigma_\omega^2}{\sigma_o^2},\ \ \alpha \in]\,0, 1[\tag{4.14}$$

which means that it must be large enough to capture at least part of the variation in the factor. This is done by setting a minimum value on α so that it must allow at least some of the variation to be captured by the common factor in all periods by setting $\alpha = \bar{\alpha}$ at the lower bound that respects this condition. We achieved this by setting $\bar{\alpha}$ as 1, minus the proportion of the unconditional variance of the mimicking asset explained by the minimum conditional variance of that asset over the sample period. That is:

$$\bar{\alpha} = \frac{\min_{1 \ll t \ll T}[\mathrm{var}_t(r_{oi,t+1})]}{\mathrm{var}(r_{oi,t+1})} \tag{4.15}$$

With these definitions in mind, we can return to the form of Equation (4.8) and note that:

$$\mathrm{cov}(f_{i,t}, f_{\omega,t}) = \mathrm{cov}(r_{i,t+1}, r_{o,t+1}) = b\sigma_\omega^2 + \omega_{i,o} \tag{4.16}$$

To obtain our expression for the components of β_i (identified by the correlation between r_i and r_o), we recognise the following:

$$\beta_i = \frac{\mathrm{cov}(r_{i,t+1}, r_{o,t+1})}{\mathrm{var}(r_{o,t+1})} \tag{4.17}$$

$$\mathrm{var}(r_{o,t+1}) = \frac{\sigma_\omega^2}{\alpha} \tag{4.18}$$

$$\mathrm{var}(r_{o,t+1}) = \frac{\omega_o^2}{1-\alpha} \tag{4.19}$$

where Equation (4.17) comes from the definition of correlation, Equation (4.18) comes from Equation (4.14) and (4.19) from the definition of the variance structure of the common factor taking into account the scaling parameter α_i. So, to obtain an expression for β_i we scale $\mathrm{cov}(r_{i,t+1}, r_{o,t+1})$ by $\mathrm{var}(r_{o,t+1})$, the second term by the equivalent value of Equation (4.17), and the third term by the value Equation (4.18), leaving the final expression for β_i as:

$$\beta_i = \alpha_i b_i + (1-\alpha_i)\frac{\omega_{io}}{\omega_o^2} \tag{4.20}$$

This expression shows that the parameter of interest in transmitting the shocks from the source asset to the target asset can be decomposed into two components. The first is the common transmission effect, and the second is the effect of changing conditional variances between the idiosyncratic shocks in the common and idiosyncratic factors. A test for a change in β_i that does not acknowledge this may mistake changes in relative volatility for structural changes in the transmission of shocks.

We are interested in tests to detect changes in b_i between periods. We omit, however, the source proposed by Sewraj et al. (2018), which adds a trend term specified in Equation (4.9).[4] This captures the changing integration of the target market with the source market because of increased global integration over time. We use relatively short sample periods. The evidence in Sewraj et al. (2018) suggests that the effects, while statistically significant, are economically very small (even over more than two decades of weekly data) and not evident in the crisis period.

Although we have illustrated this problem for a single asset related to a common mimicking factor, the model is easily extended to a vector of assets in relation to a single mimicking factor, and with some degree of greater complexity to the possibility of more than one mimicking factor, analogous to a multi-factor CAPM (Dungey and Renault, 2018). Dungey and Renault (2018) established a method for identifying these contagion effects using conditional variance. The method is simple to use and offers insights into the source of changes in the transmission matrix over subsamples.

4.2.3 Estimation strategy

Testing for statistical changes in the parameter b_i for assets can be achieved using generalised method of moments (GMM) and conditional second moment conditions. We know that the instrumented unconditional covariance between one asset r_i and another r_j (with the same mimicking portfolio asset in place for both, r_o) will be constant in our framework (Dungey and Renault (2018). However, the intuition follows from Equation (4.1). This can be expressed as:

$$E[\ z_t r_{j,t+1}(r_{i,t+1} - b_i r_{o,t+1})] \ = c_{ij}\ \forall j = 0, 1, ..., n\ \forall i \in I_n \tag{4.21}$$

where z_t is a vector of instruments used to capture conditional heteroskedasticity. It is $(n+2)$-dimensional vector containing a constant and squared returns $r^2_{j,t}, I_n = 0, 1, ..., n$. This implies that Equation (4.21) will have unconditional moment restrictions. The moment restriction can

[4]For example, trend given by $\beta_i = \gamma_{i,o} + \gamma_{i,1} t$.

be represented in a linear regression model as:

$$(r_{t+1} \otimes z_t)r_{t+1} = b_i(r_{t+1} \otimes z_t)r_{o,t+1} + [\ I_{n+1} \otimes z_t]\ c_{i\bullet} + \varepsilon_{i,t+1} \tag{4.22}$$

where $r_{t+1} = (r_{j,t+1})_{0\leq j\leq n}$, I_{n+1} is the identity matrix of dimension $(n+1)$, $c_{i\bullet} = (c_{ij})_{0\leq j\leq n}$ and $\varepsilon_{i,t+1}$ is a $(n+1)(n+2)$-dimensional martingale difference sequence.

We also know that the unconditional covariance between r_i and r_o is constant defined by:

$$E[\ r_{o,t+1}(r_{i,t+1} - \alpha_i b_i r_{o,t+1})]\ = \omega_{ij} \tag{4.23}$$

where α_i is to be chosen such that it is constrained by the fact that volatility must be sufficiently large to capture at least part of the variation in the factor. This assumes that a one- or two-factor model or its characterisation through moment conditions in Equation (4.21) and (4.23) are well specified. Estimation of these parameters can be implemented using a GMM.[5]

These two sets of moment conditions across multiple assets are demonstrated with a single mimicking portfolio that provides sufficient identification to estimate the parameters of interest, specifically b_i for different sample periods. We can then test the null hypothesis of $b_{i,L} = b_{i,H}$ as a more clearly specified test for the presence of contagion than of either $\beta_{i,L} = \beta_{i,H}$. This may be contaminated by changing idiosyncratic variances, or $\rho_{i,L} = \rho_{i,H}$, which may be contaminated by changes in both idiosyncratic variances and the relative variance of the assets over time.

Table 4.1: Markets in the sample.

Market	**Abbreviation**	**Market**	**Abbreviation**
Australia	AU	Philippines	PH
China	CN	South Korea	KR
India	IN	Singapore	SG
Indonesia	ID	Sri Lanka	LK
Hong Kong	HK	Thailand	TH
Japan	JP	Taiwan	TW
Malaysia	MY	United States	US

4.3 Dataset and stylised facts

The dataset includes 12 Asian daily equity market indices (in local currencies) and the equity market index of Australia and the US for January 2003 – December 2017 (see Table 4.1). These

[5] See Dungey and Renault (2018) for more details.

are daily (closing) equity market indices. We focused on Asian markets because of their growing importance in global financial markets.[6] Specifically, we investigated the changing vulnerability among Asian markets and the rest of the world.

Figure 4.1 plots the equity market indices for each market scaled such that the first observation is 100 in each series. Unit root tests revealed the usual characteristics of stationary returns in each series. The analysis was conducted using demeaned returns because the mean is usually extremely close to 0 and since we focus on decompositions, this assumption is innocuous. We used the data with their recorded closing time date.

Figure 4.1: Equity market indices. The sample period is January 2003 – December 2017. The source of the data is Thomson Reuters Datastream.

The US data are non-overlapping with Asian market timing so that events in the US on a given date cannot provoke a reaction in an Asian market until the following day. In the contagion analysis, we lagged US returns by one day (with sensitivity tests against contemporaneous returns).

[6]Asia's growing importance is discussed in Chapter 2.

4.4 Empirical analysis and discussion of results

Our choice to study returns rather than volatility was guided by the literature that indicates returns have less volatile spillover effects (Yilmaz, 2010). Additionally, return means have been found to transmit most information in the Asian markets (Beirne et al., 2010).

Table 4.2: Phases in the sample

Phases	**Period**	**Representing**	**Observations**
Pre-GFC	1 January 2003 – 14 September 2008	Lead-up to the global financial crisis	1,488
GFC	15 September 2008 – 31 March 2010	Global financial crisis	403
EDC	1 April 2010 – 30 December 2013	European debt crisis	979
Recent	1 January 2014 – 29 December 2017	Most recent period	1,043

Table 4.2 shows the four sub-sample periods in our empirical analysis. The first is the pre-GFC period, from January 2003 until the bankruptcy of Lehman Brothers in mid-September 2008. The second is the GFC from then until the end of March 2010. This may be regarded as overly long compared with other analyses and the literature is indeed mixed on whether it divides the US recovery from mid-2009 into a separate period. Dungey et al. (2015) discussed dating the crisis. The third period is the European debt crisis (EDC), which we designated as starting from the beginning of the International Monetary Fund's program in Greece in April 2010 until the end of December 2013, at which point only Ireland and Portugal still had to finalise their recovery from the support packages implemented during the crisis. They both achieved this in 2014.[7] The fourth period covers the most recent data from January 2014 to the end of the sample on 29 December 2017. The total number of observations in the whole sample is 3,913. Just over 30% of observations are found in the lead-up to the GFC, and approximately one quarter in each of the EDC and the post-crisis periods. The GFC period is the shortest, covering six months from the collapse of Lehman Brothers; this period contains just under 10% (403) of the total observations. Thus, each subsample has a reasonable number of observations for tractable estimation and is in line with existing demarcations of the sample periods. Table 4.3 shows the descriptive statistics for each equity market return for each country across the different subsamples.

[7]The financial crisis in Cyprus was also resolved in 2014 and was relatively minor compared with the conditions experienced earlier in the European debt crisis period.

Table 4.3: Descriptive statistics of each equity market return

Item	AU	CN	IN	ID	JP	HK	MY	PH	SG	KR	LK	TH	TW	US
Pre-GFC						01.01.2003 – 14.09.2008								
Obs.	1488	1488	1488	1488	1488	1488	1488	1488	1488	1488	1488	1488	1488	1488
Mean	0.0004	0.0004	0.0006	0.0011	0.0011	0.0003	0.0004	0.0007	0.0005	0.0007	0.0008	0.0003	0.0005	0.0003
std dev	0.009	0.0169	0.013	0.0159	0.0135	0.0125	0.0083	0.0138	0.0111	0.0139	0.0132	0.0138	0.0128	0.009
Kurtosis	5.7291	3.8583	6.8409	5.9261	4.5719	1.4816	16.8173	3.5126	2.8557	1.5977	20.948	2.5153	16.2884	2.0773
Skewness	–0.2623	–0.2021	0.045	–0.7247	–0.5222	–0.3632	–1.5032	0.0927	–0.1962	–0.2289	–0.8049	–0.2563	–0.5675	–0.0781
GFC						15.09.2008 – 31.03.2010								
Obs.	403	403	403	403	403	403	403	403	403	403	403	403	403	403
Mean	0.0001	0.0012	0.0006	0.0009	0.0013	0.0001	0.0006	0.0005	0.0004	0.0006	0.0012	0.0005	0.0006	0.0001
std dev	0.017	0.0203	0.0264	0.0226	0.0195	0.0241	0.0096	0.0191	0.0206	0.0214	0.0133	0.0184	0.0189	0.0231
Kurtosis	2.8761	2.3785	5.329	7.9424	5.6808	6.2907	3.5861	6.8702	2.7589	5.754	3.7389	1.9951	5.4976	4.5382
Skewness	–0.3706	0.0451	0.4415	0.5321	–0.3727	–0.0805	–0.0952	–0.6743	0.0541	–0.2037	0.3388	–0.0536	–0.7909	0.0471
EDC						01.04.2010 – 30.12.2013								
Obs.	979	979	979	979	979	979	979	979	979	979	979	979	979	979
Mean	0.0001	-0.0003	0.0002	0.0002	0.0005	0.0005	0.0004	0.0006	0.0001	0.0002	0.0005	0.0001	0.0006	0.0005
std dev	0.0095	0.0117	0.0118	0.0105	0.0123	0.0137	0.0058	0.0122	0.0089	0.0118	0.0088	0.0107	0.0116	0.0106
Kurtosis	1.4118	2.1793	2.7072	0.7026	6.1232	5.3418	4.3511	4.1581	1.7707	3.3208	4.1259	2.0014	3.3968	4.4625
Skewness	–0.1701	–0.2237	–0.1805	–0.0335	–0.5283	–0.7564	–0.4458	–0.4674	–0.3717	–0.2069	0.2883	–0.161	–0.1546	–0.3514
Recent						01.01.2014 – 29.12.2017								
Obs.	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043	1043
Mean	0.0002	0.0005	0.0003	0.0006	0.0004	0.0004	0	0.0004	0.0001	0.0002	0.0001	0.0003	0.0003	0.0004
std dev	0.0082	0.015	0.0102	0.0084	0.0083	0.0127	0.0048	0.0094	0.0073	0.0073	0.0047	0.0086	0.0075	0.0075
Kurtosis	1.765	7.446	2.9552	4.4753	3.7315	5.9324	3.9838	3.9585	2.9142	1.714	4.3	2.8796	6.2104	3.2866
Skewness	–0.278	–1.1872	–0.2879	–0.7474	–0.3159	-0.0207	–0.5252	–0.4318	–0.1487	–0.2335	–0.382	–0.1661	–0.4943	–0.3544

4.4.1 Evidence for spillovers

Table 4.4 shows the average historical decomposition of shocks to the observed returns of each country in the sample for the whole period. The rows represent the recipient markets for shocks spread from source countries which are shown in each column. The cell values are the average of the historical decomposition shocks in the whole sample. The shocks have different magnitude and are distinguished by sign. Negative numbers represent a reduction in returns as a result of the shock; positive shocks represent an increase in returns.

The US receives more shocks than it transmits. This is common because each market is exposed to shocks from many markets and distributes its own shocks to many markets. The US receives positive shocks from Asian countries, on average increasing its return, while it also transmits shocks, though with less magnitude, to Asian countries. These outcomes are generally consistent with the US being the safe haven market when international stress occurs. US markets benefit from flight to safety and familiarity, and benefit from the hypothesis of Kaminsky and Reinhart (2003) that the US operates as a central market that redistributes shocks received from peripheral markets to other markets.

Unlike the US, which receives positive shocks, China receives negative shocks from most other markets, although the magnitude of these shocks is low. Indonesia and Japan receive the largest positive shocks from other Asian markets, but transmit smaller shocks to other Asian markets.

Further, we considered how the transmission of shocks changes over time by examining the four periods. The results in Table 4.5 to 4.8 clearly show that the transmission of shocks from different markets changes in each phase.

During the pre-GFC period, the US became the recipient of larger positive shocks from Asian markets compared to the GFC period. The US also transmitted more shocks to Asian markets than it absorbed in the GFC period. The magnitude of shocks it received dropped in the GFC period compared with the pre-GFC period. This suggests that Asian markets were less involved in spreading shocks to the US during the GFC period. Figure 4.2a shows the estimated receipt of shocks by a market, while Figure 4.2b shows the transmission of shocks from a market. The spillover effect for each market during each phase is given in separate columns. Figure 4.2b clearly shows that in the pre-GFC period, the average spillover effect transmitted by the market to others in the system was roughly similar, mainly in the range of $0.1 - 0.2$ with the exceptions of an almost neutral transmission from Sri Lanka and the US. The average effect at -0.0063 was only negative and very small in the US.

Table 4.4: Historical decompositions for the entire period

	AU	**CN**	**IN**	**ID**	**JP**	**HK**	**MY**	**PH**	**SG**	**KR**	**LK**	**TH**	**TW**	**US**
AU	0	0.0051	0.0059	0.0089	0.0075	0.0047	0.0030	0.0064	0.0062	0.0073	–0.0011	0.0080	0.0056	0.0012
CN	–0.0472	0	–0.0511	–0.0890	–0.0626	–0.0694	0.0019	–0.0174	–0.0637	–0.0689	–0.0005	–0.0981	–0.0913	–0.0028
IN	–0.0500	–0.0449	0	0.0671	0.0049	–0.0795	–0.0107	0.0306	–0.0400	–0.0043	–0.0155	0.0385	–0.0202	–0.0374
ID	**0.1767**	**0.1859**	**0.2868**	0	**0.4789**	**0.3176**	**0.2063**	**0.4133**	0.0848	**0.4017**	**0.1355**	**0.5076**	**0.4495**	0.0437
JP	**0.1585**	**0.1787**	0.0009	–0.0598	0	**0.1900**	**0.2220**	**0.5128**	0.0356	0.0280	**0.2356**	**–0.1449**	**0.3410**	0.1001
HK	0.0313	0.0516	0.0829	0.0509	0.0754	0	0.0470	0.0479	0.0424	0.0854	0.0260	0.0412	0.0514	–0.0083
MY	0.0247	0.0078	0.0213	0.0150	0.0408	0.0258	0	0.0186	0.0203	0.0315	0.0030	0.0327	0.0219	0.0317
PH	0.0007	–0.0523	–0.0618	0.0228	0.0456	–0.0416	0.0082	0	0.0088	0.0152	0.0249	0.0237	0.0249	–0.0229
SG	–0.0879	–0.0801	**–0.2170**	–0.0538	–0.1041	**–0.1842**	–0.0830	**–0.1599**	0	–0.0854	0.0018	–0.1286	0.0182	–0.0580
KR	-0.0481	-0.0456	-0.0051	0.0060	0.0240	-0.0184	-0.0078	–0.0128	–0.0207	0	–0.0171	–0.0058	0.0241	–0.0128
LK	0.0978	**0.1476**	0.0333	**0.1547**	0.0753	**0.2707**	**0.1676**	0.1288	**0.2336**	–0.1094	0	–0.0468	**0.2078**	0.0176
TH	–0.0373	**–0.13**	–0.0514	–0.0727	–0.0434	–0.0304	–0.0221	–0.0138	–0.0823	0.0085	–0.0736	0	–0.0433	–0.1170
TW	–0.0011	–0.0004	–0.0020	0.0001	–0.0003	–0.0009	–0.0006	0	–0.0011	–0.0012	0.0002	–0.0017	0	–0.0007
US	**1.7607**	**0.8499**	**2.0792**	**1.5884**	**1.6456**	**2.3318**	**1.0282**	**1.8136**	**1.5879**	**1.8505**	**0.4639**	**1.7461**	**1.5771**	0

The sample period is January 2003 – December 2017 sample period. The bolded observations represent the largest shocks distributed across different markets.

Table 4.5: Historical decompositions for the pre-global financial crisis sample period (2003 – 2008)

	AU	**CN**	**IN**	**ID**	**JP**	**HK**	**MY**	**PH**	**SG**	**KR**	**LK**	**TH**	**TW**	**US**
AU	0	0.21	-0.184	-0.154	-0.313	-0.0774	-0.051	-0.236	-0.239	-0.162	0.199	-0.217	-0.0145	-0.119
CN	0.0307	0	0.0182	0.0385	0.151	-0.0477	0.113	0.154	0.0106	-0.0013	0.0162	0.019	-0.0046	0.0167
IN	-0.0714	-0.0411	0	0.0001	-0.0799	-0.131	-0.0846	0.0819	-0.102	-0.0531	-0.112	-0.0081	-0.116	0.0128
ID	-0.0273	0.0943	0.125	0	0.541	0.193	0.206	0.323	-0.0425	0.431	-0.136	0.735	0.737	-0.168
JP	0.0521	-0.0059	0.0526	0.0219	0	0.142	0.25	0.608	0.129	-0.0634	0.0959	-0.554	0.0472	0.0035
HK	0.122	0.491	0.371	0.287	0.347	0	0.189	0.0933	0.0145	0.367	0.111	0.11	0.311	-0.0542
MY	0.0848	-0.0466	0.0385	-0.051	0.112	0.0197	0	0.0606	0.0563	0.0995	-0.0977	-0.0191	-0.0034	0.131
PH	0.113	-0.0984	0.0636	0.0624	0.208	0.104	0.0524	0	0.149	0.153	0.0178	0.156	0.131	0.0536
SG	0.0186	0.0193	-0.0023	-0.0104	-0.012	0.0108	0.0393	0.0218	0	-0.0162	0.0116	-0.0111	-0.0355	0.0086
KR	0.0213	-0.0233	0.0423	0.0835	-0.0016	0.0828	-0.0157	-0.123	0.0241	0	0.0233	0.0359	0.0777	0.115
LK	0.038	0.179	-0.0741	0.017	-0.267	0.265	0.262	0.0704	0.285	-0.37	0	-0.195	-0.227	-0.109
TH	0.13	-0.111	0.212	0.285	-0.0469	0.134	0.131	0.105	0.159	0.307	0.0156	0	0.0174	0.0233
TW	0.0014	0.0025	0.0019	0.0053	0.0053	0.0016	0.0006	0.0089	0.0009	0.0055	-0.0004	0.0039	0	-0.0026
US	1.3848	0.877	1.8162	2.002	1.6059	1.6958	1.0832	1.8899	1.4653	1.7828	0.105	1.7334	1.3014	0

Table 4.6: Historical decompositions for the global financial crisis sample period (2008 – 2010)

	AU	**CN**	**IN**	**ID**	**JP**	**HK**	**MY**	**PH**	**SG**	**KR**	**LK**	**TH**	**TW**	**US**
AU	0	-0.0252	-0.0449	-0.0158	-0.0291	-0.0275	-0.0089	-0.0295	-0.0261	-0.0054	-0.006	-0.0252	-0.0258	-0.0318
CN	-1.4987	0	-1.4184	-1.331	-1.2764	-1.8043	-0.0597	0.519	-1.1891	-0.963	-1.0169	-1.1765	-1.3771	-0.839
IN	-0.074	-0.22	0	0.0566	-0.0921	-0.156	-0.0083	-0.226	-0.364	0.0071	0.0625	0.0837	-0.0682	-0.21
ID	0.553	0.397	0.565	0	0.911	0.573	0.432	0.332	0.302	0.726	0.892	0.651	0.903	0.644
JP	1.6928	2.1835	0.84	-0.111	0	1.7778	0.868	1.2549	0.466	0.335	0.637	0.818	1.9962	1.2752
HK	0.36	0.0427	0.952	0.0785	0.332	0	0.182	-0.186	0.653	1.1752	-0.0545	0.352	-0.215	0.0369
MY	-0.611	-0.478	-0.942	-0.812	-1.0577	-1.1346	0	-0.279	-0.911	-0.994	-0.639	-1.2619	-1.0703	-1.0102
PH	-0.119	-0.0197	-0.443	-0.104	-0.0174	-0.294	-0.008	0	-0.126	-0.108	0.297	-0.153	-0.148	-0.193
SG	-0.621	-0.249	-1.8235	-0.952	-1.1588	-1.3593	-0.463	-1.0857	0	-0.663	-0.0399	-1.3348	-0.557	-0.369
KR	-0.386	-0.115	0.0056	-0.101	0.45	-0.0034	-0.0053	0.339	-0.312	0	0.0199	-0.0727	0.18	-0.241
LK	0.116	-0.0625	-0.104	1.3762	0.699	1.1646	0.557	-0.19	1.1103	0.175	0	-0.0462	2.1467	0.106
TH	0.424	-0.0084	0.654	0.831	0.236	0.253	0.254	0.0537	0.836	0.397	0.572	0	0.395	0.518
TW	0.339	0.55	0.917	0.639	0.477	0.424	0.215	0.753	0.619	0.627	0.0914	0.698	0	0.325
US	0.602	0.179	0.621	0.44	0.474	0.746	0.256	0.533	0.518	0.43	0.22	0.397	0.529	0

Table 4.7: Historical decompositions for the European debt crisis sample period (2010 – 2013)

	AU	**CN**	**IN**	**ID**	**JP**	**HK**	**MY**	**PH**	**SG**	**KR**	**LK**	**TH**	**TW**	**US**
AU	0	0.013	-0.323	-0.0812	-0.2977	-0.1519	-0.0184	-0.3169	-0.2015	-0.1754	-0.2022	-0.1239	-0.279	-0.3942
CN	-0.2981	0	-0.2555	-0.0783	-0.0507	-0.2706	-0.0656	0.3476	-0.0217	-0.1451	-0.0465	0.0658	0.0309	-0.4409
IN	-0.0106	-0.0195	0	0.0227	-0.0094	0.0002	-0.0016	0.0188	0.0068	0.0079	-0.0388	0.0064	-0.0035	-0.0172
ID	0.1708	0.1987	0.22	0	0.1992	0.2129	0.1246	0.2335	0.1584	0.2472	0.0927	0.2461	0.1569	0.1285
JP	-0.3366	-0.2179	-0.4567	-0.2436	0	-0.1562	0.0859	0.4353	-0.2348	-0.066	0.1634	-0.3482	0.2572	-0.2536
HK	-0.0496	-0.1151	-0.1783	-0.1115	-0.3023	0	-0.1466	-0.3863	-0.086	-0.1873	-0.1197	-0.1009	-0.2148	0.0331
MY	-0.14	-0.2939	-0.2052	-0.5222	-0.3686	-0.0769	0	-0.2522	-0.2583	-0.3658	0.0364	-0.56	-0.1382	-0.1155
PH	-0.0158	-0.0321	-0.0565	0.0331	-0.0675	-0.0163	-0.0675	0	-0.0544	-0.0282	-0.1404	-0.0079	-0.0377	-0.0192
SG	0.0235	0.1073	-0.1137	0.0279	-0.0635	-0.0077	-0.0377	-0.1839	0	-0.0162	-0.0154	-0.127	0.0828	0.0488
KR	0.1131	0.0635	0.1496	0.0733	0.1092	0.1529	0.0256	0.1517	0.0649	0	0.0607	0.0989	0.0615	0.1321
LK	0.3751	0.2525	0.4133	0.2219	0.6016	0.2257	0.2449	0.6863	0.2704	0.1322	0	0.3979	0.5406	0.2042
TH	0.0338	0.0124	0.0092	-0.0373	-0.0431	0.0218	-0.0481	-0.116	-0.0241	-0.0454	-0.15	0	0.0648	-0.106
TW	-0.0298	0.2142	0.0956	0.1405	0.0955	-0.1154	-0.002	0.2481	0.0338	0.0235	0.1073	0.0327	0	-0.0788
US	3.6317	1.9786	4.6569	2.4422	3.5074	4.9758	2.1446	3.1454	3.1904	5.0325	0.7506	3.9693	3.4928	0

Table 4.8: Historical decompositions for the most recent sample period (2013 – 2017)

	AU	**CN**	**IN**	**ID**	**JP**	**HK**	**MY**	**PH**	**SG**	**KR**	**LK**	**TH**	**TAP**	**US**
AU	0	0.1705	-0.0474	0.0354	-0.0811	-0.0817	-0.0707	-0.0904	-0.0245	-0.0081	-0.0625	-0.0332	0.002	-0.0372
CN	-0.2408	0	-0.3695	-0.5253	-0.4304	-0.1757	-0.3278	-0.4781	-0.3172	-0.2927	0.0499	-0.4586	-0.2443	-0.2254
IN	0.0112	-0.015	0	-0.0367	-0.0092	0.0174	-0.0068	-0.0075	-0.0225	-0.0136	-0.0098	-0.017	-0.0052	0.0039
ID	-0.0031	-1.0677	-0.0507	0	-0.0079	-0.0256	-0.1632	0.426	-0.2265	-0.011	-0.2952	-0.3872	-0.3034	-0.6229
JP	0.2043	0.0663	0.1154	0.0957	0	0.0556	0.0167	0.2968	0.0755	-0.0057	0.0797	0.1194	0.1465	0.1028
HK	0.0101	0.0033	0.0336	0.0311	0.0388	0	0.0287	0.0293	0.0221	0.0204	0.0247	0.0227	0.0191	-0.0182
MY	0.2038	0.297	0.1263	0.0988	0.0606	0.3924	0	0.1024	-0.0358	0.059	0.0717	-0.001	0.0684	0.2344
PH	-0.0001	0.0005	0.0007	0.0001	0.001	-0.0008	-0.0001	0	0.0007	-0.0007	0.0002	-0.0007	-0.0001	0.0002
SG	0.0432	-0.3653	0.0052	0.1364	0.1144	0.004	0.0652	0.1141	0	-0.0822	0.0701	0.0441	0.1491	-0.0076
KR	0.0025	0.0738	0.12	0.0644	0.0786	0.0407	0.0508	0.0774	0.0658	0	0.0578	0.081	0.0833	0.0473
LK	0.0762	0.0306	0.0488	-0.0222	0.0021	0.0142	0.0399	-0.0546	0.0753	0.0443	0	0.0727	0.0591	0.0357
TH	0.0254	0.1007	0.0196	0.037	0.0409	0.0428	0.0145	0.0146	0.009	-0.0234	-0.0032	0	0.0288	0.0638
TW	0.0556	-0.0228	0.0489	0.0178	0.0953	0.1806	-0.0215	0.1361	0.0502	0.0767	0.0384	0.0822	0	0.0382
US	1.5591	1.4964	1.7765	1.1887	0.7753	2.7652	0.8784	1.3929	1.1747	1.1225	0.5898	1.5098	0.9088	0

Compared with the EDC and the current periods, the extent of the shocks during the pre-GFC period was small (see Table 4.5 – 4.8). Australia and India were among the countries to receive, on average, negative effects on their returns as spillovers from the rest of the markets. Indonesia; Hong Kong and Thailand received return-enhancing spillovers. The other markets fell between these two alternatives, although the range is not high.

Figure 4.2: Average shocks received and transmitted by period and market. The sample period is January 2003 – December 2017. The source of the data is Thomson Reuters Datastream.

During the GFC period, the transmission of shocks from the Asian markets generally declined compared to the pre-GFC period. While there is some evidence that the transmission of these shocks increased returns in other markets via spillovers, there is even less evidence that they reduced returns, except for spillovers from Thailand. Table 4.6 shows this is mainly through spillovers with China, Malaysia and Singapore. Spillover effects from shocks received during the GFC period vastly decreased from the pre-GFC period. Most sample markets continued to receive, on average, the same sign effect of shocks in both periods, although Malaysia and China received opposite average effects. For Japan, these were spillovers that increased returns, which is consistent with the flight to quality, safety, and familiarity in the region. The spillover effects for China were strongly negative, reflecting the expected decline in the country's economic expansion in response to a weaker global economy. Malaysia and Singapore, also open and export-dependent economies, experienced negative spillovers in the GFC period. The US gets some positive spillovers because of the flight to safety and leverage effects. South Korea experienced relatively little change, with the average effect of spillovers that remaining neutral in both periods.

The EDC period contrasts strongly to the pre-GFC and GFC periods, with the scale of spillovers into and out of markets being similar; almost all markets experienced positive spillovers (see Table 4.7). That is, spillovers resulted in higher returns in these markets, and spillovers from Asian markets resulted in higher returns elsewhere. This may reflect that the crisis originated in Europe and the debt markets of Asia were perceived as more robust, thereby providing an alternative investment opportunity during the EDC period.[8] In contrast, spillovers to and from the US were negative. In other words, spillovers from the US reduced returns in Asia, reflecting uncertainty in world markets, and spillovers from Asia reduced returns in the US.

The most recent period shows a return to conditions more similar to the pre-GFC period in terms of transmission effects. These were, if anything, slightly smaller than in the other periods, but produced positive returns in Asian markets. The exception again was the US where spillovers from it tended to reduce returns in other markets with a larger effect than in the pre-GFC period of -0.0275.

Table 4.8 shows that transmissions to Indonesia and China were important components of this overall result. In contrast, the external spillovers that other markets received in recent times generally had little effect on returns. The scale of shocks to the US was considerably larger than for other markets and these effects were positive, implying that spillovers from other markets, on average, increase US returns. Most markets received negligible spillovers from others. The exceptions were Indonesia, China and the US. Indonesia and China seemed to be intertwined in a form of feedback in which spillovers between them (see Table 4.8) mutually reinforce lower returns.[9] The spillover effects on the US were substantially larger than in the other periods, and primarily reflected combinations of Indonesian and Chinese spillovers, although offsets from Malaysia also played a role.

The different roles that China and the US played in the spillovers to and from Asian markets is evident in this analysis and because of this, we examined more closely the spillovers originating from these markets. Table 4.9 shows the total contributions of spillovers to and from China

[8] See, for example, the analysis of CDS data in Dungey et al. (2019b).
[9] See for example the literature on diabolical loops.

and the US on other markets over the four periods. This allowed for a preliminary analysis of the extent of change between the transmissions between these markets before formal tests for contagion were conducted (see Section 4.4.2).

The results of Table 4.9 are plotted in Figure 4.3. The scales in Figures 4.3a and 4.3b for the transmission of spillovers are substantially smaller than those for receiving spillovers, as explained previously. The transmissions in Figures 4.3a and 4.3b show that spillovers from China and the US were larger in the GFC period than in other periods. In both cases, the largest spillovers during the GFC period from both these sources were to Japan, indicating its importance in the region. During the EDC period spillovers were calmer, although there is evidence that some began to, on average, switch direction. Thus, Malaysia, Hong Kong and Japan, for example, demonstrated the opposite total spillover effect in this period than they did during the GFC period.

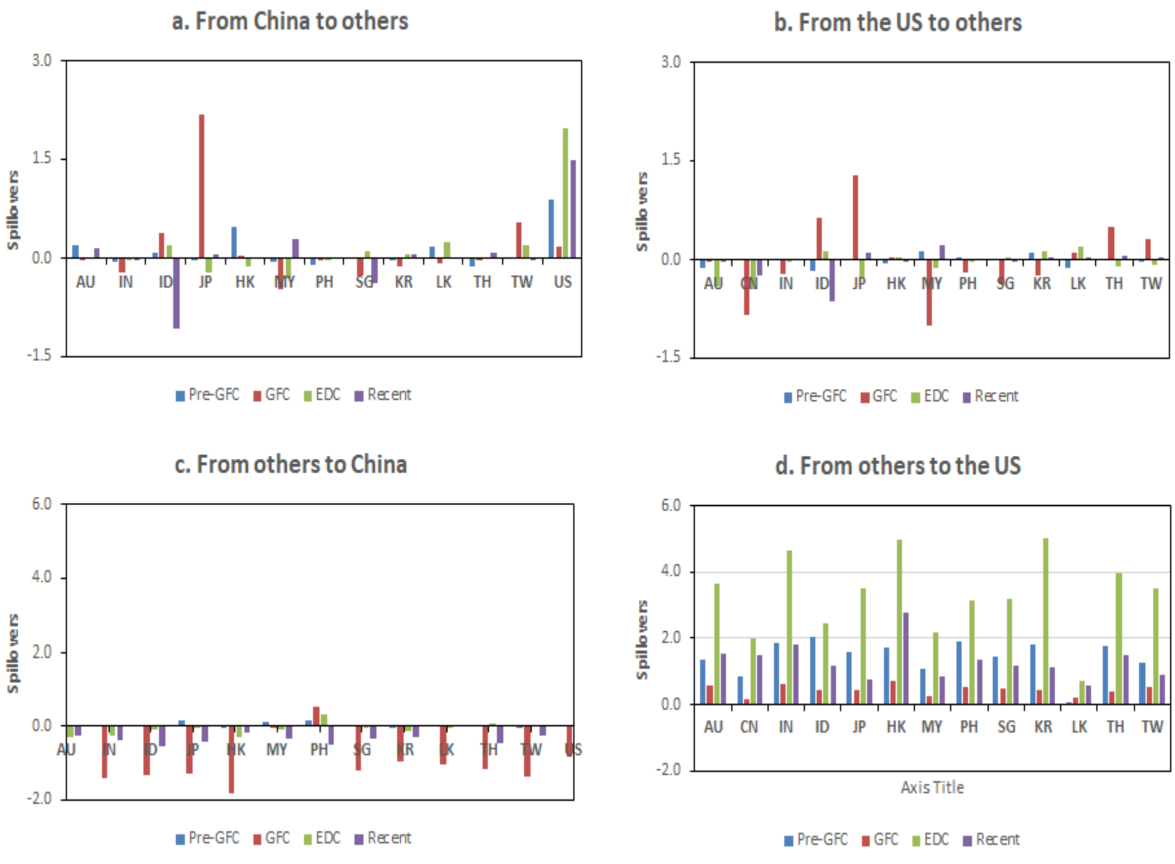


Figure 4.3: Receiving and transmitting spillovers to and from the US and China

The analysis of spillovers from other markets to China and US in Figures 4.3c and 4.3d show stark differences in scale and direction. The spillovers to China from other markets were predominantly negative, particularly during the GFC, but were on a smaller absolute scale than those to the US. The spillovers received by the US were positive for each of the four

Table 4.9: Summary of the spillovers from and to China and the US by other markets

Panel A: From China to others						Panel B: From the US to others					
FROM	TO	Pre-GFC	GFC	EDC	Recent	FROM	TO	Pre-GFC	GFC	EDC	Recent
	AU	0.2100	–0.0252	0.0130	0.1705		AU	–0.1190	–0.0318	–0.3942	–0.0372
	IN	–0.0411	–0.2200	–0.0195	–0.0150		CN	0.0167	–0.8390	–0.4409	–0.2254
	ID	0.0943	0.3970	0.1987	–1.0677		IN	0.0128	–0.2100	–0.0172	0.0039
CN	JP	–0.0059	2.1835	–0.2179	0.0663	US	ID	–0.1680	0.6440	0.1285	–0.6229
	HK	0.4910	0.0427	–0.1151	0.0033		JP	0.0035	1.2752	–0.2536	0.1028
	MY	–0.0466	–0.4780	–0.2939	0.2970		HK	–0.0542	0.0369	0.0331	–0.0182
	PH	-0.0984	-0.0197	-0.0321	0.0005		MY	0.1310	–1.0102	–0.1155	0.2344
	SG	0.0193	–0.2490	0.1073	–0.3653		PH	0.0536	–0.1930	–0.0192	0.0002
	KR	–0.0233	–0.1150	0.0635	0.0738		SG	0.0086	–0.3690	0.0488	–0.0076
	LK	0.1790	–0.0625	0.2525	0.0306		KR	0.1150	–0.2410	0.1321	0.0473
	TH	–0.1110	–0.0084	0.0124	0.1007		LK	–0.1090	0.1060	0.2042	0.0357
	TW	0.0025	0.5500	0.2142	–0.0228		TH	0.0233	0.5180	–0.1060	0.0638
	US	0.8770	0.1790	1.9786	1.4964		TW	–0.0026	0.3250	–0.0788	0.0382

Panel C: From others to China						Panel D: From others to the US					
FROM	TO	Pre-GFC	GFC	EDC	Recent	FROM	TO	Pre-GFC	GFC	EDC	Recent
AU		0.0307	–1.4987	–0.2981	–0.2408	AU		1.3848	0.602	3.6317	1.5591
IN		0.0182	–1.4184	–0.2555	–0.3695	CN		0.8770	0.1790	1.9786	1.4964
ID		0.0385	–1.3310	–0.0783	–0.5253	IN		1.8162	0.6210	4.6569	1.7765
JP		0.1510	–1.2764	–0.0507	–0.4304	ID		2.002	0.4400	2.4422	1.1887
HK		–0.0477	–1.8043	–0.2706	–0.1757	JP		1.6059	0.4740	3.5074	0.7753
MY	CN	0.1130	–0.0597	–0.0656	–0.3278	HK	US	1.6958	0.7460	4.9758	2.7652
PH		0.1540	0.5190	0.3476	–0.4781	MY		1.0832	0.2560	2.1446	0.8784
SG		0.0106	–1.1891	–0.0217	–0.3172	PH		1.8899	0.5330	3.1454	1.3929
KR		–0.0013	–0.9630	–0.1451	–0.2927	SG		1.4653	0.5180	3.1904	1.1747
LK		0.0162	–1.0169	–0.0465	0.0499	KR		1.7828	0.4300	5.0325	1.1225
TH		0.0190	–1.1765	0.0658	–0.4586	LK		0.105	0.2200	0.7506	0.5898
TW		–0.0046	–1.3771	0.0309	–0.2443	TH		1.7334	0.3970	3.9693	1.5098
US		0.0167	–0.8390	–0.4409	–0.2254	TW		1.3014	0.5290	3.4928	0.9088

periods (this was an average effect for the period) and were greatest during the European debt crisis period. The spillovers to the US reduced but remained positive during the GFC, compared with the pre-GFC period for many markets implying reduced attractiveness of US markets during this crisis. During the EDC, when US assets became much more attractive than those of crisis-hit Europe, spillovers to the US from Asian markets increased substantially. In the most recent period, the extent of average spillovers reduced, but remained higher than in the pre-GFC period.

The clearest result from the analysis of Table 4.9 and Figure 4.3 is that spillovers from China to the US were negative but shrinking across the four periods, while spillovers from the US to China were positive and arguably growing. This is consistent with the narrative that the US and China are becoming more internationally intertwined, and that improvements in both economies can be expected to flow through to each other. In recent times, there is less evidence of fear of China's spillovers having negative implications for the US economy, pointing to a more developed market relationship. Arslanalp et al. (2016) showed that the effect of shocks from China on the US is increasing.

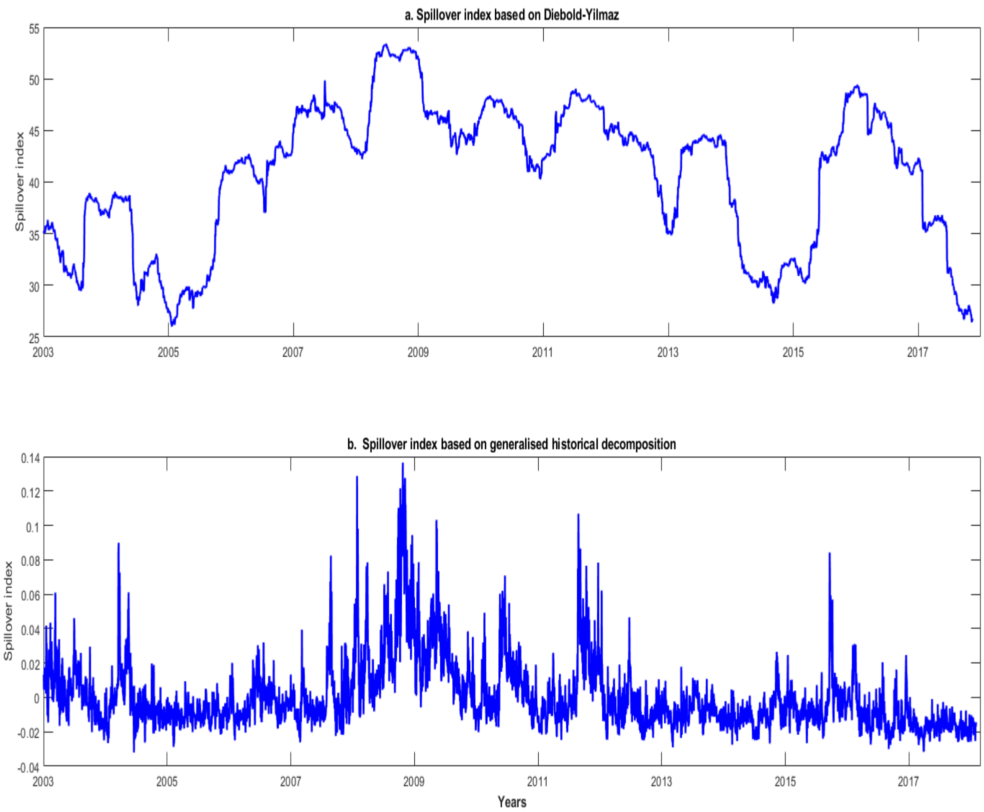


Figure 4.4: Spillovers index based on Diebold–Yilmaz and generalised historical decomposition

Given the dominant role of transmissions from China and the US in our analysis of spillovers, we now explore the more abrupt changes in transmission by examining the evidence for contagion across these markets and sub-samples. Figure 4.4a shows the DY spillover index for the network of returns produced using a 200-day moving window. As the corresponding generalised historical decomposition (GHD) figure for returns is uninformative, we instead provide the GHD for the volatility network in Figure 4.4b.

The results show that the spillover index for the entire network ranged from $30\% - 50\%$ over the $2003 - 2017$ sample period, beginning and ending near the minimum of the range. The DY spillover index shows a substantial increase in spillovers between markets from 2005. This peaked in the second half of 2008, and is consistent with the timing of the collapse of Lehman Brothers and the associated turmoil. The index calmed somewhat after the GFC period, with an increase in spillovers associated with the EDC. In the most recent period, however, the index fell in 2014, rose over 2015, and dropped rapidly in 2017. A prominent feature of the index is the role of the choice of window length. Here, sensitivity to the choice is readily apparent in Figure 4.4a, as critical observations drop in and out of the rolling sample.

The GHD spillover index in Figure 4.4b shows distinct periods in which transmissions contributed to higher or lower volatility in the entire financial system. Observations below the zero line indicate cases in which transmissions in the network dampened volatility; that is, the network was robust in the sense that shocks were dampened by its structure. Positive observations indicate instances in which the network's structure amplified the effects of the shocks. Figure 4.4b shows that from mid-2004 to mid-2007 the network primarily dampened the shocks; that is, it displayed a robust structure. There was a slight period of amplification in late 2006, but this is dwarfed by subsequent high-amplification effects in the network from mid-2007 to mid-2009. These are the largest absolute values in Figure 4.4b and indicate that shocks during this period caused a substantial amplification in the network's volatility transmission. The network became fragile in line with Acemoglu et al. (2015) and Haldane (2009). The results concur with the analysis of Dungey et al. (2019b), in which the fragility of a network of global sovereign and financial institution CDS increased to the stage that almost the entire network can be expected to default in response to a tail shock. The GHD spillover index shows that the amplification effect calmed somewhat in 2009, before flaring again during the Greek debt crisis in 2010 and the European debt crisis in $2011 - 2012$.

From late 2012 to 2015, the network returned to a more robust structure, in which its effects dampened the impact of shocks. Some abrupt interruptions to the GHD spillover index during $2015 - 2016$ indicate short, sharp periods of amplification in the network. These are linked to

China; for example, August 2016 witnessed changes to the exchange rate regime and 8% was wiped from the value of the country's stock market on Black Monday. Arslanalp et al. (2016) documented the extreme movements in the Chinese equity market and examined the strong co-movement of Asian markets with China on 11 August 2015 and 4 January 2016. Global markets were rocked again by the unexpected outcome of a June 2016 vote in the UK to leave the European Union and the subsequent political turmoil across global markets. Although political uncertainty continued to affect major markets for the rest of 2016, it did not trigger the same level of network fragility. The network was robust again by 2017, when shocks were no longer amplified by the network structure.

4.4.2 Evidence for contagion

For completeness, we provide the results of the uncorrected and Forbes and Rigobon (2002) corrected contagion tests for each period preceding the subsequent period–that is, whether there is contagion (a statistically significant rise in correlation), interdependence (no significant change) or decoupling (a statistically significant fall in correlation) from one period to the next.[10] Table 4.10 shows the results for transmissions from China and US as source markets for each period. The usual Forbes–Rigobon (FR) style results are evident; without the correction for changing variance, the correlation tests reject the null of no contagion almost always. After the correction, the prevailing evidence is for interdependence or decoupling. The original FR approach did not test for decoupling; instead, only a one-sided test was done to detect a rise in correlation as contagion. Later research extended this to two-sided tests and, more recently, Caporin et al. (2018) labelled the reduced correlation outcome as decoupling. Table 4.10 shows the difficulty of reconciling the evidence from different contagion-based tests. Tests must be conducted with a thorough understanding of the compromises made in the procedure to achieve identification and empirical tractability. The arguments presented in this chapter' (see Section 4.2.2) examined the reasons for preferring the approach in Dungey and Renault (2018) to use conditional correlations rather than those based on unconditional correlations from Forbes and Rigobon (2002), both with and without corrections.

Table 4.11 presents the evidence for contagion from the conditional correlation tests of Dungey and Renault (2018) using the US market as the mimicking factor during each period. We conducted a Ghysels-Hall test for structural change between the adjacent periods and a Hall

[10]Contagion and decoupling refer to the distinct and abrupt positive and negative changes in the transmission of shocks between markets after controlling for what would be expected from normal spillover effects. That is, they are transmissions that would not have been expected ex-ante based on existing historical relationships.

Table 4.10: Contagion results for China and the US using the Forbes–Rigobon uncorrected and corrected tests and the Dungey–Renault test

	Originating with the United States									**Originating with China**								
	Pre-GFC to GFC			**GFC to EDC**			**EDC to recent**			**Pre-GFC to GFC**			**GFC to EDC**			**EDC to recent**		
	FRU	FRC	DR	FRU	FRC	DR	FRU	FRC	DR	FRU	FRC	DR	FRU	FRC	DR	FRU	FRC	DR
AU	D	I	D	C	C	D	D	I	D	**C**	**C**	**C**	**C**	**C**	**C**	**D**	**D**	**D**
CN	I	I	C	I	C	C	I	C	C	-	-	-	-	-	-	-	-	-
IN	D	I	D	I	C	D	I	C	D	**C**	**C**	**C**	I	C	C	I	D	D
JP	D	I	D	I	C	D	I	I	D	C	C	D	I	C	C	**D**	**D**	**D**
HK	I	I	D	I	C	D	I	C	C	C	C	D	I	C	C	**D**	**D**	**D**
MY	D	I	D	D	I	D	I	C	D	C	C	D	I	C	C	I	D	D
PH	D	I	D	I	I	D	C	C	D	C	I	D	I	C	C	**D**	**D**	**D**
SG	I	I	D	I	I	D	I	I	D	**C**	**C**	**C**	D	I	D	I	I	D
KR	D	I	D	I	C	C	D	I	D	C	C	D	I	C	C	**D**	**D**	**D**
LK	D	I	C	I	C	C	I	I	D	C	C	D	I	C	C	**D**	**D**	**D**
TH	I	I	D	I	I	D	I	I	C	I	I	C	I	I	C	C	I	D
TW	D	I	D	D	I	D	I	C	D	C	C	D	I	C	C	**D**	**D**	**D**
US	-	-	-	-	-	-	-	-	-	I	I	D	I	C	C	I	I	C

Note: C = contagion, D = decoupling, I = interdependence, DR = Dungey–Renault, FRU = Forbes–Rigobon uncorrected, FRC = Forbes–Rigobon corrected. - represent no detection to itself. Bold represents the scenario in which all the contagion tests results come to the same conclusion.

test for the stability of parameters between the periods. The individual results are not reported because, in each case, the null of no change was rejected at standard significance levels.

Table 4.11: Estimates of b_i for each subperiod with mimicking factor given by the US market

Market	**Pre-GFC**	**GFC**	**EDC**	**Recent**
AU	2.066	1.402	1.483	0.173
CN	0.485	1.209	0.786	3.053
IN	3.817	0.866	1.055	0.759
ID	4.416	1.133	1.618	0.102
JP	3.664	1.195	1.072	2.06
HK	2.965	1.759	1.944	1.095
MY	4.094	0.650	1.323	0.250
PH	4.068	1.674	1.759	0.578
SG	3.750	0.609	1.488	0.258
KR	5.129	0.927	2.620	0.372
LK	–0.500	0.747	0.275	0.609
TH	3.044	0.130	1.795	0.497
TW	3.964	0.961	1.601	0.145

In each case, estimates are statistically significant at a 1% level and are statistically different for each market between periods.

Figure 4.5 arranges the estimated b_i parameter by market and sample period. It is clear from Figures 4.5a and 4.5b that the loading on the mimicking factor in the pre-crisis period is generally greater than at any other part of the sample period. For most markets the part of the relationship that is stable and not dependent on the relative volatilities of the individual and mimicking markets is higher in the pre-GFC period, and lower in other periods. In fact, for nine of the 12 markets, the value of the b_i parameter dropped markedly from the pre-GFC to the GFC period and increased again (though only slightly) in the EDC before falling in the most recent period. Consequently, we observed a decoupling of these markets from the US market over the four periods. From the GFC period to the EDC, there is some evidence of recoupling (after the GFC), but this is limited and short-lived in size compared with the extent of the decoupling. This is consistent with Kim et al. (2015), who found that the contagion effect of the US financial crisis on Asian economies was detectable but short-lived.

A few other countries–Japan, China, Sri Lanka and Thailand–displayed different patterns in their relationship with the US mimicking factor. Sri Lanka was the only market to show a negative relationship with the mimicking factor in the pre-GFC period and in the sample as a whole. This could relate to the Sri Lankan civil war occurring at that time effectively outweighing external financial events. The occurrence of the GFC period resulted in a substantial

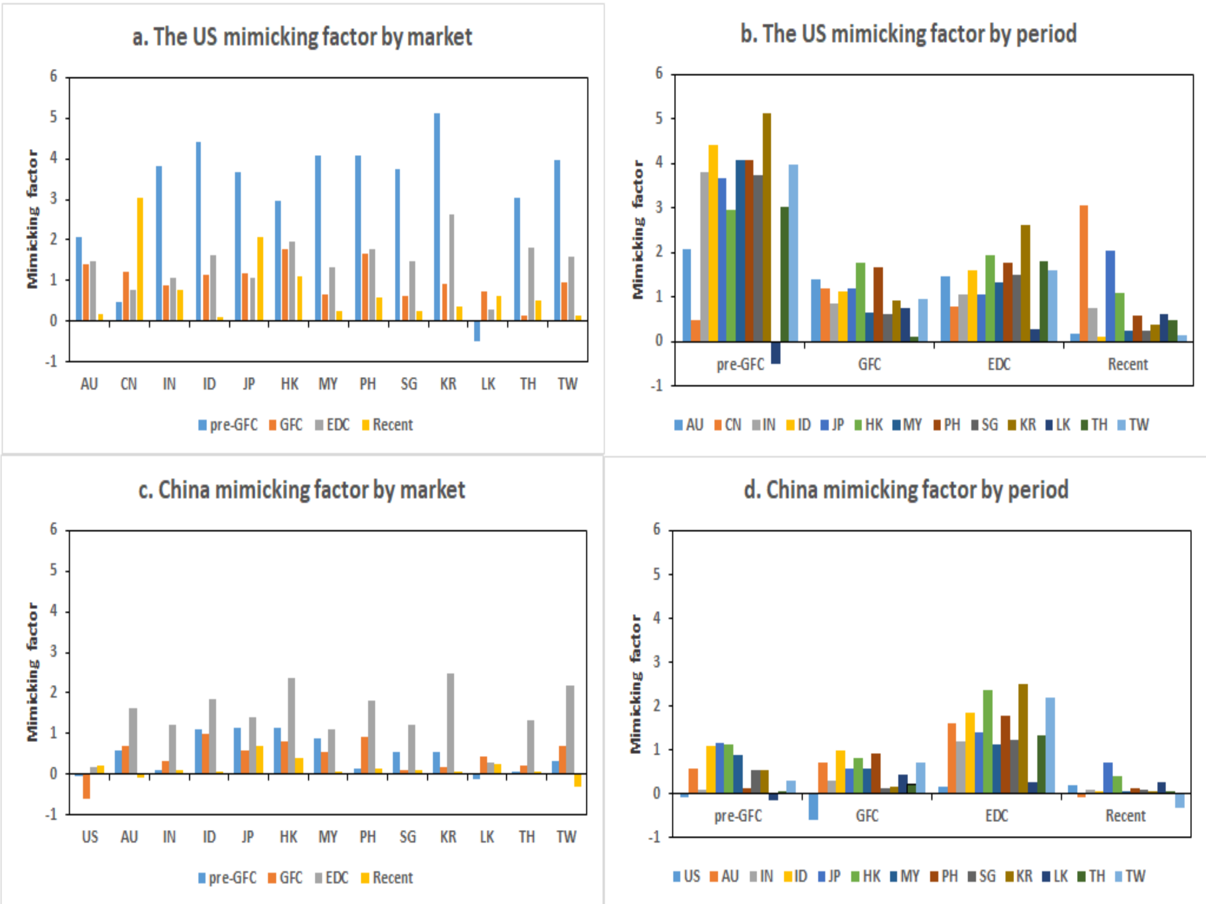


Figure 4.5: Structural transmission parameters to and from the US and China

increase in the estimated b_i parameter for Sri Lanka indicates substantial contagion. From the GFC, however, the relationship between the Sri Lankan market and the US mimicking factor returned to the steady decoupling pattern observed with most of the other markets. Thailand differed from the other markets in that it experienced a substantial decoupling from the pre-GFC to the GFC period. After recoupling during the European debt crisis period, Thailand decoupled but remained more connected to the US mimicking factor than it was during the GFC period. This is unusual relative to the other markets.

In Japan's case, the market decoupled from the US mimicking factor during the GFC and the European debt crisis periods, which is consistent with the resilience of Japanese markets during these periods of stress.[11] In the most recent period, however, Japan recoupled with the US market.

This relationship is not as strong as it was in the pre-GFC period, but is more pronounced than in the intervening periods and it has the second highest parameter value for the most recent period. China had the largest relationship with the US mimicking factor in the most recent period. Unlike the other markets, the relationship between China and the US markets increased over the entire sample period, albeit with a slight disruption during the EDC. That is, a formal test for contagion identified an increased correlation between the pre-GFC and GFC periods, and the EDC and most recent periods, both of which are consistent with contagion. China became more sensitive to shocks emanating from the US mimicking factor in the most recent period.

The analysis so far is consistent with the emerging importance of China as a major financial market for Asia. Due to the increasing influence of China, we now consider the test results when using the country as the mimicking factor of world conditions. In other words, what evidence is there of contagion from market conditions to other Asian countries when China represents the behaviour of the global factor? The resulting b parameter estimates are shown in Table 4.12 and Figures 4.5c and 4.5d. The results show that using China as the mimicking factor does not result in loadings that are as large as when using the US as the mimicking factor. This is not surprising given the role of the US in the world and it indicates that the country is a better indicator of the common conditions faced by these markets. This is consistent with much of the literature. However, it also indicates that the nature of the relationship with the mimicking factor defined by China market has altered over time (Yilmaz, 2010).

The relationship of most of the 12 countries with the China mimicking factor was highest during

[11] See Botman et al. (2013) for evidence on Japanese markets acting as a safe haven.

Table 4.12: Estimates of b_i for each sub-period with the mimicking factor of the Chinese market

Market	Pre-GFC	GFC	EDC	Recent
AU	0.583	0.712	1.624	–0.093
IN	0.105	0.314	1.208	0.107
ID	1.108	0.979	1.860	0.047
JP	1.148	0.584	1.409	0.711
HK	1.140	0.815	2.383	0.413
MY	0.900	0.564	1.116	0.045
PH	0.124	0.936	1.795	0.126
SG	0.547	0.115	1.227	0.091
KR	0.532	0.163	2.498	0.060
LK	–0.140	0.430	0.271	0.266
TH	0.057	0.220	1.340	0.069
TW	0.309	0.711	2.200	–0.307
US	–0.061	–0.595	0.177	0.203

In each case, estimates are statistically significant at a 1% level and are statistically different for each market between periods.

the EDC; this is consistent with evidence of contagion represented by a significant change in the b_i parameter from the GFC period to this period emanating from China market. The interesting aspect of this is that the increase in correlation was not necessarily a 'bad' outcome for many markets. This provided an avenue of alternative financial leadership and investment opportunities during a period of turmoil in developed markets. As far as we are aware, this feature has not been noted before. Here, we have an instance in which the propagation of shocks from one market source (with China as the mimicking factor) to individual markets increased in a statistically significant way. This is consistent with the definition of contagion but would not be viewed as necessarily harmful in this application.

We now explore the possibility that the China market does not mimic the crisis-originating part of the market but should instead be considered a diversification opportunity. Here, there are two potentially offsetting effects: a turmoil factor for developed markets represented by the US market and an opportunistic alternative for investment funds in the Asian region. This may represent a market that is better understood as having two countering forces. A similar argument has been mounted for the role of Greece and Germany in the European debt crisis, where Greece represents the problem of the crisis countries and Germany the countries that experienced demand via flight to quality (Caporin et al., 2018; Dungey and Renault, 2018). A similar situation occurred when Mexico joined the North American Free Trade Agreement. Rigobon (2002) noted that Mexico's market changed from being clearly aligned with Latin

American markets to behaving more in line with North American markets.

To examine this hypothesis more closely, we specified the conditional correlation model to consider the possibility of two distinct sources of market information, with China and the US markets providing the mimicking factors. This represents a generalisation of the model given for contagion in the discussion on detecting contagion and vulnerability in Equation (4.6), where:

$$r_{it} = \beta_{i,1} f_{\omega 1,t} + \beta_{i,2} f_{\omega 2,t} + f_{\omega i,t} \tag{4.24}$$

The two common factors and the associated propagation parameters can be expressed as:

$$\beta_{i1} = \alpha_1 b_{i,1} + (1 - \alpha_1)\frac{\omega_{i,o1}}{\omega_{o,1}^2} \tag{4.25}$$

$$\beta_{i2} = \alpha_2 b_{i,2} + (1 - \alpha_2)\frac{\omega_{i,o2}}{\omega_{o,2}^2} \tag{4.26}$$

The tests of interest are the stability of the parameters b_{i1} and b_{i2} over the different sub-samples, in which both are estimated in a joint specification.[12] This specification has the distinct advantage of dealing with multiple sources of contagion simultaneously, which is not typically accessible in the standard FR correlation tests, though it can be encompassed in other approaches. When using this model, we found the parameterisation was not supported by the data. The independence of the two factors is compromised in the specification because China's returns are themselves subject to large effects from the US. Therefore, we conclude that the two-factor specification based on China and the US as the two mimicking factors is not sufficiently empirically supported in the data.

4.5 Robustness tests

he empirical results discussed in Section 4.4.1 seem to be robust with respect to adding exogenous regressors to the analysis. Table 4.13 compares the our previous results with additional of exogenous regressors (S & P 500 volatility index and the US 90 days treasury bill rates as a proxy of interest rate) to test whether the US might be acting as a proxy of omitted global factors. The results in Table 4.13 shows that our results (Section 4.4.1) arrive to same conclusions and thus are robust.

[12] See Dungey and Renault (2018) for further details on a multivariate implementation.

Table 4.13: Historical decompositions for the entire period

	AU	CN	IN	ID	JP	HK	MY	PH	SG	KR	LK	TH	TW	US
AU	0.0000	-0.0408	-0.0595	-0.0346	-0.0483	-0.0243	0.0084	-0.0301	-0.0324	-0.0175	0.0107	-0.0563	-0.0131	-0.0022
CN	0.0104	0.0000	0.0156	0.0123	0.0087	0.0136	0.0039	0.0031	0.0130	0.0122	-0.0013	0.0099	0.0118	-0.0008
IN	-0.0920	-0.0166	0.0000	-0.0821	-0.0898	-0.0575	-0.0323	-0.0926	-0.0940	-0.0998	0.0305	-0.0477	-0.1223	-0.0223
ID	0.2031	0.0417	0.2396	0.0000	0.3129	0.3069	0.2232	0.3094	0.1244	0.3516	0.1904	0.3553	0.2453	0.0976
JP	-0.0019	0.1130	-0.0522	-0.1540	0.0000	0.0234	0.2614	0.8451	0.0801	0.3266	0.1144	0.2012	0.3578	0.0182
HK	0.0682	0.0176	0.0682	0.2575	0.1664	0.0000	0.1206	0.0815	0.0984	0.2149	0.0092	0.1044	0.1578	-0.0365
MY	0.0009	-0.0199	0.0087	-0.0525	0.0016	0.0206	0.0000	-0.0300	0.0073	0.0128	-0.0106	-0.0025	-0.0412	0.0131
PH	0.0025	0.0040	0.0094	0.0036	-0.0044	0.0087	-0.0010	0.0000	0.0022	-0.0030	0.0013	-0.0047	-0.0051	0.0000
SG	0.0005	0.0018	-0.0054	0.0026	0.0057	-0.0091	0.0027	0.0020	0.0000	0.0045	0.0039	0.0031	0.0138	0.0006
KR	-0.0177	-0.0185	0.0084	0.0383	0.0054	-0.0296	0.0089	0.0122	0.0024	0.0000	-0.0257	-0.0017	0.0299	0.0131
LK	0.3555	0.7599	0.7357	-0.0627	0.0363	0.8018	0.6423	0.2172	0.4969	0.4121	0.0000	0.0356	0.6936	0.1197
TH	0.0542	0.1040	0.1245	0.0190	0.0331	0.0938	0.0658	0.1307	0.0553	0.1188	-0.0323	0.0000	-0.0012	-0.0079
TW	0.0154	-0.0065	-0.0159	0.0131	0.0310	-0.0107	0.0169	0.0886	-0.0217	0.0076	-0.0011	0.0299	0.0000	0.0063
US	1.0321	0.4493	1.0685	0.5825	0.8431	1.4562	0.6015	1.2293	0.7267	0.8249	0.2384	1.0002	0.6719	0.0000

The sample period is January 2003 – December 2017 sample period.

4.6 Implications of results

The results of testing for changing spillovers and the presence of contagion effects between the four periods strongly support the finding that the network between Asian equity markets changed over $2003 - 2017$. This confirms results already established with many other methods in the literature.

Several proposals have been made for to identify the driving forces of changing financial market networks. The most common are trade and financial linkages, primarily through international banking, private and public debt ownership and related areas. There is evidence that growing international trade is associated with increasing financial integration. Elekdag et al. (2012) and Aizenman et al. (2015), for example, both used a type of CAPM to show how the estimated beta of Asian markets is increasing, and that the increase is positively associated with growing trade. Arslanalp et al. (2016) reported that increasing spillovers from China to other Asian markets are related to trade linkages. However, Avdjiev et al. (2019) showed that trade effects can be offset by the impact of financial flows in their study on the impact of dollar's appreciation on emerging market capital flows. An appreciating dollar results in lower cross-border bank flows for emerging economies, that despite improved export prospects, the portfolio channel of transmission can dominate to the extent that it worsens economic growth prospects. Thus, the foundations of the trade channel of transmission are more complex than they first appear, and it is not clear that equity market spillovers can be expected to mirror trade spillovers.

Recent research has investigated the effects of cooperation versus self-directed policy outcomes. These coordination effects have been found to be small in the monetary policy literature. Agénor et al. (2017), however, applied a similar approach to macro-prudential policies. They constructed a stylised dynamic stochastic general equilibrium model to examine how spillovers in financial markets can affect countries experiencing financial frictions. The model was calibrated to consider the problem of the benefits of coordination between emerging and advanced economies when viewed through a core-periphery lens. They found that substantial gains can come from coordinating macro-prudential policy responses across countries; however, these gains are correlated with both the size of the economies and the degree of financial friction.

We considered the simple correlation of our spillover results with trade measured as the average annual trade volume in dollars (from United Nation Comtrade statistics) and to the size of an economy, using gross domestic product (GDP) per capita. We identified the correlation between incoming spillovers and GDP per capita as positive at 0.1335. However, GDP per capita and outward spillovers were correlated at -0.0170. That is, as an economy increases in size, the spillovers it transmits have a progressively more dampening effect on other markets. This aligns with the centre and periphery style of analyses, in which larger core developed markets receive more shocks than do perpetrators (Kaminsky and Reinhart (2002)), although we emphasise that these results are weak. We also consider the relationship of GDP per capita to absolute spillovers (|Receipts| + |Transmissions|) and identified a correlation of 0.1728. Thus, our evidence only slightly supports the hypothesis in Agénor et al. (2017)–that spillovers and the size of an economy are positively related. The correlation of the different spillover measures with trade measured as either imports, exports, the sum of imports and exports, and net trade show that receiving spillovers is correlated with imports. Here, the correlation coefficient is 0.4021, which is more than the correlation of exports with outward spillovers at -0.1880. The sum of absolute spillovers transmitted and received was also positively related to the sum of exports and imports (or the openness of an economy) at 0.3960 in our sample. These results attest to the difficulties in directly relating spillovers to trade, particularly for exports.

Agénor et al. (2017) showed that the distribution of gains from macro-prudential coordination is distorted towards larger emerging market economies and away from core economies. This is likely to cause political tensions in trying to coordinate with smaller emerging markets that end up benefiting less than larger emerging markets, and where most of the transfer will come from advanced economies. Further, obtaining redistributions from emerging markets, even when they can be demonstrated to be welfare-improving at the global level, may be politically contentious. It is worth noting that the Agénor et al. (2017) model has limitations and simplifications, including restricting nations to balanced budgets. Thus, there is a pressing need to assess these potential trade-offs further in more realistic modelling frameworks.

4.7 Chapter summary

This chapter examined the evidence of spillovers, contagion, and decoupling for 12 Asian markets, Australia, and the US using equity market indices. Spillovers were modelled using historical decomposition framework on VAR models. We found distinct evidence of changes in spillovers between these markets, with increasing evidence of growing effects over the four periods. The continued effects of the US markets on Asia were also apparent. There is a high degree of spillovers from China and the US, both to each other and to other Asia markets.

Contagion was estimated through portfolio mimicking factor framework using moment conditions. The findings showed strong evidence of both contagion and decoupling effects using the US as the global mimicking factor. The Asian markets showed evidence of decoupling from the shocks in the US market during the GFC period. Specifically, the Asian markets were less influenced by turmoil in the US markets than would have been anticipated by the degree of spillovers evident in the pre-GFC period. The European debt crisis and the most recent periods also showed signs of change in the transmission of events via the contagion route, although these effects did not bring the transmissions back to pre-GFC period levels.

Our findings in this chapter show the importance of estimating spillovers in the global context. Our results are based on a single regime, which is limited because extreme events in the financial system changes across different market conditions. This motivates us to investigate whether spillovers changes depending on the given state of the market. Chapter 5 focuses on investigating evidence of spillovers across different states of the market, considering the global market with emphasis on Asian markets.

5 Detecting signed spillovers in global financial markets: A Markov-switching approach

Abstract

This chapter analyses the dynamics of the signed-spillover across financial markets using historical decomposition approach. By incorporating Markov-switching framework into the VAR model, this chapter investigates the dynamics of signed spillover during turbulent periods and period of tranquility. Additionally, this approach enables us to detect the source and direction of the spillover and identify its signs. We show that this approach outperforms the classical single-regime spillover estimation by distinguishing shocks under different economic conditions. The methodology is applied on realised variance data for the sample period 1999 – 2017. Our empirical findings clearly indicate that spillovers are intense during period of turbulence and moderate during periods of tranquility.

Keywords: Financial stability, spillover, financial markets, financial crises

JEL classifications: G15, C21, N25, G01

5.1 Literature review

The reoccurrence of crisis events has highlighted the role of shock transmission across different financial markets. This has resulted in the development of methods that can be used to detect the transmission of spillovers across different markets. Our study is closely related to two strands of literature that focus on detecting spillover with the aim of proposing better ways to monitor these adverse events.

The first strand of literature focuses on detecting spillovers in a single regime. Different approaches of detecting spillovers under a single regime have been proposed. Commonly used approaches include; Granger causality (Billio et al., 2012) and Diebold–Yilmaz (DY) spillover index, which is based on generalised variance decomposition (Diebold and Yilmaz, 2009, 2012). Forbes and Rigobon (2002) and Dungey and Renault (2018) proposed contagion tests to detect changes in correlations levels during periods of stress. In investigating the changes in spillovers during crises, Leung et al. (2017) applied generalised autoregressive conditional heteroskedasticity (GARCH) model to estimate volatilities of major equity markets. They found increased spillovers during time of stress. This is consistent with other studies (Diebold and Yilmaz, 2009; Gai and Kapadia, 2010; Mensi et al., 2018; Yilmaz, 2010) that showed spillovers increased during periods of crises. DY spillover index has been used in many studies.

Several recent studies have used the DY spillover index. Zhang and Fan (2019) used it to study short-run dynamics in the housing prices in China. They found that housing prices across cities were increasingly interconnected could be associated with higher systemic risk. Ma et al. (2019) studied spillovers between oil and stock returns in the US energy sector and found that the price changes of West Texas intermediate (WTI) were mainly contributed by US energy markets. Zhang et al. (2019) studied the impact of the US and China on global markets and found that the Chinese influence in the global market has increased while the US market remains the dominant player. Ji et al. (2019) also examined the dynamic interconnectedness and integration in cryptocurrency markets and found that interconnectedness via negative returns was largely stronger than via positive returns. They also found that spillover in these markets were driven by uncertainty, trading volume and global financial effects.

The other strand of literature utilises the Markov-switching models to detect spillovers in the financial system. Turner et al. (1989) and Chu et al. (1996) were among the first to employ a Markov-switching autoregressive (MS-AR) approach to capture regime-switching behaviour of stock markets. They found volatility to be higher under negative return regimes than under positive return regimes.

This Markov-switching approach has also been applied in various studies. For example, Baele (2005) introduced the regime-dependent model to investigate the effects of volatility spillovers in the European market. Their findings showed increased in spillover intensity with high probability of switching from low to high sensitivity. Kanas (2005) employed Markov-switching vector autoregression (MS-VAR) to investigate regime linkages between the Mexican currency market and six emerging equity markets. They discovered evidence of regime dependence between these markets and Mexican currency.

Psaradakis et al. (2005) proposed a switching bivariate VAR model with time-varying parameters to examine changes in Granger causality. They specifically focused on the relationship between US money, interest rates (IRs) and output. Their findings suggested that causality patterns of the variables fluctuate over time. Białkowski and Serwa (2005) introduced the concept of causality in a Markov-switching framework to examine inter-dependence in financial markets and found strong evidence of spillovers between the Japanese and Hong Kong stock markets. Kanas and Kouretas (2007) used the bivariate Markov-switching vector error correction model (MS-VECM) to study the relationship between the parallel and official foreign currency in Greece. They determined that the volatility regime to be associated with political and economic events in Greece between 1970s and 1980s.

In re-examining the effects of spillover over time, Zheng and Zuo (2013) introduced a Markov-switching causality method. They found the volatility effects to be severe during crisis periods. Guo et al. (2011) also investigated contagion effects using a MS-VAR framework. They found more contagion effects during the risky regime that had an adverse impact on the economy. Khalifa et al. (2014) used a multi-chain Markov-switching (MC-MS) model to investigate patterns of volatility transmission. They found evidence of changing transmission of volatility between the markets and the global variables that included oil price, the US stock index and the Morgan Stanley capital international (MSCI) world index. Ye et al. (2016) proposed a Markov regime switching quantile regression model to detect financial contagion. Their results showed increased interdependence between the European and US markets during the global financial crisis (GFC) periods.

Henry (2009) incorporated a Markov-switching exponential generalised autoregressive conditional heteroskedasticity (MS-EGARCH) framework to investigate the relationship between UK equity returns and the short-term IRs. The study discovered evidence of a regime-dependent relationship between equity return volatility and shorter-term IRs differentials in the UK market. Walid et al. (2011) also used MS-EGARCH to examine the dynamic linkages for emerging countries. Their findings showed that the relationships between the stock and foreign exchange (FX) for these markets are, in fact, regime dependent.

Chiang et al. (2011) adopted a Markov-switching generalised autoregressive conditional heteroskedasticity (MS-GARCH) framework to examine the volatility of Chinese market and found the positive return to be associated with high-volatile regimes. Lopes and Nunes (2012) considered a Markov-switching vector autoregression conditional heteroskedastic (MS-VARCH) model to study contagion effect. They find strong evidence of contagion during the European monetary system (EMS) crisis. Mandilaras and Bird (2010) extended the multivariate version of the Forbes–Rigobon (FR) contagion test by incorporating a Markov-switching model to investigate contagion effect in the EMS and discovered strong evidence of contagion in crisis regimes.

Gallo and Otranto (2008) investigated transmission of volatility between Asian markets using Markov-switching bivariate model (MS-BM) and found a significant change in volatility from low to high, especially during period of stress. Semmler and Chen (2014) used a Multi-regime vector autoregression (MR-VAR) model to investigate the impact of financial shocks on the macro-economy. They found shocks to have large and persistent impacts on the regimes of high stress. Nomikos and Salvador (2014) investigated volatility transmission using a regime-switching multivariate GARCH framework. They reported that the intensity of spillovers were higher during periods of high volatility.

Recently, Liow and Ye (2017) employed both univariate and multivariate switching regime beta models to investigate whether different crises had effects on volatility spillovers and found that crisis events increased the volatility of spillovers in the world market. Chen and Semmler (2018) utilised multi-regime global vector autoregression (MR-GVAR) model to investigate spillover effects in financial markets and found that shocks from one country in a high stress regime have negative effects on other markets. BenSaïda (2018) developed a Markov regime-switching vine copula approach to detect contagion effects in European sovereign debt markets. Contagion was reported to be high during crisies. Casarin et al. (2018) proposed a Bayesian Markov-switching correlation model to analysis contagion effects on financial markets. Focusing on Asia-Pacific currencies, their result showed a volatility switch in regimes, implying presence of contagion effects in the currency market.

Unlike the proposed measures of spillovers, this chapter introduces the Markov-switching approach on signed spillover measures based on generalised historical decomposition (GHD) from a VAR model. Specifically, we examined signed spillover in different states to distinguish which state is associated with intense spillovers. Distinguishing spillovers in different states guides policy makers and regulators in monitoring the financial system, and thus, promoting financial stability.

5.1.1 Theoretical motivation

Theoretical literature (such as Claessens and Forbes, 2013; Dungey and Tambakis, 2005) on financial crises, contagion, and volatility spillovers is extensive. Spilovers tend to increase during period of stress (Diebold and Yilmaz, 2009; Leung et al., 2017; Mensi et al., 2018). These shocks transmissions would have adverse effects to the entire financial system. Grobys

(2015) found volatility spillover effects to be high during period of economic turbulence and almost non-existent during normal period. This suggest that shock propagation would be high during turbulent period and low during normal times. Spillover can also be driven with the market conditions (Chu et al., 1996; Turner et al., 1989). Gębka and Serwa (2006) found that spillovers become stronger in the turmoil regime and weaker in the normal periods. This imply that spillovers would also change depending on the state of the market.

Although there is increase in the literature on shock propagation in the financial system, differentiation of spillovers under distinct market conditions is still missing. Based on the theoretical motivation and related literature, this chapter outline two main hypotheses:

Hypothesis 1: Positive spillovers occurs during turbulent period while negative spillover is associated with normal times.

This hypothesis tests whether positive and negative spillovers are associated with specific period. we examine the impact of volatility spillover on financial markets during turbulent and normal period. Taking advantage of the historical decomposition approach in estimating the spillovers, we were able to distinguish the signs of the spillovers. We found positive spillovers to having adverse effects on the financial system, while negative spillovers to having less effect to the economy. Following We hypothesise that increased and positive spillovers occur during periods of stress, while decreased and negative spillovers occur in normal times.

Hypothesis 2: Spillovers are high during intense regimes and low during moderate regimes.

This hypothesis aims to investigate whether spillover the market conditions have impact on spillover estimations. Following prior studies (see for example BenSaïda, 2018; Rigobon, 2019) that showed that financial markets evolve according to different states of the market, we aimed to detect the signed spillovers under different market conditions. Our study was restricted to two states of the market–moderate and intense regimes. We hypothesise that spillovers are high during intense regimes and low during moderate regimes.

5.2 Markov-switching vector autoregressive model

5.2.1 General setup

A Markov-switching framework was introduced to measure spillovers across different financial markets. This framework extends the spillover methodology proposed by Dungey et al. (2018b), which is based on the historical decomposition approach.

Following Cavicchioli (2014), consider an M-state MS-VAR model for a given series specified as:

$$y_t|S_t = \nu_{S_t} + \sum_{l=1}^{L} \Phi_{S_t,l}\ y_{t-l} + \mu_{S_t,t} \tag{5.1}$$

where y_t is a n-dimensional random vectors of observation conditions on the state variable S_t such that $y_t = (y_{1,t}, y_{2,t}, ..., y_{n,t})'$ for $t = 1, ..., T$, ν_{S_t} a $n \times 1$ state-dependent vector of intercepts, $\Phi_{S_t,l}$ being $n \times n$ state-dependent matrices, $l = 1, 2, ..., L$ number of lags in the model; and $\mu_{S_t,t}$ represents the vector of residuals associated with the state of the market, S_t.

Let us set $\mu_{S_t,t} = \Sigma_{S_t}\varepsilon_t$ given that ε_t is a sequence of zero mean white noise process assumed to be multivariate normal. That is, $\varepsilon_t \sim NID(0_n, I_n)$, where 0_n is a $n \times 1$ vector of zeros, I_n is the $n \times n$ identity matrix. Σ_{S_t} is $n \times n$ matrix representing a lower triangular of state-dependent Choleski factorisation of the variance-covariances matrix, Ω_{S_t} which can be represented as $\Omega_{S_t} = \Sigma_{S_t}\Sigma'_{S_t}$. Equation (5.1) can be expressed as:

$$y_t|S_t \sim NID(\nu_{S_t}, \Omega_{S_t}) \tag{5.2}$$

We assumed the parameters to be unknown, θ in each state to be characterised by its own state-dependent autoregressive matrices, $\{\Phi_{S_t,l}\}_{l=1}^{L}$; vector of intercept ν_{S_t}, and variance-covariance matrix, Ω_{S_t}. Additionally, the state variable S_t evolved according to a discrete, irreducible and ergordic M-state Markov process with a $M \times M$ unknown transitional probability, $\mathbf{P}$, for M regimes such that $S_t = \{1, 2, ..., M\}$ (Cavicchioli, 2014; Lanne et al., 2010). The likelihood function of the conditional density, $y_t|S_t$ can be expressed as:

$$f(y_t \mid S_t) = (2\pi)^{-\frac{n}{2}} \det(\Omega_{S_t})^{-\frac{1}{2}} exp\left\{ -\frac{1}{2}\mu'_{S_t,t}\ \Omega_{S_t}^{-1}\ \mu_{S_t,t} \right\} \tag{5.3}$$

where $\mu_{S_t,t} = y_t - \nu_{S_t} + \sum_{l=1}^{L} \Phi_{S_t,l}\ y_{t-l}$

Additionally, we assumed that each varying intercept of the state-switching VAR model is associated to the state variable, S_t at that specific time. This implies that each value of $\mathbf{P}$ represents the probability of being in regime i at time t given that being in regime j at time

$t-1$. The transitional probability condition on being in state S_t can be represented as:

$$\mathbf{P} = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,M} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,M} \\ \vdots & \vdots & \ddots & \vdots \\ p_{M,1} & p_{M,2} & \cdots & p_{M,M} \end{pmatrix} \tag{5.4}$$

where M is the total possible number of regimes, $p_{i,j} = Pr(S_t = j \mid S_{t-1} = i), i, j = 1, 2, ..., M$. and the sum of each column in $\mathbf{P}$ adds up to 1, i.e. $\sum_{i=1}^{M} p_{i,j} = 1$. Additionally, following Hamilton (1994), the transitional probability provided us with the expected duration that a given financial system would stay in certain regime, which is defined as:

$$E(D_j) = \frac{1}{1 - p_{j,j}}, \ j = 1, 2, ..., M \tag{5.5}$$

where D denotes the duration of staying in a given state.

Following Hamilton (1994), we defined the ergodic and unconditional probability as π which is the eigenvector of $\mathbf{P}$ which corresponds to the unit eigenvector normalised by its sum, which satisfies $\mathbf{P}\pi = \pi$ and $1'_M\pi = 1$ where 1_M is a $M \times 1$ is a vector of ones. This can formally be written as:[1]

$$A\pi = e_{M+1} \tag{5.6}$$

where e_{M+1} denotes a $M \times 1$ column vector of I_{M+1} and

$$\underset{(M+1)\times M}{A} = \begin{bmatrix} I_M - \mathbf{P} \\ 1' \end{bmatrix}$$

Premultiplying Equation (5.6) by $(A'A)^{-1}A'$ yields:

$$\pi = (A'A)^{-1}A'e_{M+1} \tag{5.7}$$

This implies that π is the $(M+1)^{th}$ column of $(A'A)^{-1}A'$. According to Hamilton (1994), consideration of a steady-state or unconditional probabilities of two regimes in a special case

[1] More details can be found in (Hamilton, 1994, p. 684).

can be expressed as:

$$\pi_1 = Pr(s_t = 1) = \frac{1-p}{2-p-q}$$
$$\pi_2 = Pr(s_t = 2) = \frac{1-q}{2-p-q} \tag{5.8}$$

5.2.2 Estimation procedure

An essential part of this analysis is understanding how the MS-VAR model was estimated. We used the classical maximum likelihood estimation (MLE) and assumed conditional normality for any given state, S_t. We let $S_t = m$ (the conditional likelihood of y_t based on regime m), then the past information can be defined as:

$$f(y_t \mid S_t = m, Y_{t-1}) = (2\pi)^{-\frac{n}{2}} \det(\Omega_m)^{-\frac{1}{2}} exp\Big\{ -\frac{1}{2}\mu'_{m,t}\ \Omega_m^{-1}\ \mu_{m,t}\Big\} \tag{5.9}$$

We further defined the following:

$$\eta_{m,t} = \begin{bmatrix} f(y_t \mid s_t = 1, Y_{t-1}) \\ \vdots \\ f(y_t \mid s_t = M, Y_{t-1}) \end{bmatrix} = \begin{bmatrix} (2\pi)^{-\frac{n}{2}} \det(\Omega_1)^{-\frac{1}{2}} exp\Big\{ -\frac{1}{2}\mu'_{1,t}\ \Omega_1^{-1}\ \mu_{1,t}\Big\} \\ \vdots \\ (2\pi)^{-\frac{n}{2}} \det(\Omega_m)^{-\frac{1}{2}} exp\Big\{ -\frac{1}{2}\mu'_{m,t}\ \Omega_m^{-1}\ \mu_{m,t}\Big\} \end{bmatrix} \tag{5.10}$$

where $Y_{t-1} = (y_{-l+1}, ..., y_{t-1})$ and $\mu_{m,t} = y_t - \nu_m + \sum_{l=1}^{L} \Phi_{m,l}\ y_{t-l}$

Incorporating the unobservable regime variable leads to:

$$f(y_t \mid Y_{t-1}) = \sum_{i=1}^{M} f(y_t \mid S_t = m, Y_{t-1}) Pr(S_t = m \mid Y_{t-1}) \tag{5.11}$$

The log-likelihood function can further be expressed as:

$$\ln L = \sum_{i=1}^{T} \ln[f(y_t \mid Y_{t-1})] \tag{5.12}$$

where T represents the total number of observations. For a given regime, we maximised the log-likelihood function with respect to the unknown parameters. For the optimisation to work, state parameters must be known at any given point. The evolution of the discrete state variable

S_t depends on $S_{t-1}, S_{t-2}, ..., S_{t-r}$ and is referred to as the r-th order Markov-switching process.[2] Kim (1994) assumed a two state Markov-switching process and specified the transitional probabilities as:

$$\mathbf{P} = \begin{pmatrix} p & 1-q \\ 1-p & q \end{pmatrix} \tag{5.13}$$

where:

$$\begin{aligned} p = Pr(s_t = 1 \mid s_{t-1} = 1) = \frac{1-p_o}{2-p_o-q_o} \\ q = Pr(s_t = 2 \mid s_{t-1} = 2) = \frac{1-q_o}{2-p_o-q_o} \end{aligned} \tag{5.14}$$

p_o and q_o in Equation (5.14) are values assumed to be bounded between 0 and 1.

To begin the optimisation, we maximised the likelihood function with respect to the regime-dependent parameters, ν_m, $\mu_{m,t}$, β_m, Ω_m, $\eta_{m,t}$ p and q. The optimisation process starts with the initialisation of the parameters. The parameters estimated using the single-regime VAR were used as the initial values of the first regime. To avoid identification problems in different regimes, parameters in the next regime were initialised by multiplying the parameters obtained from the single regime with a factor ($\delta^{(m-1)}$) such that $\delta = 1.1$ for $m = 1, 2, ..., M$. We choose arbitrary values of p_o and q_o for the optimiser to search for the optimal values of the transitional probabilities. Herwartz and Lütkepohl (2014) assigned $\mathbf{P} = M^{-1}1_{M,1}1'_{M,1}$ as the initial starting values of the transitional probability matrix.

Once the unknown parameters at each regime were obtained, the next step was to obtain the filtered probabilities. The filtered probability $\hat{\xi}_{t|t}$ represents the probability of being in regime m at a given time t given the known information, I at previous time $t-1$, that is, $\hat{\xi}_{t|t} = Pr(s_t = m \mid I_{t-1})$. Hamilton (1994, p. 692) estimated the filtered probability by iterating the following equation:

$$\hat{\xi}_{t|t} = \frac{\eta_t \odot \mathbf{P}\hat{\xi}_{t-1|t-1}}{1'_{M,1}(\eta_t \odot \mathbf{P}\hat{\xi}_{t-1|t-1})} \tag{5.15}$$

where $\hat{\xi}_{t-1|t-1}$ are probabilities obtained from a particular step of estimation. Note that $\odot$ denotes the element-wise multiplication (Hadamard product). The optimisation was iterated many times until the convergence criteria were achieved.

[2] See (Kim, 1994, p. 62) for more details.

The log-likelihood function can also be evaluated as a weighted average of the different likelihood in each regime multiplied by the filtered probabilities. This is expressed as follows:

$$\ln L = \sum_{i=1}^{T} \ln[\eta_t' \mathbf{P} \hat{\xi}_{t-1|t-1}] \tag{5.16}$$

Both the filtered probabilities and the log-likelihood estimates were stored. Then, smoothed probabilities can be estimated, $\hat{\xi}_{t|T} = Pr(s_t = m \mid I_T)$, given that the filtered probabilities are already stored. The smoothed probabilities can be estimated using forward–backward algorithm proposed by Kim (1994) and defined as:

$$\hat{\xi}_{t|T} = [\mathbf{P}'(\hat{\xi}_{t+1|T} \oslash \hat{\xi}_{t+1|t})] \odot \hat{\xi}_{t|t} \tag{5.17}$$

where $\oslash$ denotes element-wise division and the forward step defined by $\hat{\xi}_{t+1|T} = \mathbf{P}\hat{\xi}_{t|t}$. The filtered probability vector $\hat{\xi}_{T|T}$, $t = T-1, T-2, ..., 1$ (backward) in Equation (5.15) is used to start the recursion.

Given the initial transitional matrix ($\mathbf{P}$) from the optimisation, we followed Herwartz and Lütkepohl (2014) to estimate the transition matrix in the next step as a $M^2 \times 1$ vector, vec($\hat{\mathbf{P}}'$). This was easily achieved given the initial traditional matrix, filtered and smoothed probabilities were known. The transitional matrix can be expressed as:

$$\text{vec}(\hat{\mathbf{P}}') = \hat{\xi}^{(2)} \oslash (1_{M,1} \otimes \hat{\xi}^{(1)}) \tag{5.18}$$

where $\otimes$ stands for Kronecker product and:

$$\begin{aligned}
\hat{\xi}^{(2)} &= \sum_{t=1}^{T-1} \hat{\xi}^{(2)}_{t|T} \\
\hat{\xi}^{(2)}_{t|T} &= \text{vec}(\mathbf{P}') \otimes [(\hat{\xi}_{t+1|T} \oslash \mathbf{P}\hat{\xi}_{t|t}) \otimes \hat{\xi}_{t|t}] \\
\hat{\xi}^{(1)} &= (1'_{1,M} \otimes I_M)\hat{\xi}^{(2)}
\end{aligned} \tag{5.19}$$

5.3 Spillover concept

Dungey et al. (2018b) developed a signed spillover measure based on GHD from a VAR model. This decomposition rearranges the information from the VAR model to record the direction, source and sign of spillover effects. Let:

$$y_t \mid S_t = \omega_{S_t} + \sum_{l=1}^{L} \Phi_{S_t,l}\, y_{t-l} + \mu_{S_t,t} \tag{5.20}$$

where the parameters of the model are as previously defined and ω_{S_t} is a vector obtained by taking the infinite order inverse autoregressive lag-operator of ν_{S_t}. This is represented as $\omega_{S_t} = (\sum_{l=1}^{L} \Phi_{S_t,l})^{-1}\nu_{S_t}$. The moving average of VAR(L) in regime $S_t = m$ can be defined as:

$$y_t \mid S_t = \theta(L)\varepsilon_{m,t} = \sum_{i=0}^{\infty} \theta_{m,i}\varepsilon_{m,t-i} \tag{5.21}$$

where $\theta(L)$ is a matrix of the moving average in the lag operator L. For a particular period, $t + j$, Equation (5.21) can be rewritten as:

$$y_{t+j} \mid S_t = \underbrace{\sum_{i=0}^{j-1} \theta_{m,t+j-i}\varepsilon_{m,t-i}}_{\text{i}} + \underbrace{\sum_{i=j}^{\infty} \theta_{m,i}\varepsilon_{m,t+j-i}}_{\text{ii}} \tag{5.22}$$

which represent the historical decomposition ($HD_{m,t+j}$) of variable j at time t in a specific regime m. The decomposition of Equation (5.22) has two terms:

i. The first term represents the 'base projection' of y_{t+j} for specific regime m given the information available at time t.
ii. The second term represents the difference between the actual series and the base projection for specific regime m due to the structural innovations in the variables subsequent to period t. This shows the gap between the actual series and the base projection for a given regime m as the sum of weighted contributions of the innovation to particular series.

The elements of $HD^m_{t,ij}$ show the dynamic properties of the network for specific regime m and represent the connectedness measure from i to j denoted by $c^m_{t,i\to j}$. Given this, one can analyse the connectedness matrix $C^m_t = [HD^m_{t,ij}]$ for specific regime m with off-diagonal elements representing the pairwise directed connectedness. Letting $c^m_{t,j\to i}$ and $c^m_{t,i\to j}$ be in-degree and out-degree respectively for specific regime m, we can then define the net-pairwise directed connectedness of i as $c^m_{t,i} = c^m_{t,j\to i} - c^m_{t,i\to j}$, which is not restricted to be positive.

Total directional connectedness for specific regime m from and to others is given by:

$$\begin{aligned} c^m_{t,i\leftarrow others} &= \sum_{i=1,j\neq i}^{n} HD^m_{t,ij} \\ c^m_{t,others\leftarrow i} &= \sum_{i=1,j\neq i}^{n} HD^m_{t,ij} \end{aligned} \tag{5.23}$$

Pairwise directional connectednesss for sample n for specific regime m:

$$c^m_{ij} = \frac{1}{n}\sum_{t=1}^{T} HD^m_{t,ij},\ \forall i \neq j \tag{5.24}$$

5.4 Dataset and descriptive statistics

Our analysis utilised daily data from 32 economies; data were available for January 1999 – December 2017. The main reason for choosing these economies was to investigate whether spillover differs in different regions under different regimes. Specifically, our empirical analysis utilised realised variance (RV) daily data estimated from intra-day high frequency log returns. RV is a more robust proxy of volatility (Andersen and Bollerslev, 1998; Andersen et al., 2001; Koopman et al., 2005) . The countries chosen are listed in Table 5.1.

We extracted intra-day prices on constituents of these main stock indices for the economies in our sample from Thomson Reuters DataScope Select using Tick-History. These data consist of five-minute intra-day prices from January 1999 – December 2017. The trading period chosen was 9.30 am – 4.00 pm for the American and Asian regions and between 9.00 am to 5.00 pm for the European region. This is because most of these countries trade during these periods. A full trading day for the American and Asian regions has $D = 78$ non-overlapping intra-day prices, while there are $D = 96$ non-overlapping intra-day prices for the European region. By convention, intra-day prices are considered the last trade of the five-minute intervals. Five-minute intra-day prices were selected due to the fact that they are popular across the literature (see for example Andersen and Bollerslev, 1998; Andersen et al., 2001; Bollen and Inder, 2002). We then estimated intra-day log returns using Equation (5.25) from intra-day data, in which each day is divided into five-minute intervals. This estimate was calculated using:

Table 5.1: List of country-specific stock indices with their corresponding Thomson Reuters DataScope Select RIC codes

Country	**Stock index**	**RIC code**	**Country**	**Stock index**	**RIC Code**
AT:Austria	ATX index	.ATX	BR:Brazil	Bovespa Index	.BVSP
BE:Belgium	Bel-20 index	.BFX	CL:Chile	SASE Gral (IGPA)	.IGPA
FR:France	CAC 40 index	.FCHI	AU:Australia	S&P ASX All Ordinaries index	.AORD
DE:Germany	DAX index -Price	.GDAXIP	CN:China	Shanghai Composite index	.SSEC
GR:Greece	General index	.ATG	IN:India	S&P BSE Sensex index	.BSESN
HU:Hungary	BUDAPEST SE index	.BUX	ID:Indonesia	JSX Composite index	.JKSE
IE:Ireland	ISEQ Overall index	.ISEQ	JP:Japan	Nikkei 225 index	.N225
NL:Netherlands	AEX index	.AEX	HK:Hong Kong SAR	Hang Seng Index	.HSI
NO:Norway	OBX index	.OBX	MY:Malaysia	FTSE Bursa KLCI index	.KLSE
PT:Portugal	PSI 20 Index	.PSI20	NZ:New Zealand	NZSX All index	.NZCI
ES:Spain	BCN Global 100 Index	.IGRA.BC	PH:Philippines	PSEi Index	.PSI
CH:Switzerland	Swiss Market index	.SSMI	SG:Singapore	FTSE Straits times index	.STI
TR:Turkey	BIST 100 index	.XU100	KR:South Korea	KOSPI index	.KS11
GB:United Kingdom	FTSE 100 Index	.FTSE	LK:Sri Lanka	All Share	.CSE
MX:Mexico	S&P/BMV IPC	.MXX	TH:Thailand	SET index	.SETI
US:United States	S & P 500 index	.SPX	TW:Taiwan	Weighted index	.TWII

The country abbreviation was obtained from the bank for international settlements (BIS).

$$r_{d,i} = (\Delta \ln P_{d,i}) \times 100 \tag{5.25}$$

where $P_{d,i}$ is the five-minute price data of the individual country, $d = 1, 2, ..., D$ represents the days in the sample and $i = 1, 2, ..., I$ are the five-minutes intervals. [3]

Following Andersen and Bollerslev (1998), Corsi et al. (2008) and Alexeev and Dungey (2015), we estimated the daily realised variance at day d, RV_d as the sum of squared intra-day five-minutes intervals log returns defined by:

$$RV_d = \sum_{i=1}^{I} r_{d,i}^2 \tag{5.26}$$

Table 5.2 presents descriptive statistics of the RV for each market in our sample. The means of the RV were positive for all economies with a standard deviation ranging from 0.0039 – 0.0168. These results show that the RVs were strongly right-skewed. Our findings are similar to those of Areal and Taylor (2002), Andersen et al. (2001) and Alexeev and Dungey (2015), who showed that the distribution of the RVs were are skewed to the right and were also highly leptokurtic with greater values of kurtosis. The ADF statistic tests show that RVs were stationary series without unit roots and were therefore suitable to be used to investigate spillover effects. In our empirical analysis, we used the log realised variance (log RV). This is consistent with other research methodologies that use log RV in their empirical analysis (Bollerslev et al., 2013).

By taking advantage of the long horizon with a substantially large number of observations (4,778), our sample was divided into four phases as shown in Table 5.3; Phase 1 is the pre-crisis (4 January 1999 – 14 September 2008) period, Phase 2 is the global financial crisis (GFC) (15 September 2008 – 31 March 2010) period, Phase 3 is the European debt crisis (EDC) (01 October 2010 – 21 November 2013) and phase three is the most recent period (22 November 2014 – 31 December 2017). In choosing these dates, we followed Dungey et al. (2015) and Dungey and Renault (2018).

Our choice to study volatility rather than returns was guided by the initial findings in the SAR model in Chapter 3. Additionally, using RV as a proxy of volatility is a robust approximation of daily volatility (Andersen and Bollerslev, 1998). Volatility in financial markets with large variation acts as a channel through which shocks spread in the financial sector. We used daily

[3] $P_{d,0}$ is the opening price of a given day, d.

Table 5.2: Descriptive statistics of the realised variance for each market

Country	Mean	Min	Max	Std. dev	Kurtosis	Skewness	ADF test	No. obs.
AT	0.0099	0.0022	0.1478	0.0078	52.7524	4.9966	–22.7772**	4778
BE	0.0097	0.0001	0.1031	0.0091	16.5751	2.8310	–28.3706**	4778
FR	0.0118	0.0019	0.0980	0.0083	18.8668	2.9533	–20.6577**	4778
DE	0.0124	0.0013	0.1218	0.0088	23.4763	3.1935	–20.3623**	4778
GR	0.0143	0.0024	0.2517	0.0106	75.5505	5.2259	–20.9659**	4778
HU	0.0123	0.0031	0.1961	0.0087	80.3034	6.0111	–20.6268**	4778
IE	0.0123	0.0007	0.2934	0.0168	125.7966	9.4006	–40.7008**	4778
NL	0.0109	0.0017	0.0959	0.0082	18.8124	3.0249	–20.9311**	4778
NO	0.0110	0.0002	0.1297	0.0081	32.0230	3.8772	–20.2574**	4778
PT	0.0099	0.0003	0.0888	0.0062	30.4147	3.8630	–20.6975**	4778
ES	0.0122	0.0023	0.1246	0.0081	22.0082	3.0092	–20.5896**	4778
CH	0.0090	0.0015	0.0947	0.0067	28.1285	3.6506	–20.7296**	4778
TR	0.0179	0.0030	0.1769	0.0123	19.5292	2.8807	–17.1904**	4778
GB	0.0093	0.0013	0.0766	0.0065	19.1431	2.9875	–19.3069**	4778
BR	0.0147	0.0024	0.1378	0.0086	36.6463	4.2979	–18.1597**	4778
CL	0.0044	0.0008	0.0870	0.0039	128.5500	8.4700	–28.1440**	4778
MX	0.0092	0.0011	0.1039	0.0069	26.1698	3.4055	–24.2183**	4778
US	0.0089	0.0012	0.0776	0.0065	15.6887	2.7654	–18.8933**	4778
AU	0.0075	0.0012	0.0673	0.0053	19.3095	3.1682	–20.7637**	4778
CN	0.0117	0.0018	0.0897	0.0082	15.5750	2.7136	–17.4973**	4778
IN	0.0126	0.0008	0.1260	0.0089	25.5009	3.5253	–17.1246**	4778
ID	0.0102	0.0020	0.1158	0.0076	29.5038	3.9627	–21.9442**	4778
JP	0.0122	0.0016	0.1149	0.0081	24.0148	3.1659	–20.5978**	4778
HK	0.0121	0.0020	0.0928	0.0082	17.1180	2.9167	–19.0641**	4778
MY	0.0066	0.0011	0.0793	0.0053	30.6048	3.7183	–23.5529**	4778
NZ	0.0050	0.0000	0.0519	0.0035	33.9238	4.1501	–22.7759**	4778
PH	0.0094	0.0008	0.1627	0.0078	90.5677	6.4730	–28.4884**	4778
SG	0.0092	0.0024	0.0906	0.0046	46.6535	4.4773	–18.4601**	4778
KR	0.0121	0.0022	0.0992	0.0089	12.9090	2.3845	–19.7825**	4778
LK	0.0070	0.0004	0.1696	0.0077	114.1009	7.9089	–26.8626**	4778
TH	0.0103	0.0025	0.1039	0.0067	29.2017	3.5735	–18.5999**	4778
TW	0.0107	0.0016	0.1605	0.0084	34.2882	3.5931	–24.6895**	4778

The sample period is January 1999 – December 2017. The augmented Dickey-Fuller (ADF) statistic tests for a unit root.** indicate statistical significance at a 5% level.

Table 5.3: Number of observations in each subsample period.

Phases	**Time period**	**Representing**	**No. of Observations**
All phases	04.01.1999 – 31.12.2017	Whole sample	4,778
1	01.01.1999 – 14.09.2008	Pre-crisis	2,438
2	15.09.2008 – 31.03.2010	Global financial crisis	389
3	01.04.2010 – 21.11.2013	European debt crisis	919
4	22.11.2013 – 31.12.2017	Recent period	1,032

volatility estimated from five-minute return because more shocks are expected to be transmitted and received within the financial markets with the increase in intra-day activities.

5.5 Empirical analysis and discussion of the results

To conduct the analysis, appropriate lag length for the MS-VAR model must be selected. Our choice of MS-VAR length was based on information criteria (IC). We found the appropriate lag length for the MS-VAR model to be nine ($L = 5$) for each of the individual log RV series in the sample. This is based on the Schwarz information criterion (SIC) and Hannan-Quinn information criterion (HQIC). This is also in consistent with Finta et al. (2017) who showed that 5 lags would be appropriate for the realised variance. For our analysis, MS-VAR(5) was used to estimate signed spillover.

5.5.1 Single regime spillover

We began our empirical analysis by investigating how spillover changed under a single regime. The estimation of the single regime spillover is equivalent to that introduced by Dungey et al. (2018b). In general, high volatility is known to be associated with stress periods, while low volatility is associated with normal periods. Contrary to distinguishing high and low volatility spillover, we emphasised whether the spillover was good or bad. By taking advantage of the signs in spillover, we can categorise spillovers as either **good** or **bad**. This is useful in explaining the different changes in volatility and helps gauge its impact on the financial system. Good and bad spillover concepts were defined considering the RV data in our empirical analysis. Good spillover was defined as the low spillover associated with negative values while bad spillover is the high spillover associated with positive values. To be precise, we associated high spillover to periods of financial stress and negative spillover to moderate times. Distinguishing whether spillover is bad or good will help approximate current and future market expectations in relation to spillovers.

Figure 5.1 presents the average signed spillover under a single regime for the countries in our sample for the entire sample period. The horizontal black line distinguishes between positive and negative spillovers. The sign in the spillover indicates the effect of the shock at a specific point in time. These results show that volatility spillover changes over time. Spikes were observed during periods when the financial system was under stress and were associated with high spillovers (bad spillovers). For example, the spillover reached its peak during the GFC.

Figure 5.1 also shows that spillover is high during other crises; the bursting of dot-com bubbles, the EDC and the recent Chinese market crash. The increase in spillover over time was associated with the presence of contagion in the financial system. As highlighted by Glasserman and Young (2015), interconnectedness among these market entities creates a potential channel of contagion especially in times of stress in the financial system. When this happens, the financial system becomes more fragile and could collapse during periods of high volatility spillover.

Our results also revealed that as these financial markets co-moved with each other, they became more responsive to shocks, leading to changes in the magnitude of the spillover over time. This aligns with the findings of Balli et al. (2015a). This implies that as these individual countries become more integrated in terms of financial transactions, the shocks transmitted across the borders also tend to increase. From these results, it can be observed that low spillover (good spillover) is associated with periods when the financial system is normal or moderate. We related periods to times when the financial system was robust and financial institution benefited from existing linkages.

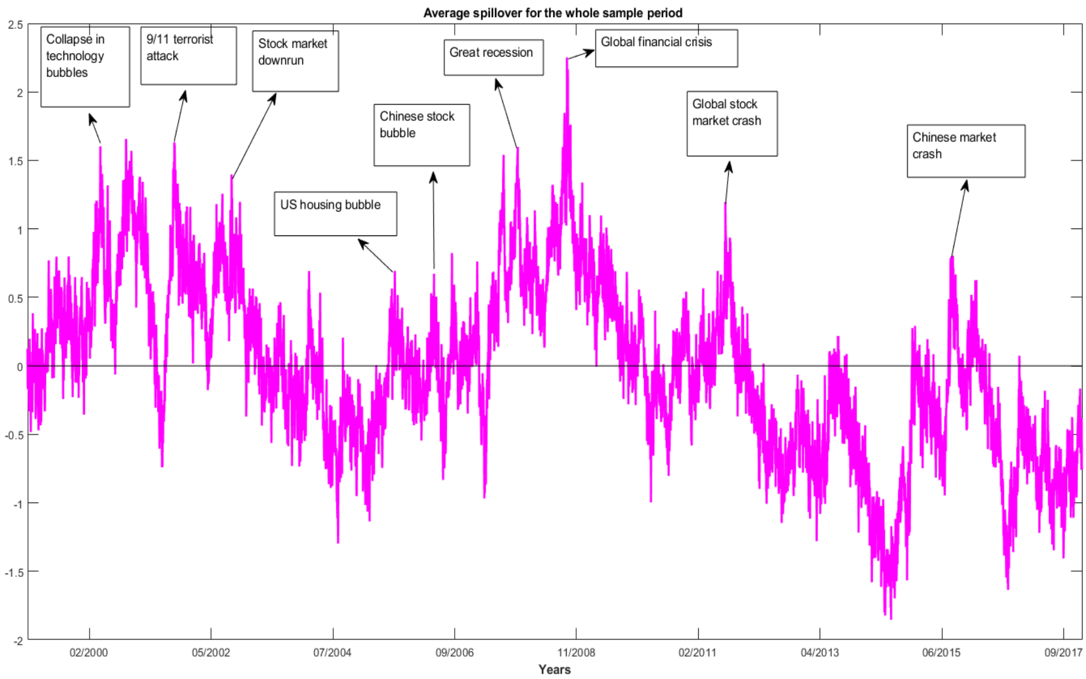


Figure 5.1: Average signed spillovers for the entire sample in a single regime

5.5.2 Markov regime-switching spillover

Here, we present our findings on the variation of signed spillover in different regimes. Studies have argued that financial markets evolve in different distinct regimes. For instance, BenSaïda

(2018) and Rigobon (2019) asserted that financial markets can be grouped into two regimes: low and high risk. The low-risk regime is associated with non-crises periods while the high-risk regime is associated with crises. This motivated us to consider two regimes in our study: moderate (low-risk) and intense (high-risk) regimes respectively. We associated intense regimes as periods with large shifts (bad spillover) in the signed spillover and moderate regimes as periods with low shifts (good spillover) in spillover. These shifts can be in both directions. As defined previously, we refer to negative spillover as **good** and positive spillover as **bad**.

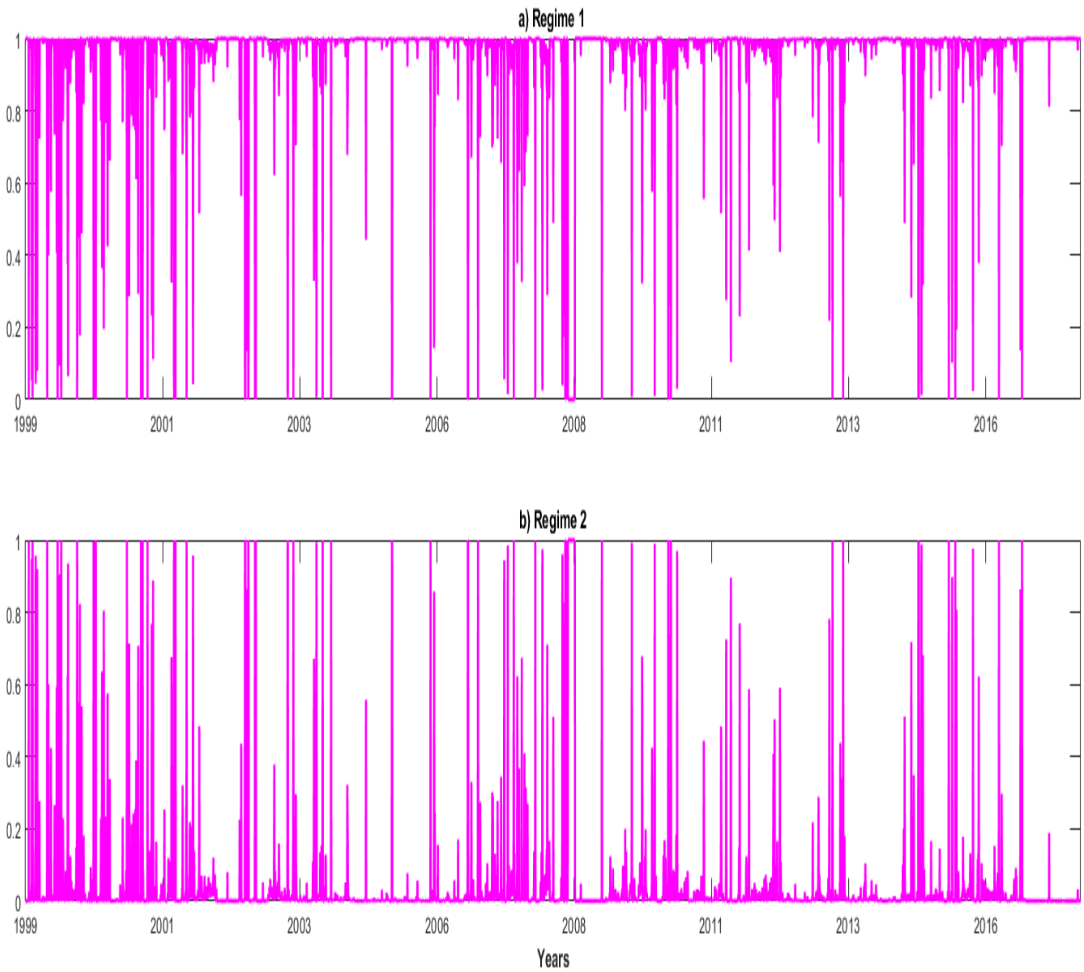


Figure 5.2: Smoothed probabilities of both moderate and intense regimes

Figure 5.2 presents the smoothed probability of being in both regimes; Figure 5.2a is the smoothed probability associated with Regime 1 (moderate regime) and Figure 5.2b is the smoothed probability associated with Regime 2 (intense regime). The result revealed that probability changed during periods of stress. For instance, under regime 2 which is associated with intense spillover regimes–the probability increased while under Regime 1, the probability decreases. These periods corresponded to the Gulf war which began in 2001 – 2002, the dot-com bubble of 2002, the GFC of 2007 – 2009, the EDC of 2010 – 2013, the recent Chinese market crash of 2015 and the Brexit vote in mid-2016. The smoothed probability also shows that probability shifted from one regime to the other more frequently. In general, our smoothed probabilities were consistently associated with well-known periods of increasing fragility in the case of Regime 2 and associated with periods of low risk in the case of Regime 1.

The transition matrix (5.27) shows that shifts between moderate and intense regime occur at high probabilities: 92.59% and 63.79% at good and bad times respectively. The results also suggest that once spillovers occur in a low-risk regime, then on average 92.59% of the time it will remain in that regime before switching to a high-risk regime in the next day. Additionally, when spillovers occur in the high-risk regime, 63.79% of the time they remain on that regime before switching to low-risk regime in the next day. This suggests a high probability of moving from moderate regime spillover to intense regime spillover; the probability of moving from an intense spillover regime to a moderate regime spillover is low.

$$\mathbf{P} = \begin{bmatrix} 0.9259 & 0.0741 \\ 0.3621 & 0.6379 \end{bmatrix} \tag{5.27}$$

Spillover in different regimes

Tables 5.4 and 5.5 present detailed static signed spillovers in both regimes without identification problems. These results are based on the coefficients obtained from the Markov regime-switching model. The static results were the average signed spillover in the whole sample period. As can be observed in both tables, the total spillover in Regime 2 (51.3%) was greater than the total spillover in Regime 1 (26.7%), indicating a period of high risk in the financial system. This result is a clear indication that the intensity of the spillover increased in Regime 2. As a consequence, the spillover in Regime 2 had more adverse effects than that in Regime 1. This was supported by BenSaïda (2018), who found that the contagion effect is higher in regimes associated with crisis events.

The results in both tables highlight key findings that cannot be obtained in a single-regime specification. For example, the shift in spillovers was moderate in Regime 1 and large in Regime 2. Changes in sign of shocks transmitted and absorbed were observed in both regimes. These findings suggest that the spillover intensities were large in Regime 2 than Regime 1,

Table 5.4: Average signed spillovers under Regime 1

	AT	BE	FR	DE	GR	HU	IE	NL	NO	PT	ES	CH	TR	GB	BR	CL	MX	US	AU	CN	IN	ID	JP	HK	MY	NZ	PH	SG	KR	LK	TH	TW	Cont. FROM
AT	0.000	-0.012	-0.032	-0.021	-0.002	-0.007	-0.011	-0.020	-0.016	-0.003	-0.021	-0.012	-0.002	-0.002	0.004	0.012	0.004	-0.006	-0.005	0.002	-0.007	0.001	-0.015	-0.008	-0.003	0.010	-0.005	-0.012	-0.007	-0.009	0.003	0.003	-0.198
BE	0.010	0.000	0.017	0.016	0.001	0.007	0.004	0.016	0.005	0.002	0.009	0.013	0.002	0.000	-0.003	-0.006	-0.003	0.002	0.002	-0.002	0.003	0.000	0.006	0.003	0.002	-0.004	0.001	0.004	0.003	0.004	0.000	-0.002	0.113
FR	0.009	0.011	0.000	-0.011	0.000	0.000	0.002	0.012	0.010	0.000	0.021	-0.001	0.001	0.001	-0.002	0.003	0.002	0.002	0.005	-0.004	0.002	0.000	0.009	0.002	-0.002	-0.003	0.002	0.003	0.004	0.000	0.000	0.001	0.081
DE	0.011	-0.002	-0.003	0.000	0.001	-0.008	-0.003	-0.005	-0.009	0.000	-0.017	-0.002	-0.001	-0.002	0.003	-0.007	0.001	-0.002	-0.005	0.002	-0.003	-0.006	-0.003	-0.005	-0.001	0.004	-0.005	-0.002	-0.005	0.002	-0.004	-0.003	-0.078
GR	0.030	0.051	0.043	0.040	0.000	0.030	0.018	0.048	0.027	0.010	0.028	0.039	0.003	0.003	-0.008	-0.014	-0.011	0.005	0.005	-0.005	0.009	-0.003	0.015	0.012	0.004	-0.011	0.006	0.011	0.009	0.014	-0.002	-0.003	0.401
HU	0.005	-0.003	0.007	0.023	0.002	0.000	0.002	0.019	0.006	0.000	0.005	0.011	0.001	0.000	-0.004	-0.005	-0.006	0.002	0.001	-0.001	0.003	-0.002	0.005	0.002	0.002	-0.003	0.001	0.005	0.003	0.004	-0.001	-0.005	0.079
IE	0.004	0.020	0.017	0.004	0.000	0.002	0.000	0.015	0.003	0.003	0.010	0.011	0.001	0.000	-0.001	-0.003	-0.003	0.003	0.003	-0.002	0.003	0.000	0.004	0.006	-0.001	-0.005	0.002	0.005	0.003	0.004	-0.002	-0.001	0.104
NL	-0.009	0.026	0.001	0.006	0.001	0.009	0.001	0.000	-0.009	-0.003	-0.008	0.007	0.000	0.001	-0.001	0.005	-0.002	0.000	-0.003	0.001	-0.001	0.000	-0.001	0.000	-0.001	-0.001	0.001	-0.002	0.000	0.001	0.001	-0.002	0.020
NO	0.037	0.063	0.061	0.042	0.005	0.022	0.011	0.035	0.000	0.012	0.052	0.027	0.005	0.005	-0.009	-0.022	-0.011	0.008	0.008	-0.007	0.011	-0.003	0.022	0.011	0.004	-0.016	0.009	0.016	0.011	0.016	-0.004	-0.001	0.421
PT	0.025	0.057	0.040	0.025	0.003	0.012	0.013	0.032	0.019	0.000	0.035	0.015	0.003	0.003	-0.005	-0.013	-0.004	0.005	0.008	-0.006	0.008	-0.005	0.015	0.011	0.003	-0.010	0.007	0.009	0.007	0.008	-0.003	-0.001	0.316
ES	0.011	0.027	0.034	0.008	0.001	0.006	0.007	0.006	0.020	0.005	0.000	0.008	0.002	0.003	-0.002	-0.012	-0.002	0.005	0.005	-0.002	0.006	0.005	0.006	0.006	0.004	-0.010	0.004	0.009	0.006	0.005	-0.001	-0.002	0.166
CH	0.007	-0.012	0.004	0.008	0.002	0.010	0.009	0.010	0.005	0.002	0.002	0.000	0.000	0.000	-0.002	0.003	-0.001	-0.003	0.002	0.001	0.001	-0.003	-0.003	0.001	0.001	0.002	0.000	0.000	-0.001	0.003	0.000	-0.002	0.044
TR	0.038	0.073	0.064	0.048	0.007	0.030	0.012	0.062	0.036	0.013	0.046	0.038	0.000	0.009	-0.013	-0.022	-0.009	0.011	0.011	-0.007	0.014	-0.003	0.028	0.015	0.007	-0.015	0.010	0.018	0.015	0.020	-0.003	-0.006	0.547
GB	0.086	0.156	0.156	0.119	0.015	0.064	0.038	0.123	0.087	0.031	0.110	0.090	0.013	0.000	-0.024	-0.048	-0.023	0.024	0.027	-0.017	0.030	-0.007	0.062	0.039	0.015	-0.039	0.023	0.041	0.032	0.042	-0.008	-0.014	1.242
BR	0.042	0.052	0.049	0.056	0.008	0.021	0.013	0.058	0.028	0.010	0.030	0.038	0.005	0.005	0.000	-0.013	-0.007	0.006	0.009	-0.004	0.009	-0.003	0.018	0.012	0.006	-0.010	0.006	0.011	0.009	0.015	-0.003	-0.007	0.470
CL	0.029	0.052	0.058	0.043	0.004	0.021	0.013	0.041	0.036	0.013	0.040	0.041	0.005	0.004	-0.009	0.000	-0.011	0.006	0.008	-0.006	0.011	-0.004	0.018	0.012	0.005	-0.013	0.007	0.014	0.011	0.016	-0.003	-0.002	0.459
MX	0.031	0.041	0.056	0.038	0.004	0.019	0.008	0.043	0.016	0.008	0.032	0.032	0.003	0.004	-0.007	-0.007	0.000	0.007	0.009	-0.005	0.008	-0.005	0.017	0.010	0.004	-0.010	0.007	0.012	0.009	0.014	-0.002	-0.003	0.393
US	0.015	0.033	0.038	0.015	0.001	0.008	0.007	0.024	0.019	0.004	0.026	0.013	0.002	0.001	-0.004	-0.008	-0.004	0.000	0.005	-0.003	0.007	0.000	0.012	0.007	0.004	-0.009	0.005	0.015	0.008	0.009	-0.002	-0.004	0.243
AU	0.036	0.059	0.062	0.060	0.007	0.024	0.022	0.055	0.036	0.015	0.044	0.035	0.005	0.005	-0.009	-0.017	-0.010	0.009	0.000	-0.007	0.012	-0.004	0.024	0.016	0.006	-0.014	0.010	0.015	0.012	0.014	-0.003	-0.006	0.512
CN	0.062	0.097	0.093	0.079	0.011	0.044	0.020	0.086	0.047	0.017	0.062	0.070	0.011	0.010	-0.019	-0.028	-0.017	0.013	0.018	0.000	0.020	-0.002	0.036	0.023	0.011	-0.023	0.015	0.025	0.020	0.029	-0.002	-0.007	0.819
IN	0.009	0.017	0.023	0.006	0.001	0.004	0.007	0.005	0.011	0.004	0.014	0.011	0.002	-0.001	-0.004	-0.008	0.000	0.003	0.006	-0.003	0.000	-0.003	0.010	0.008	0.002	-0.007	0.004	0.007	0.006	0.006	0.001	-0.001	0.142
ID	0.011	0.013	0.018	0.004	0.001	0.007	0.004	0.011	0.006	0.005	0.010	0.005	0.001	0.002	-0.003	0.000	-0.001	0.003	0.004	-0.001	0.003	0.000	0.007	0.005	0.002	-0.001	0.003	0.004	0.003	0.004	-0.002	-0.002	0.126
JP	0.012	0.025	0.009	0.017	0.000	0.004	0.000	0.022	0.017	0.005	0.019	0.008	0.002	-0.001	-0.002	-0.011	-0.001	0.002	0.000	-0.001	0.002	0.000	0.000	0.000	0.002	-0.003	0.001	0.002	0.002	0.002	-0.001	0.002	0.135
HK	0.017	0.051	0.049	0.027	0.002	0.013	0.009	0.038	0.019	0.010	0.027	0.024	0.004	0.005	-0.006	-0.013	-0.009	0.009	0.010	-0.005	0.008	0.000	0.022	0.000	0.005	-0.011	0.008	0.011	0.012	0.011	-0.003	-0.004	0.343
MY	0.014	0.016	0.014	0.006	0.001	0.007	0.003	0.003	0.007	0.003	0.010	0.008	0.001	-0.001	-0.003	-0.001	-0.001	0.002	0.004	-0.001	0.003	-0.001	0.004	0.003	0.000	-0.006	0.003	0.006	0.004	0.004	0.000	0.001	0.111
NZ	0.040	0.074	0.078	0.053	0.006	0.026	0.018	0.048	0.035	0.014	0.054	0.037	0.006	0.003	-0.011	-0.023	-0.009	0.010	0.013	-0.008	0.012	-0.004	0.026	0.015	0.006	0.000	0.010	0.018	0.015	0.017	-0.004	-0.004	0.572
PH	0.006	0.006	0.009	0.007	0.002	0.008	0.002	0.011	0.009	0.000	0.004	0.022	0.002	0.001	-0.003	-0.006	-0.001	0.003	0.002	-0.001	0.002	0.000	0.005	0.002	0.001	-0.002	0.000	0.003	0.002	0.003	-0.001	0.001	0.098
SG	-0.016	-0.025	-0.005	-0.012	-0.002	-0.006	0.006	-0.016	-0.001	-0.003	-0.003	-0.005	-0.001	-0.003	0.001	0.001	0.004	0.000	0.002	0.002	0.002	-0.003	0.001	0.003	0.001	-0.004	0.000	0.000	0.001	-0.003	-0.002	-0.001	-0.087
KR	0.009	0.026	0.026	0.014	0.003	0.007	0.004	0.019	0.014	0.002	0.019	0.012	0.002	0.002	-0.004	-0.008	-0.004	0.005	0.003	-0.002	0.005	0.001	0.011	0.005	0.003	-0.007	0.004	0.007	0.000	0.011	-0.002	-0.005	0.185
LK	0.007	0.014	0.012	0.004	0.001	0.005	0.002	0.007	0.008	0.003	0.012	0.005	0.002	0.001	-0.002	-0.006	-0.001	0.001	0.002	-0.001	0.002	-0.001	0.004	0.002	0.000	-0.002	0.002	0.003	0.002	0.000	0.000	0.000	0.086
TH	0.025	0.049	0.057	0.033	0.005	0.020	0.013	0.042	0.027	0.012	0.038	0.035	0.004	0.006	-0.008	-0.015	-0.008	0.007	0.010	-0.006	0.012	-0.002	0.017	0.017	0.006	-0.014	0.008	0.012	0.013	0.016	0.000	-0.005	0.426
TW	0.019	0.022	0.028	0.025	0.003	0.009	0.007	0.025	0.017	0.006	0.018	0.016	0.003	0.002	-0.004	-0.005	-0.004	0.006	0.005	-0.002	0.005	-0.003	0.013	0.007	0.002	-0.006	0.004	0.008	0.006	0.009	-0.002	0.000	0.240
Cont. TO	0.633	1.080	1.086	0.781	0.093	0.419	0.261	0.878	0.534	0.199	0.729	0.649	0.084	0.065	-0.162	-0.295	-0.150	0.145	0.172	-0.104	0.200	-0.062	0.396	0.242	0.101	-0.244	0.154	0.280	0.218	0.291	-0.059	-0.085	**0.267**

The sample period is 4 January 1999 – 29 December 2017. The right column (Contr. FROM) represents the average contributions from other economies and the bottom row (Contr. TO) gives the average contributions to other economies. The bold bottom-right element is the total spillover (average 'FROM' or average 'TO').

Table 5.5: Average signed spillovers under Regime 2

	AT	BE	FR	DE	GR	HU	IE	NL	NO	PT	ES	CH	TR	GB	BR	CL	MX	US	AU	CN	IN	ID	JP	HK	MY	NZ	PH	SG	KR	LK	TH	TW	Cont. FROM
AT	0.000	-0.060	-0.078	-0.054	0.006	-0.029	-0.017	-0.059	-0.029	-0.004	-0.052	-0.036	-0.001	0.030	0.030	0.043	0.026	-0.009	-0.005	0.018	-0.016	0.003	-0.036	-0.016	-0.012	0.047	-0.021	-0.030	-0.015	-0.019	0.016	0.023	-0.357
BE	0.028	0.000	0.040	0.035	-0.002	0.019	0.007	0.038	0.012	0.003	0.024	0.027	0.001	-0.014	-0.016	-0.020	-0.015	0.003	0.002	-0.009	0.007	-0.001	0.017	0.007	0.006	-0.020	0.009	0.013	0.007	0.010	-0.006	-0.012	0.197
FR	0.028	0.038	0.000	0.003	-0.004	0.011	0.004	0.032	0.017	0.000	0.039	0.009	0.000	-0.015	-0.015	-0.010	-0.007	0.003	0.005	-0.013	0.007	0.000	0.020	0.007	0.002	-0.021	0.011	0.012	0.008	0.005	-0.005	-0.008	0.163
DE	0.001	-0.018	-0.018	0.000	0.004	-0.016	-0.004	-0.018	-0.013	0.000	-0.029	-0.010	0.000	0.012	0.015	0.001	0.010	-0.003	-0.004	0.008	-0.006	-0.008	-0.011	-0.007	-0.005	0.020	-0.012	-0.009	-0.009	-0.003	-0.001	0.004	-0.131
GR	0.090	0.138	0.117	0.099	0.000	0.069	0.029	0.117	0.050	0.012	0.077	0.082	0.001	-0.045	-0.049	-0.061	-0.049	0.010	0.006	-0.030	0.024	-0.008	0.048	0.024	0.018	-0.065	0.032	0.040	0.023	0.031	-0.021	-0.036	0.775
HU	0.023	0.021	0.029	0.044	-0.002	0.000	0.005	0.042	0.013	0.001	0.020	0.024	0.000	-0.013	-0.016	-0.020	-0.018	0.004	0.001	-0.008	0.007	-0.004	0.015	0.006	0.007	-0.019	0.009	0.013	0.007	0.010	-0.007	-0.016	0.179
IE	0.020	0.045	0.040	0.019	-0.004	0.012	0.000	0.034	0.009	0.003	0.024	0.024	0.000	-0.015	-0.013	-0.017	-0.014	0.004	0.003	-0.009	0.007	-0.001	0.014	0.009	0.002	-0.023	0.010	0.014	0.007	0.009	-0.009	-0.011	0.194
NL	-0.010	0.034	0.003	0.009	0.002	0.012	0.001	0.000	-0.009	-0.003	-0.008	0.009	0.000	0.003	-0.002	0.008	-0.003	0.001	-0.002	0.001	-0.001	0.000	0.000	0.000	-0.001	0.000	0.001	-0.002	0.000	0.001	0.002	-0.004	0.042
NO	0.110	0.169	0.153	0.110	-0.011	0.066	0.023	0.113	0.000	0.015	0.116	0.076	0.002	-0.056	-0.059	-0.082	-0.054	0.014	0.009	-0.038	0.031	-0.008	0.064	0.027	0.022	-0.084	0.041	0.052	0.027	0.037	-0.029	-0.038	0.817
PT	0.075	0.134	0.104	0.072	-0.008	0.042	0.022	0.087	0.037	0.000	0.079	0.049	0.001	-0.039	-0.039	-0.054	-0.033	0.009	0.008	-0.028	0.021	-0.009	0.044	0.021	0.015	-0.056	0.029	0.034	0.019	0.023	-0.019	-0.026	0.614
ES	0.041	0.074	0.075	0.035	-0.006	0.024	0.013	0.039	0.032	0.005	0.000	0.028	0.001	-0.025	-0.023	-0.039	-0.020	0.007	0.005	-0.015	0.014	0.005	0.024	0.013	0.013	-0.043	0.018	0.025	0.013	0.015	-0.012	-0.019	0.316
CH	0.009	-0.014	0.006	0.011	0.001	0.013	0.010	0.013	0.005	0.002	0.003	0.000	0.000	-0.001	-0.003	0.003	-0.003	-0.003	0.001	0.001	0.001	-0.005	-0.003	0.001	0.001	0.002	0.001	0.000	0.000	0.003	-0.001	-0.005	0.051
TR	0.126	0.203	0.174	0.132	-0.012	0.085	0.026	0.162	0.069	0.016	0.121	0.099	0.000	-0.065	-0.075	-0.094	-0.061	0.018	0.011	-0.044	0.037	-0.009	0.079	0.034	0.029	-0.097	0.049	0.062	0.034	0.046	-0.031	-0.054	1.071
GB	0.280	0.438	0.399	0.303	-0.027	0.184	0.070	0.339	0.160	0.037	0.275	0.225	0.004	0.000	-0.158	-0.206	-0.139	0.039	0.027	-0.099	0.081	-0.020	0.173	0.079	0.062	-0.221	0.109	0.136	0.075	0.099	-0.072	-0.120	2.532
BR	0.108	0.145	0.128	0.120	-0.006	0.060	0.024	0.133	0.052	0.012	0.083	0.084	0.002	-0.047	0.000	-0.063	-0.045	0.011	0.009	-0.030	0.026	-0.009	0.053	0.025	0.022	-0.067	0.034	0.042	0.023	0.034	-0.024	-0.044	0.897
CL	0.095	0.147	0.140	0.106	-0.010	0.062	0.024	0.113	0.062	0.016	0.096	0.087	0.001	-0.051	-0.054	0.000	-0.051	0.011	0.008	-0.035	0.028	-0.009	0.055	0.026	0.021	-0.074	0.037	0.046	0.026	0.035	-0.025	-0.037	0.894
MX	0.083	0.114	0.120	0.086	-0.007	0.050	0.016	0.100	0.033	0.009	0.075	0.068	0.000	-0.038	-0.041	-0.045	0.000	0.011	0.009	-0.026	0.021	-0.010	0.045	0.020	0.017	-0.056	0.029	0.036	0.020	0.029	-0.019	-0.032	0.717
US	0.050	0.086	0.085	0.047	-0.007	0.029	0.012	0.064	0.032	0.004	0.058	0.038	0.000	-0.030	-0.029	-0.038	-0.024	0.000	0.005	-0.018	0.016	-0.002	0.033	0.015	0.013	-0.045	0.020	0.033	0.015	0.019	-0.015	-0.025	0.443
AU	0.115	0.173	0.161	0.136	-0.009	0.072	0.036	0.143	0.066	0.018	0.111	0.089	0.001	-0.058	-0.062	-0.079	-0.056	0.015	0.000	-0.040	0.032	-0.010	0.069	0.032	0.025	-0.086	0.044	0.052	0.029	0.037	-0.028	-0.047	0.982
CN	0.187	0.276	0.246	0.197	-0.017	0.122	0.039	0.225	0.092	0.021	0.164	0.157	0.004	-0.095	-0.108	-0.129	-0.092	0.022	0.017	0.000	0.052	-0.010	0.107	0.049	0.042	-0.138	0.071	0.085	0.048	0.065	-0.041	-0.075	1.584
IN	0.032	0.049	0.052	0.026	-0.005	0.018	0.011	0.028	0.018	0.004	0.034	0.026	0.000	-0.024	-0.021	-0.029	-0.013	0.004	0.005	-0.015	0.000	-0.006	0.024	0.012	0.008	-0.032	0.016	0.020	0.011	0.012	-0.007	-0.014	0.244
ID	0.028	0.037	0.039	0.017	-0.003	0.018	0.006	0.029	0.011	0.005	0.024	0.015	0.000	-0.014	-0.015	-0.013	-0.011	0.004	0.003	-0.009	0.007	0.000	0.017	0.008	0.007	-0.016	0.012	0.013	0.006	0.009	-0.010	-0.013	0.211
JP	0.028	0.050	0.027	0.032	-0.003	0.013	0.002	0.041	0.024	0.006	0.034	0.019	0.001	-0.013	-0.012	-0.026	-0.009	0.003	0.001	-0.008	0.006	0.000	0.000	0.004	0.006	-0.017	0.008	0.009	0.006	0.007	-0.006	-0.003	0.228
HK	0.070	0.130	0.116	0.077	-0.010	0.045	0.017	0.099	0.038	0.011	0.071	0.061	0.000	-0.044	-0.044	-0.058	-0.043	0.013	0.010	-0.030	0.023	-0.002	0.054	0.000	0.019	-0.064	0.033	0.038	0.024	0.027	-0.020	-0.034	0.627
MY	0.028	0.034	0.030	0.017	-0.002	0.015	0.004	0.015	0.011	0.003	0.021	0.016	0.000	-0.013	-0.013	-0.011	-0.009	0.003	0.003	-0.007	0.006	-0.002	0.011	0.006	0.000	-0.021	0.010	0.012	0.007	0.007	-0.005	-0.006	0.171
NZ	0.122	0.193	0.181	0.129	-0.011	0.076	0.031	0.137	0.064	0.017	0.123	0.093	0.002	-0.065	-0.067	-0.089	-0.056	0.016	0.013	-0.043	0.033	-0.010	0.072	0.032	0.026	0.000	0.046	0.058	0.032	0.041	-0.030	-0.047	1.117
PH	0.020	0.024	0.026	0.019	-0.002	0.017	0.004	0.027	0.014	0.000	0.014	0.033	0.001	-0.012	-0.015	-0.018	-0.011	0.004	0.001	-0.007	0.006	0.000	0.013	0.005	0.005	-0.014	0.000	0.010	0.006	0.007	-0.005	-0.007	0.164
SG	-0.025	-0.040	-0.013	-0.021	-0.001	-0.011	0.005	-0.026	-0.004	-0.004	-0.008	-0.010	-0.001	0.000	0.004	0.004	0.010	0.000	0.001	0.004	0.000	-0.004	-0.003	0.001	0.000	-0.002	-0.003	0.000	-0.001	-0.004	-0.002	0.001	-0.153
KR	0.043	0.077	0.070	0.046	-0.004	0.029	0.010	0.058	0.027	0.003	0.049	0.035	0.001	-0.027	-0.027	-0.036	-0.024	0.007	0.004	-0.016	0.014	0.000	0.031	0.013	0.012	-0.040	0.019	0.024	0.000	0.021	-0.014	-0.026	0.380
LK	0.021	0.036	0.030	0.016	-0.002	0.015	0.004	0.022	0.014	0.004	0.025	0.015	0.001	-0.011	-0.013	-0.019	-0.009	0.002	0.003	-0.007	0.006	-0.002	0.012	0.005	0.003	-0.015	0.009	0.010	0.005	0.000	-0.005	-0.008	0.167
TH	0.092	0.147	0.143	0.095	-0.011	0.062	0.024	0.117	0.051	0.014	0.095	0.082	0.001	-0.053	-0.055	-0.070	-0.049	0.012	0.010	-0.036	0.030	-0.006	0.056	0.031	0.023	-0.079	0.040	0.046	0.028	0.036	0.000	-0.042	0.834
TW	0.054	0.071	0.071	0.058	-0.005	0.030	0.013	0.064	0.029	0.007	0.047	0.040	0.001	-0.027	-0.028	-0.032	-0.024	0.008	0.004	-0.016	0.015	-0.006	0.033	0.014	0.011	-0.038	0.019	0.025	0.014	0.019	-0.014	0.000	0.457
Cont. TO	1.974	2.952	2.699	2.021	-0.177	1.211	0.472	2.327	0.989	0.239	1.803	1.553	0.026	-0.867	-1.025	-1.299	-0.896	0.242	0.173	-0.601	0.539	-0.156	1.129	0.502	0.417	-1.384	0.729	0.918	0.497	0.669	-0.465	-0.780	**0.513**

The sample period is 4 January 1999 – 29 December 2017. The right column (Contr. FROM) represents the average contributions from other economies and the bottom row (Contr. TO) gives the average contributions to other economies. The bold bottom-right element is the total spillover (average 'FROM' or average 'TO').

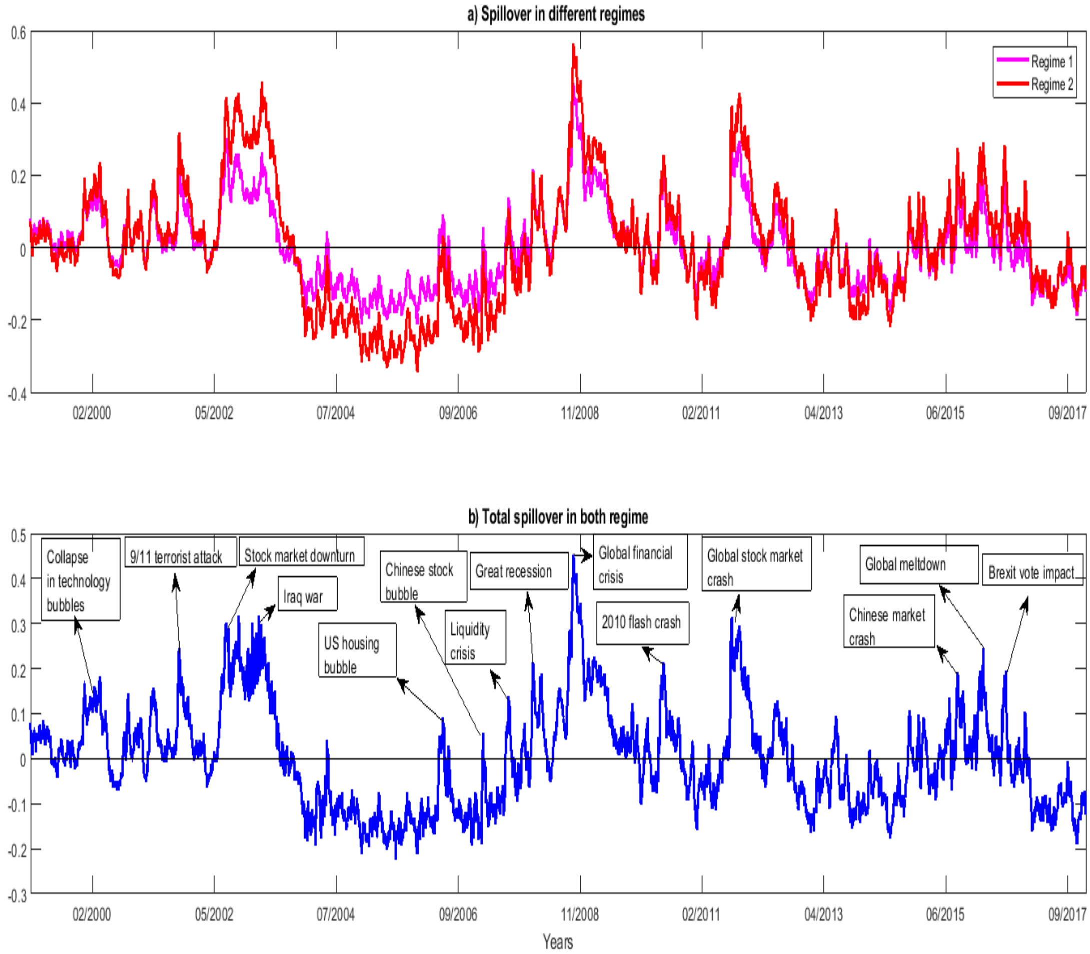


Figure 5.3: Average signed spillovers for the whole sample in different regimes. Figure 5.3a displays signed spillover in the two regimes while Figure 5.3b displays the total spillover in both regimes. The sample period is 4 January 1999 – 29 December 2017.

thereby inflicting having adverse effects on the stability of the economy.

The results also revealed country-specific signed spillover effects which is consistent with previous findings. Considering spillover in Regime 2, we observed, that China received large shocks from other markets. The average magnitude of shocks it received (1.584) under Regime 2 almost doubled from that in Regime 1 (0.819). This agrees with Beaino et al. (2019), who showed that China was more prone to shocks from other markets, including the US.

The results also revealed that European economies mostly comprising developed markets transmitted, on average, large shocks to other markets over the whole sample period. These economies showed their dominant role was spreading shocks to other financial markets. A plausible explanation for this phenomenon could be the increased financial inter-linkages with other economies. This was supported by Glasserman and Young (2015), who found the spillover effect to be stronger from economies with a high number of interlinkages.

In general, the signed spillover effect intensified more in Regime 2 than in regime 1. This implies that the financial system was more exposed to financial stress in Regime 2, which is associated with intense spillovers. Therefore, the cross-border spillovers tended to rise as countries became more integrated in terms of financial transactions. Additional static results at each phase are presented in Appendix A.3.1.

Figure 5.3a displays the signed spillover in the two distinct regimes. The signed spillover in Regime 1 was moderate compared to that of Regime 2. We also observed that the spillovers alternated between regimes of low and high risk. From Hamilton (1994), we noted that the expected duration of a spillover remaining in Regime 1 (associated with moderate spillover) before switching to Regime 2 was 13.5 days, while the expected duration of staying in Rregime 2 (associated with intense spillover) was 2.76 days.[4]

These results show the distinction of spillovers in both regimes, unlike in the case of single regime spillover analysis. We observed the trend of spillovers in Regime 2 changing over time with higher increases i associated to period of stress in the financial system. The signed spillover between these economies became more intense with large positive magnitudes. This corresponded to the crisis periods and was associated with the bursting of dot-com bubbles, the GFC, the EDC and the recent Chinese market crash of 2015. These shifts in spillovers, especially in Regime 2 were associated to contagion (Dungey and Renault, 2018; Forbes and Rigobon, 2002). Our findings are supported by Sun and Chan-Lau (2017), who showed that fragility in the financial system tends to increase during times of economic stress since institutions tend to amplify adverse shocks.

Total spillover for both regimes

The total signed spillover can be estimated by considering the probabilities and corresponding spillover in each regime. Let us define total signed spillover as:

$$Total\ spillover_t = prob'_{m_1,t} * spillover_{m_1,t} + prob'_{m_2,t} * spillover_{m_2,t} \tag{5.28}$$

where $prob_{m,t}$ is the filtered probability and $spillover_{m,t}$ is the spillover associated with regime m respectively.

[4]The expected duration in moderate and intense regime is estimated as $\frac{1}{1-p}$ and $\frac{1}{1-q}$ respectively (see Hamilton, 1994).

Figure 5.3b displays the total signed spillover in the financial market. Large spikes in spillover were associated to different key events in the global financial market. For instance, large spillovers on 10 March 2000 was associated with the collapse in technology bubbles which had an impact on the global economy. The 11 September 2001 spillover was associated with the 9/11 terrorist attack in the US that led to the shutdown of New York stock exchange (NYSE). These results also show that the stock market downturn of 2002 had a considerable impact on the economy, leading to a drastic drop in global stock prices especially in the US, Europe, Asia and Canada. The 2003 Iraq war also affected the global market. The spike in early 2006 was associated with a peak in the house prices. The Chinese stock bubble of early 2007 also had a significant impact on the global economy. We associated the spike in mid-2007 with the credit crunch that led to loss of confidence in investor resulting in a liquidity crisis. The early 2008 great recession in the US was also apparent. The trend on 15 September 2008 corresponds with the period when the GFC entered its acute stage due to failures of large financial institutions. The rise in spillover of 6 May 2010 related to the 2010 flash crash in the US stock market. This had an impact on other global stock markets. The spike of August 2011 was associated with the when the US and global stock market crashed (also is referred to as 'Black Monday'). The global market crash of August 2011 was due to fears of contagion from the EDC. The 24 August 2015 were associated with the fall of Shanghai's stock index, which was part of the Chinese market crash. The global meltdown of early 2016 when the Chinese market experienced a sharp sell-off affected the global stock market. The 24 June 2016 was associated with the Brexit vote's impact on the global economy. All these events had adverse effects on the stability of the financial system.

From these results, it can be concluded that total spillover is persistently high during periods of stress and low in periods of moderation. This is consistent with other research that shows that spillover tends to increase when the financial system is under stress. This suggests that crises intensify spillover in the financial system, indicating the presence of financial contagion (Mensi et al., 2018). Haldane (2009) related high spillover in the financial system with increased cross-border activities, including trade and financial relations.

5.5.3 Regional experience

The increasing interdependence among regional markets has led to increased financial activities across different markets. We categorised countries in our sample into three economic regions: European (43.75%), American (12.5%) and Asian (43.75%). We estimated the total signed

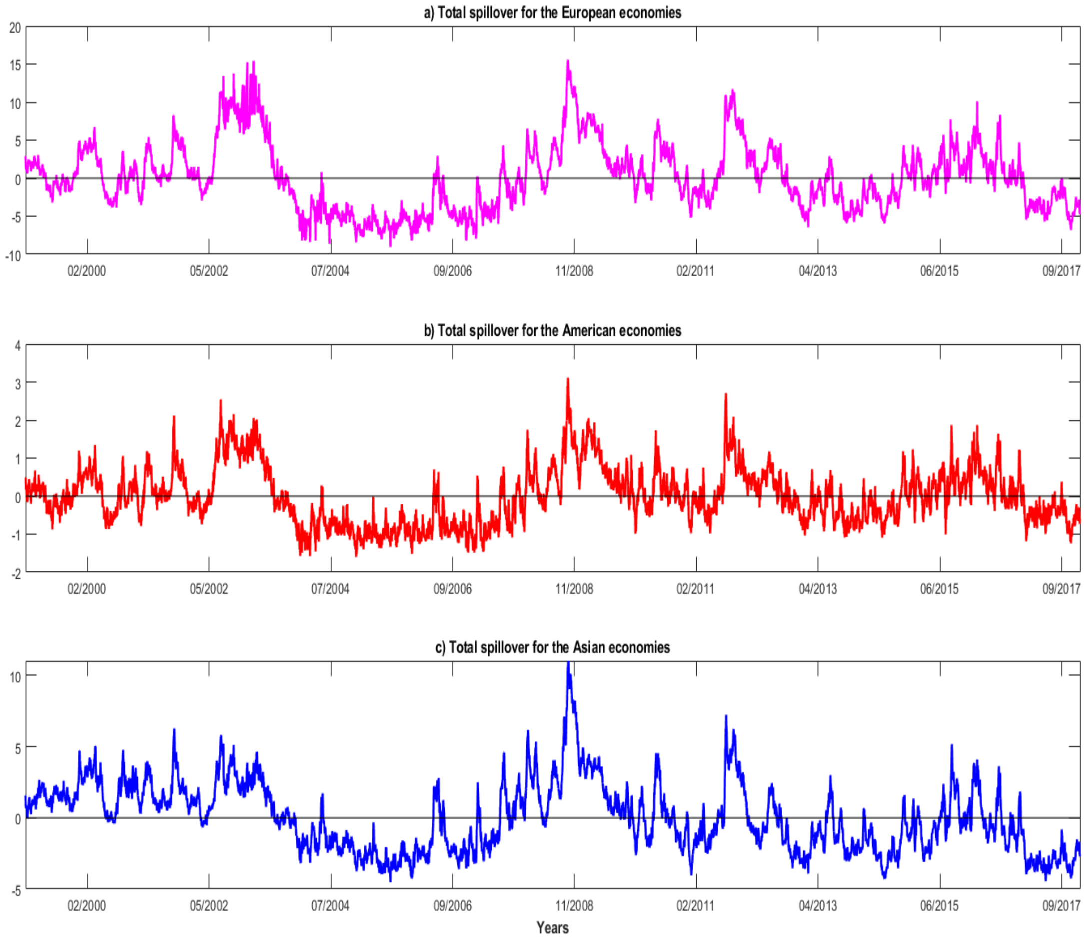


Figure 5.4: Total signed spillovers for the whole sample in different regions. Figure 5.4a displays the total spillovers for Europe, Figure 5.4b for America and Figure 5.4c for Asia. The sample period is January 1999 – December 2017.

spillover of these regional groupings as displayed in Figure 5.4. Figure 5.4a shows the total spillover for European markets. The total signed spillover intensity was greater for European economies than for other regions. One of the main reasons for this is that the European markets comprise mostly advanced economies with greater cross-border activities that tend to have many interconnections with other markets. This increases their potential risk of being affected by major events (Haldane, 2009). Battiston and Caldarelli (2013) highlighted that inter-linkages among financial institutions leads to financial instability, which has potential effects on the entire financial system. This finding is also consistent with Kim et al. (2015), who asserted that developed markets with high integration act as a channel of shock transmission in the financial system.

The total signed spillover for the American economies (Chile, Brazil, Mexico and the US) is displayed in Figure 5.4b. We observed that the total spillover in these economies was relatively low with the exception of the period with turmoil events. The influential role of the US market was evident during the GFC, when the spillover reached its peak. This was supported by Liu (2014), who found that the impact of the US risk increased when the market was volatile. These results also showed that the US plays a key role in shock transmission. This is similar to Kim et al. (2015), who reported that strong spillover from the US had an effect on emerging Asian economies during the crisis period. The role of emerging markets is also evident because the potential total signed spillover in the American region was lower.

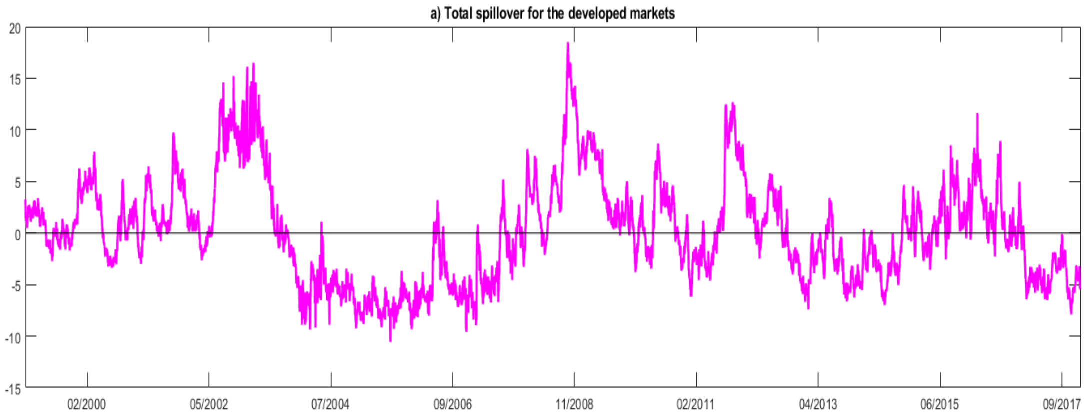
In the case of the Asian economies (see Figure 5.4c), the magnitude of the total signed spillover was lower than in European economies. One of the reasons for this low magnitude is that most Asian markets are emerging. The total signed spillover in the Asian markets tended to be high during periods of stress in the financial system. This observation is partly consistent with Guimarães-Filho and Hong (2016), who argued that the Asian markets (most being emerging markets) are affected by exposures from advanced economies, and thus, are becoming more vulnerable to spillovers from other regions.

The total signed spillover in the regional context still exhibited large positive shocks (bad shocks) during the stress periods associated with the bursting of dot-com bubbles, the GFC, the EDC and the recent Chinese market crash.

5.5.4 Advanced and emerging markets

Recent financial growth has led to an increased financial system in terms of size and financial activities, including trade. This has prompted an increase in financial interaction between different markets. Advanced economies with large markets are key players. Therefore, spillovers from these economies have adverse effects on the entire financial system. Emerging markets are also increasingly becoming more important in driving growth in the global economy. Recent research has shown that emerging markets are becoming increasingly influential in the global market and more involved global economic growth. An example is the recent growth of the Chinese market in terms of cross-border activities with other global markets.

We now estimate the total signed spillover for both the emerging (44%) and advanced (56%) economies in our sample. We categorised these economies as advanced or emerging economies based on IMF 2017 classification. Figure 5.5 compares the total signed spillover among the developed (Figure 5.5a) and emerging (Figure 5.5b) economies. The sample period is January 1999 to December 2017. The figure represents the total signed spillover for both economies



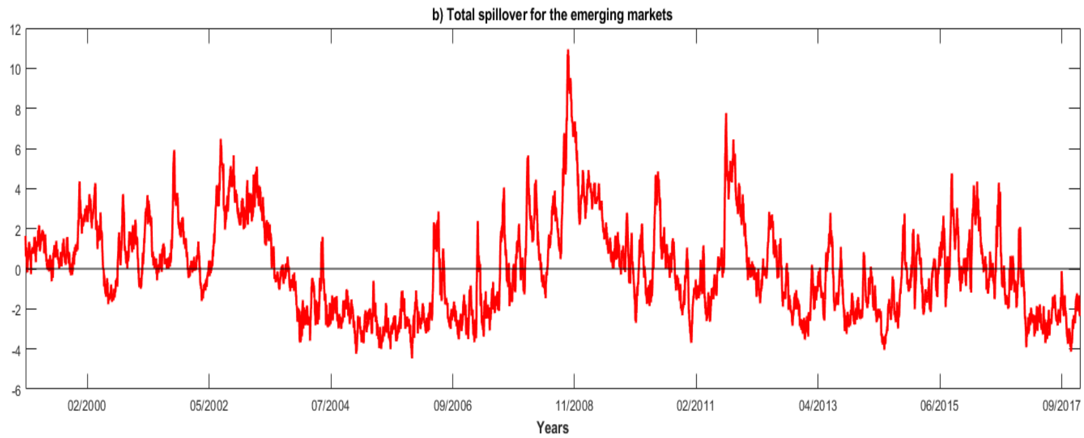


Figure 5.5: Total signed spillovers for both developed and emerging economies. Figure 5.5a represents the total spillovers for developed markets and Figure 5.5b represents the spillovers for emerging markets. The sample period is January 1999 – December 2017.

within the period.

Figure 5.5 reveals that the total signed spillover for both economies tended to increase during times of financial stress. This was supported by Sun and Chan-Lau (2017), who showed that fragility in the financial system tended to increase during times of economic distress since institutions tended to amplify adverse shocks. Figure 5.5 also reveals the role of these economies in spreading and transmitting shocks over time.

The magnitude of total signed spillover for advanced economies was larger than that of emerging economies. This suggests that advanced economies with greater market size are more vulnerable in spreading and receiving shocks than are emerging economies. This is consistent with the existing literature, which indicates advanced economies have greater potential negative effects, especially when, under stress. For example, Balli et al. (2015b) reported that more shocks from the developed markets were evident during crises implying their increased role in transmitting shocks.

Advanced economies with greater cross-border activities tended to have many interconnections with other markets, thereby increasing their risk of spreading shocks. This is consistent with Battiston and Caldarelli (2013), who highlighted that interlinkages among financial institutions can lead to financial instability, which may have an effect on the entire financial system. This is supported by Kim et al. (2015), who asserted that developed markets with high integration act as a channel of shock transmission in the financial system. This was evident, with spikes displayed from the various episodes when the entire market was in distress. Although the magnitude of the spillover is smaller, these results are partly consistent with Guimarães-Filho and Hong (2016), who asserted that emerging markets are increasingly having greater influence over other countries. Emerging markets are more exposed to spillovers from advanced economies making them more vulnerable to collapse. This aligns with Aizenman et al. (2016a), who found that emerging markets continually suffer from shocks emanating from advanced economies.

5.5.5 Focus on Asian economies

The Asian region is becoming more integrated with other regions in terms of trade and other financial transactions. The main players in Asia include China, Australia, South Korea and Hong Kong were becoming key players in the global economy with their increased cross-border activities with other regions. This led us to investigate how Asian economies are affected by shocks from other markets and their role in shock propagation during periods of intense

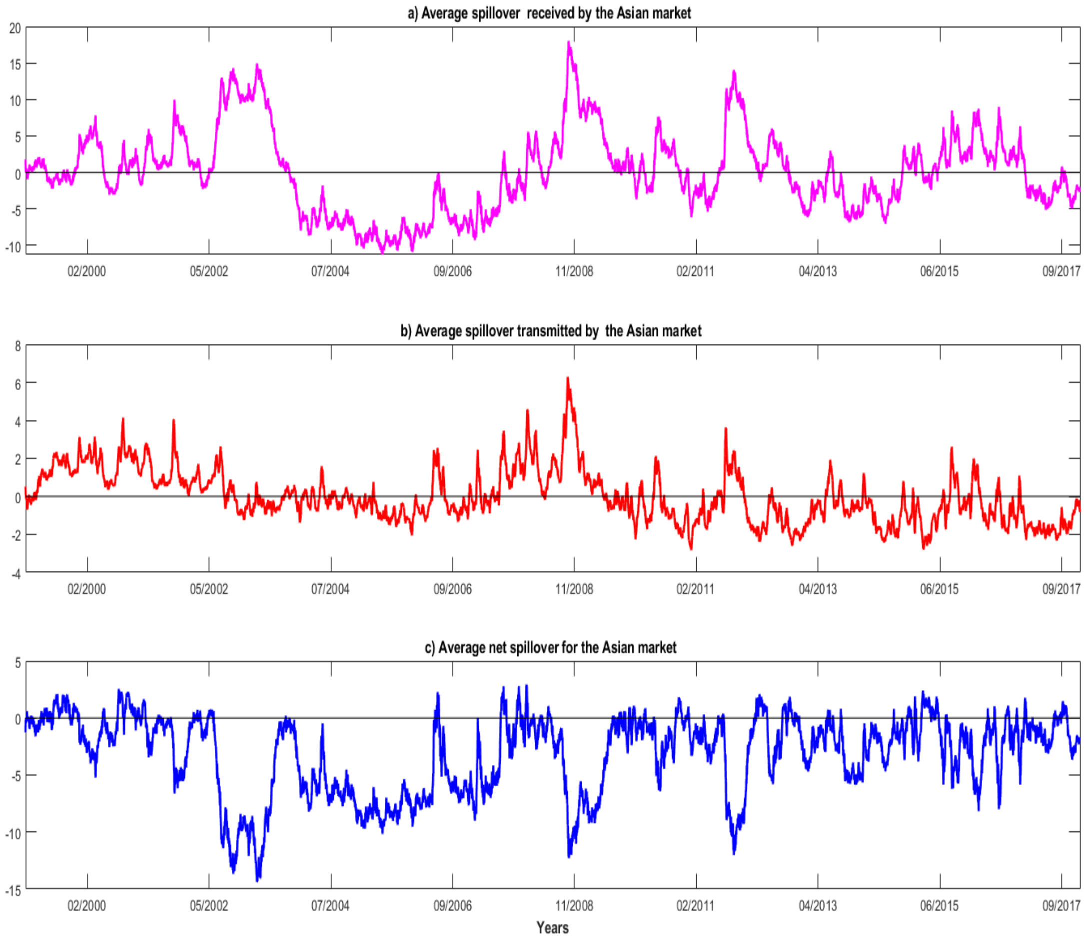


Figure 5.6: Average signed spillovers for Asian economies in Regime 2. Figure 5.6a represents the shocks received, Figure 5.6b depicts the shocks transmitted and Figure 5.6c illustrates the net spillovers. The sample period is January 1999 – December 2017.

spillovers (Regime 2).

Figure 5.6 displays the average signed spillover that Asian economies received and transmitted in the whole sample period. Figures 5.6a and 5.6b show that the magnitude of shocks received was slightly higher than those transmitted by these economies. It is important to note that the trend of shocks received by the Asian economies resembles the total spillover for this region. The implication of this is that Asian economies are affected more by shocks from other regions. On average, Asian economies received more spillover during the bursting of the dot-com bubble, the GFC, the EDC and the recent Chinese market crash.

Our results also revealed that on average, Asian economies transmitted moderate shocks in the financial system. The shocks transmitted by Asian markets peaked during the GFC. This implies that Asian economies became channels of shock transmission, especially during the GFC.

Figure 5.6c presents the average net spillover for these economies in the whole sample period during the period of intense spillover (Regime 2) in financial markets. We defined net spillover as the difference between the absolute shocks transmitted by any market and the absolute shocks received by the same market at a specific point in time (t) within the specific regime (m). That is expressed by:

$$net\ spillover_{m,t} = |transmitted_{m,t}| - |received_{m,t}| \tag{5.29}$$

The results demonstrate the changing nature of Asian economies in terms of being either net receivers or transmitters of shocks over time. During the beginning of the sample period, Asian markets were net transmitters of shocks that could be effects from the Asian crisis. They became net receivers of shocks during the bursting of dot-com bubble, the GFC and the EDCs. This was associated to the growing linkages between Asian and European economies. This is consistent with Haldane (2009), who asserted that increased cross-border interlinkages facilitated shock transmission in the financial system, thereby increasing fragility in the entire financial system. In 2015, the Asian market became the net transmitter of shocks to other markets, associated with spillovers from the Chinese market crash. These results suggest that the Asian markets are affected by shocks from other markets, especially when the financial system is fragile, and become a potential channel of shock transmission. We determined trade linkages among these economies to be a major channel of shock transmission to other markets.

An interesting question to address is the role of spillovers for individual Asian markets in times of intense spillovers (Regime 2). Figures 5.7 and 5.8 display the shocks that each individual Asian market received and transmitted respectively in times of intense spillover. Additionally, plots in Figure 5.9 present the net spillover of each individual Asian country in Regime 2. Results revealed distinct findings. For example, we observed that individual Asian countries were sensitive to spillovers to and from other markets. We noted that the magnitude of shocks received and transmitted by each individual Asian market differs.

Individual Asian markets

- China

  China received adverse shocks during the bursting of dot-com bubble, the GFC and the EDC. This finding is supported by Wang et al. (2016), who found China to be affected by shocks during the GFC and the EDC China transmitted large shocks during the Chinese stock bubble of 2007 and the recent Chinese market crash. Figure 5.8 reveals China's role in transmitting adverse shocks to other economies during these periods. On average, China was the net recipient of shocks especially during the GFC. Figure 5.9 depicts China as a shock transmitter during the Chinese market crash. This shows how China is becoming a more influential economy in Asian, especially in recent periods (Chow, 2017). This finding is supported by Fukuda and Tanaka (2017), who found that the Chinese impact on other financial markets has risen in recent years. It can also be observed that China's integration into the global market has increased in the recent periods, increasing its potential to transmit shocks to other Asian markets and extend these shocks to other global markets (Hung, 2019). These findings are supported by Morck and Yeung (2016), who showed that the Chinese growth adversely affected neighbouring countries by transmitting shocks to other Asian markets. The increase in cross-border activities not only facilitated growth of the economy, it also acted as a channel of spillover (Haldane, 2009).

- India

  India received and transmitted large shocks during periods of major crises. This implies that India acts as a channel to spread shocks it receives from other markets. In general, India acted as a shock transmitter during the GFC. Figure 5.9 shows that India was the net transmitter of shocks in 2013 – 2014, which was associated a period of considerable depreciation of the rupee. This had an impact on its trading partners (Roy and Roy, 2017).

- Indonesia

  Figures 5.7 and 5.8 indicate that Indonesia received more and transmitted fewer shocks to other Asian countries. Like other Asian markets, it received bad spillovers during the bursting of the dot-com bubbles, the GFC, the EDC and the recent Chinese market crash. Further, Figure 5.9 reveals that within the sample period, Indonesia, on average, recieved more shocks from other Asian markets. The results also show that Indonesia transmitted more shocks at the beginning of the sample period.

- Japan

  Japan was affected by bad spillovers from other economies, especially during period of crises. It also transmitted large shocks during the GFC. T Figure 5.9 shows that Japan was the net transmitter of shocks especially during the GFC. This is because of its linkages with other countries, especially in developed markets. This agrees with Miyakoshi (2003), who found that Japan was more influential in terms of shock propagation to other Asian markets. Asian markets are becoming more sensitive to shocks from Japan, and trade relationships with other markets are a possible channel of spillover for the Japanese economy. This is supported by Morck and Yeung (2016), who showed that China, as a significant trading partner of Japan, acts as a major source of shock transmission to Japanese market.

- Hong Kong

  Hong Kong received and transmitted more shocks, especially during periods of stress. This suggests that Hong Kong, with more interconnections with other markets, acts as a potential channel of shock transmission in the financial system. It became the net receiver of shocks during the bursting of dot-com bubble and the net transmitter during the GFC.

- Malaysia

  Malaysia received spillover from other countries especially during crises. Unlike other countries, Malaysia showed a different trend in transmitting shock to other countries. We observed that it transmitted more shocks during the most recent periods. Figure 5.9 shows that Malaysia is the net transmitter of shocks especially in the most recent periods.

- New Zealand

  New Zealand received large shocks during crises. Unlike other Asian countries, New Zealand had less impact in shock transmission. In fact, Figure 5.9 shows New Zealand as the net recipient of spillover from other markets.

- The Philippines

  The Philippines received more shocks, especially in major crises. This is consistent with Sok-Gee et al. (2010), who reported that the Philippines was more vulnerable to shocks from other markets. On average, the Philippines was a net transmitter of shocks, especially during periods of stress.

- Singapore

  Singapore received good spillovers from other economies, and transmitted bad spillovers to other markets. On average, Singapore was a net transmitter of shocks to other markets especially during crisis periods. This is consistent with other studies that demonstrated its integration with other markets, Singapore acted as a channel of shock transmission to the entire financial system.

- South Korea

  South Korea received and transmitted more spillover, especially in periods associated with crises. We regarded trade linkages of South Korea with other markets to be the channel through which it received shocks from other markets. This is consistent with Morck and Yeung (2016), who reported that China's significant trade in the recent past led to transmission of shocks to the South Korean economy .

- Sri Lanka

  We observed Sri Lanka receiving bad spillovers, especially during period of stress. Conversely, Sri Lanka transmitted large spillovers in 2006. Figure 5.9 shows Sri Lanka as the net transmitter of shocks, especially before the GFC. This period aligns with Sri Lanka's civil war. The war had an impact on the Sri Lankan stock market, which spread to its trading partners, especially Asian markets. This also suggests that external factors, including civil war, have an impact on shock transmission.

- Thailand

  Thailand received more shocks from other markets, especially during major crises. Figure 5.9 shows Thailand as the net receiver of shocks from other markets. This finding is consistent with Sok-Gee et al. (2010), who showed that Thailand has become more vulnerable to shocks especially from other Asian markets.

- Taiwan

  Taiwan received and transmitted spillover to other markets especially during stressful periods. The findings show that Taiwan was the net transmitter of shocks, particularly during crises. This suggests that it acts as a bridge of shock transmission to other markets, especially during crisis events.

In conclusion, our results demonstrate the sensitivity of Asian economies in both absorbing and spreading shocks, especially during times of intense spillover. These results are supported by Yarovaya et al. (2016b), who found existence of asymmetry in shock reception and transmission by these economies. We also observed that most fluctuations in spillover for Asian economies occurred during the global crisis. This is consistent with Hu et al. (2018) and Kim et al. (2015), who showed that the US is the main contributor of spillover to the Asian region.

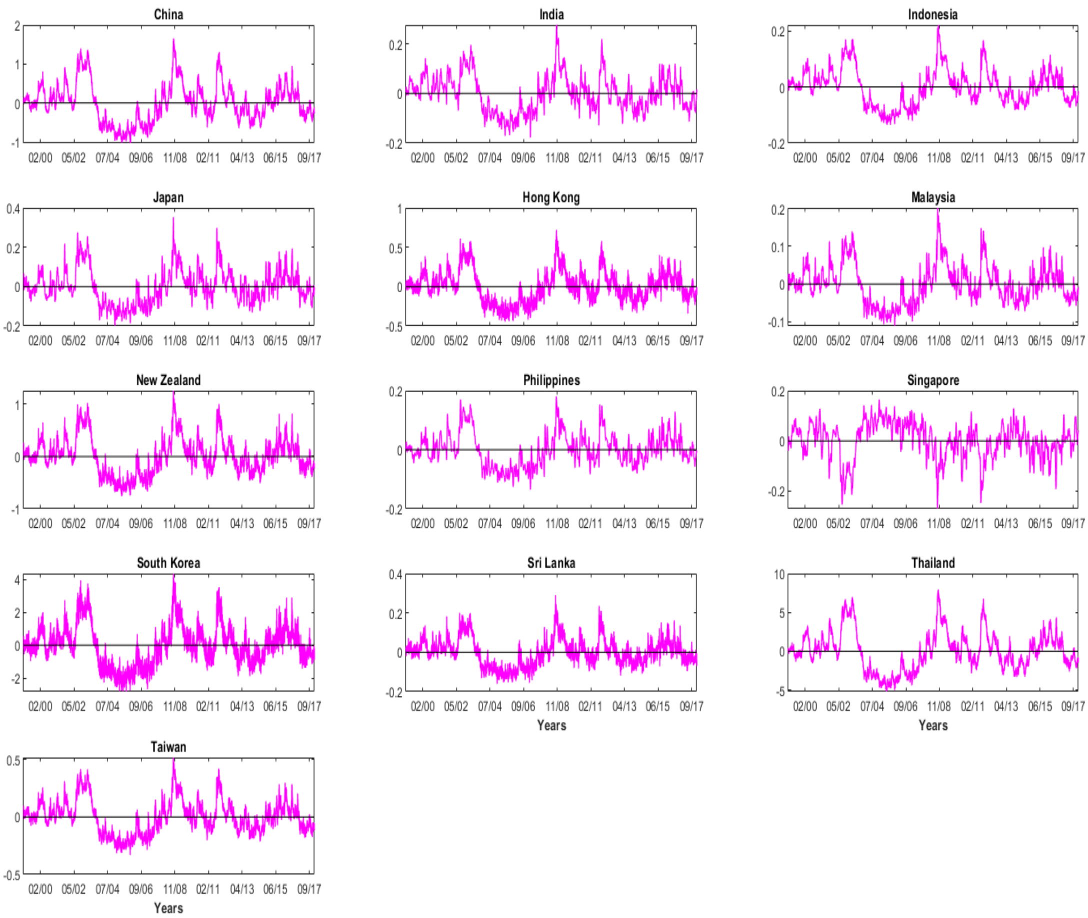


Figure 5.7: Average spillovers received by each of Asian economies in Regime 2

5.5.6 Robustness

Previously, we used 5 lags for the MS-VAR model that was based on AIC to estimate the signed spillover. Therefore, it is logical to discuss the robustness of our results based on the choice of

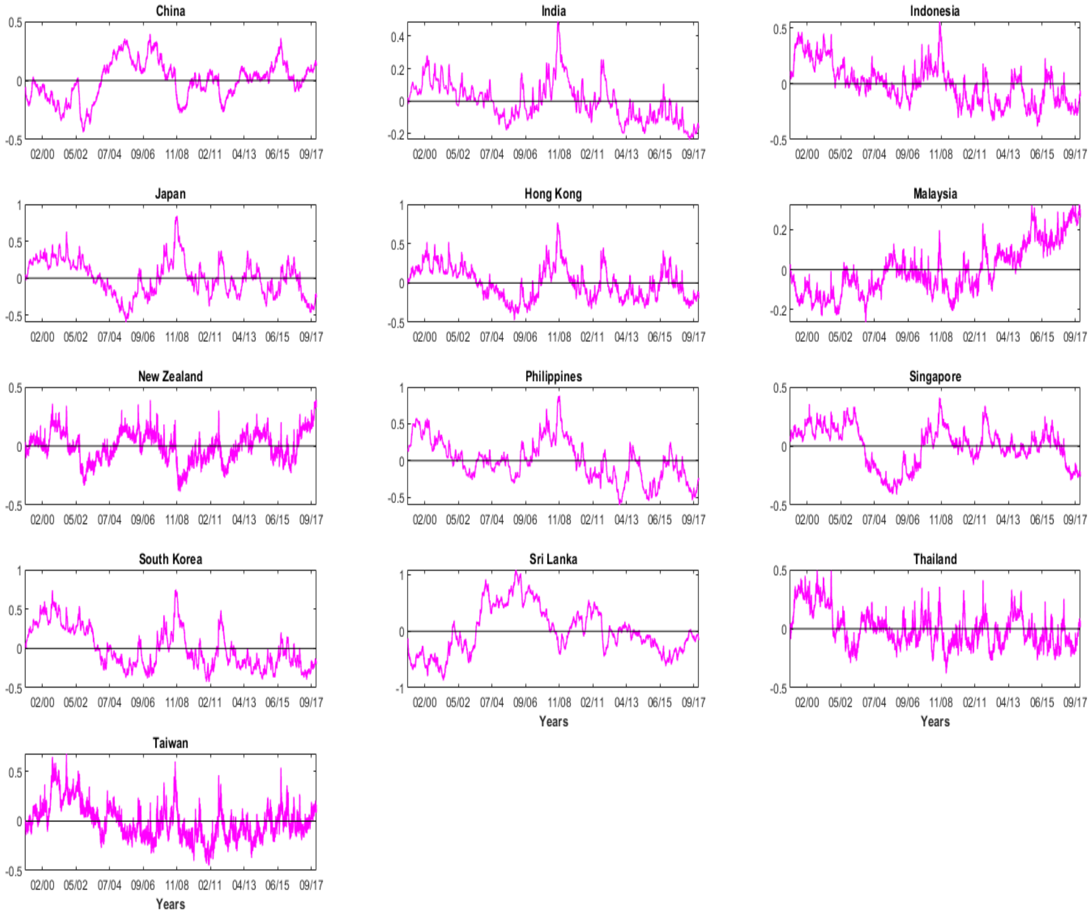


Figure 5.8: Average signed spillovers transmitted by each of Asian economies in Regime 2

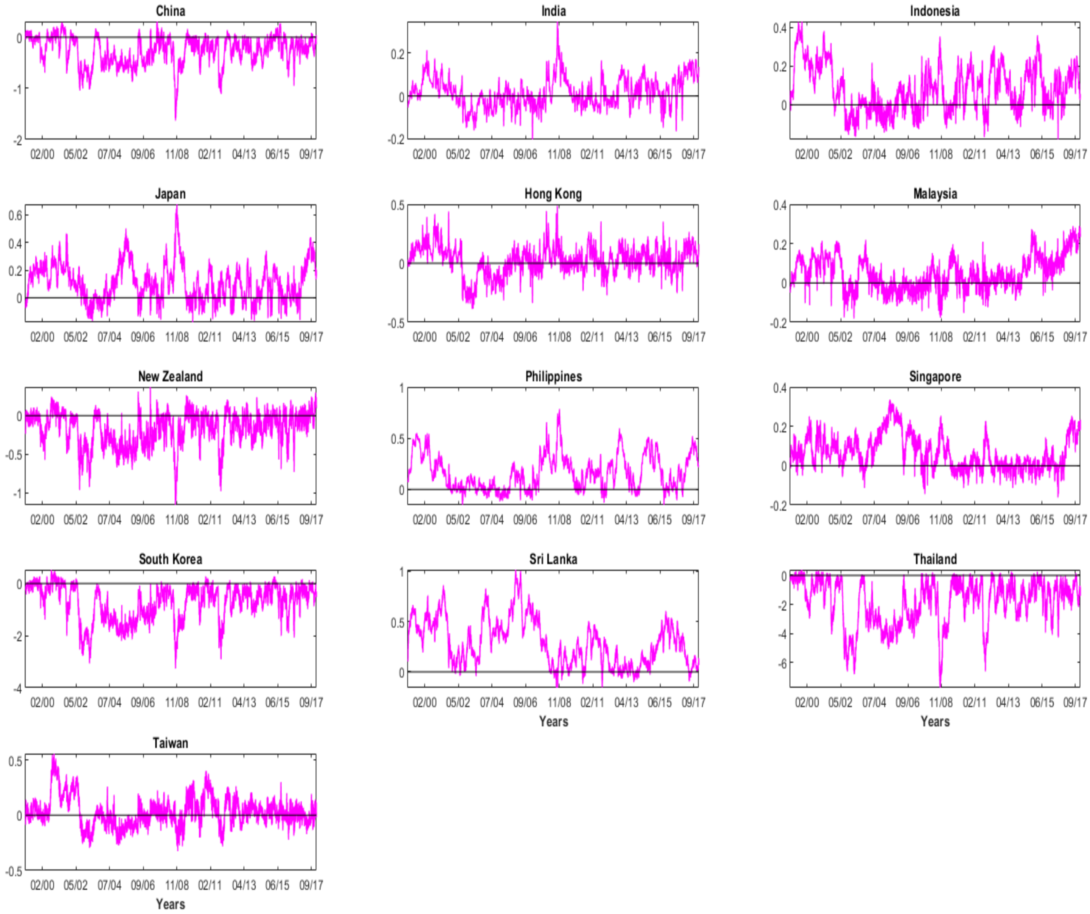


Figure 5.9: Net spillovers for each of Asian economies under Regime 2

the lag length. We do this by estimating the total signed spillover at both higher and lower ($L = 12$ and $L = 2$) lags.

Figure 5.10 and Figure 5.11 display the signed spillover in both regimes and the total signed spillovers. These figures offered a similar conclusion that of Figure 5.3. This is consistent with Chowdhury et al. (2019), who reported that the choice of lag-order of the VAR model is not sensitive to altering results. The magnitude of the signed spillover either increased or decreased when the number of lags decreased and increased respectively. Figure 5.11 displays a clearer distinction between the signed spillovers in both regimes. For instance, this figure shows that the signed spillover was more intense in Regime 2 than in Regime 1. This suggests that more shocks were transmitted and received when the financial system was under stress.

We also slightly modified the factor $\delta = 1.4$ in distinguishing the two regimes to avoid identification of parameters in both regimes. The results and conclusion remained the same. Thus, we conclude that our findings are robust based on the above adjustments.

We also considered alternative realised variance estimator which is based on high/low range estimation. We estimate the daily range from five-minutes intra-day high and low prices obtained from Thomson Reuters DataScope Select using Tick-History. Following Andersen et al. (2006), we used log range which follows a normal distribution to estimate the total spillovers in both regimes. [5] Figure 5.12 displays a comparison of total spillover in both regime using realised variance and range-based estimators for the period January 1999 to December 2017. Figures 5.12a and 5.12b slightly differ in patterns but the trend is almost identical. Both realised variance and range-based spillovers estimates arrive to same conclusion that the total spillovers tend to increase during crisis periods and remain low during normal times. We also note that using different volatility estimators may exhibit different behaviours and thus may result to different patterns of the total spillovers as observed in Figure 5.12. We conclude that our results in Section 5.5 are robust and can be relied on based on Figure 5.12b (using range-based estimator).

5.5.7 Implications of signed spillover to the economy

The financial system is continuously increasing size. This has led to the growth of different interactions between economic agents, which has created channels for shock transmission and absorption. This was our motivation for investigating the implication of the signed spillover

[5]See Chou et al. (2010); Garman and Klass (1980); Parkinson (1980) for more details on range volatility estimations.

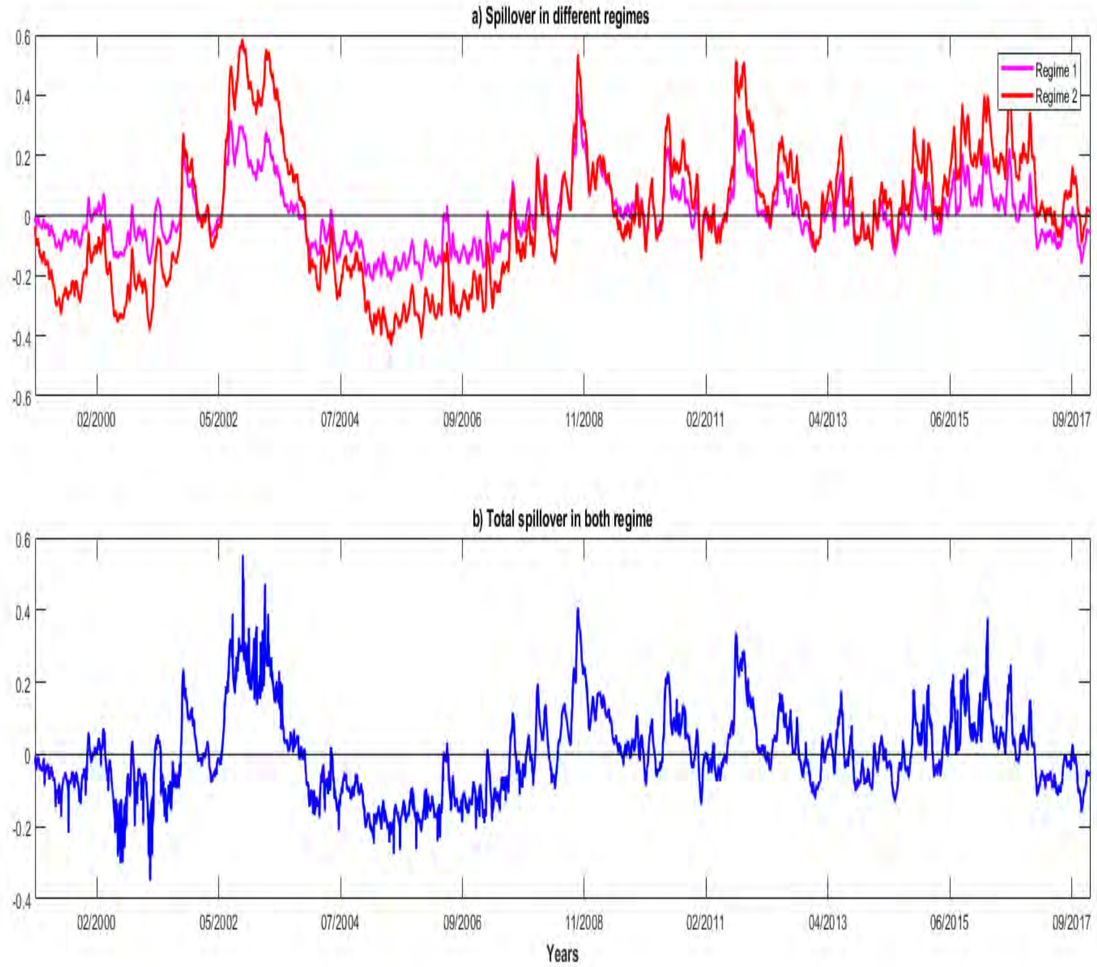


Figure 5.10: Average signed spillovers for the whole sample in different regimes based on twelve lags. Figure 5.10a display absolute spillovers in the two regimes while Figure 5.10b displays the total spillovers in both regimes. The sample period is from January 1999 to December 2017.

on the economy in terms of the size of the financial sector and the market risk. This was done by considering a simple correlation of the signed spillover with the size of financial sector and market risk factor. The size of the financial sector was measured as the average market value of the economies in our sample. For market risk factor, we used ExRM proposed, by Fama and French (1993) as a proxy which represents the excess market return over 90 days' treasury bills (T-Bills) rates. We obtained excess market returns for all economies in the sample and employed the average. The market value, stock prices and 90 days' T-Bills rates for all economies in our sample were obtained from Thomson Reuters Datastream. We used the average excess market returns from these economies for the analysis.

Our results indicate that the correlation between our sign spillover and the market risk factor was negative at -0.3134. This suggests that as market risk factor increased, signed spillover spread on financial markets had a negative effect.

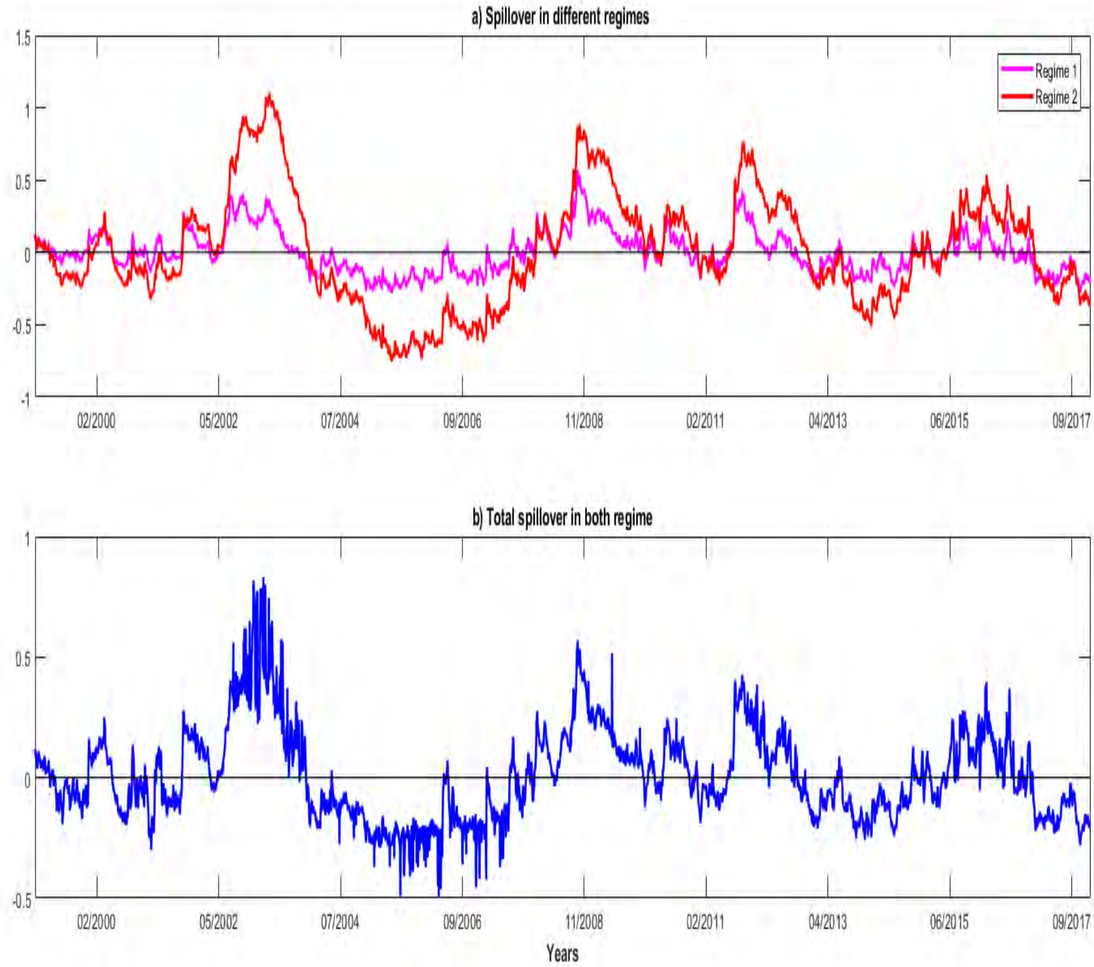


Figure 5.11: Average signed spillovers for the whole sample in different regimes based on six lags. Figure 5.11a display absolute spillovers in the two regimes while Figure 5.11b displays the total spillovers in both regimes. The sample period is from January 1999 to December 2017.

Additionally, the correlation between the signed spillover and the size of the financial system is negative at -0.0181. This suggests that as the size of the financial system increases, the financial system becomes more exposed to shocks thereby increasing its impact. The shocks, transmitted and absorbed, have negative effects on entire financial system.

5.6 Chapter summary

This chapter investigated whether volatility spillover in the financial market changes across different regimes. We further distinguished the spillover with signs to investigate the impact of the shocks transmitted and received in the financial system. This aimed to distinguish between **good** and **bad** spillovers. The empirical part of this chapter used realised volatility data estimated from high frequency data.

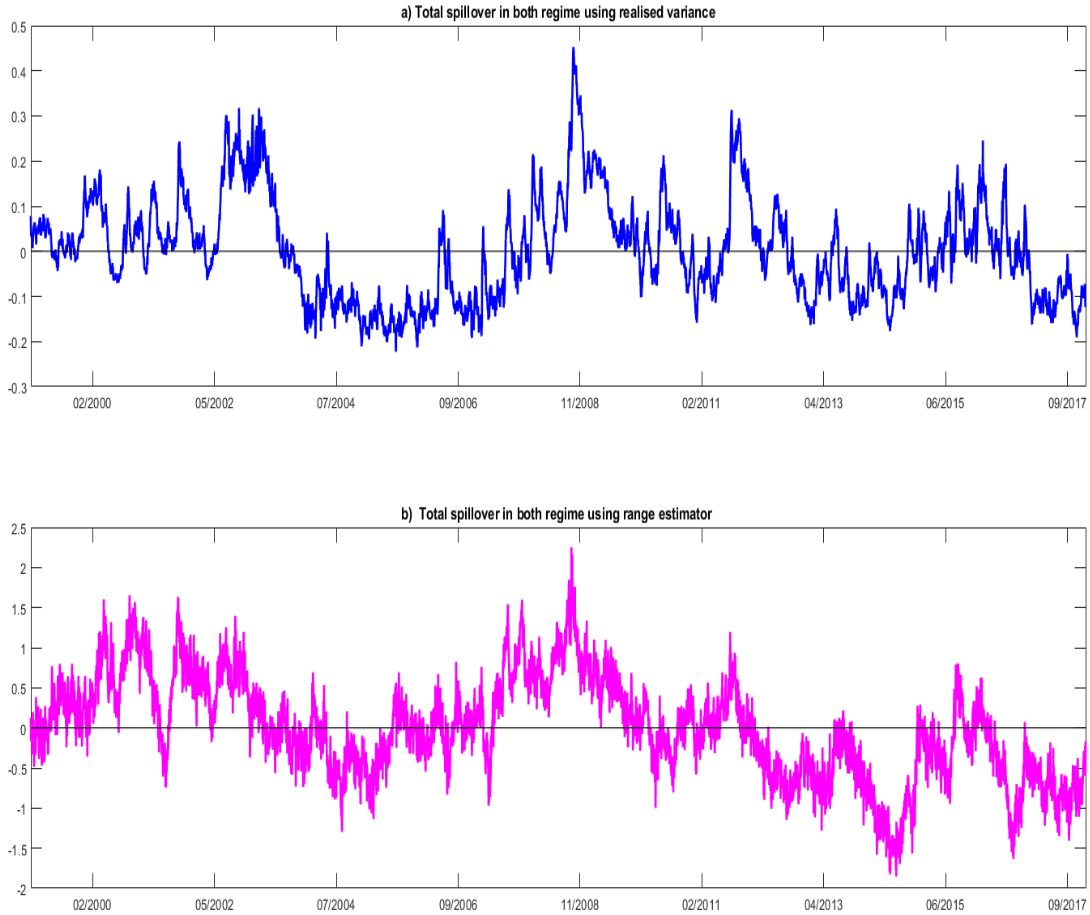


Figure 5.12: Total spillovers based on realised variance and range estimators. The figures compare the total spillovers in both regimes using realised variance and range-based estimators. The sample period is from January 1999 to December 2017.

Our findings show spillover in the financial system differs depending on the regime. For example, spillover remained higher in Regime 2 (high-risk regime) compared to Regime 1 (low-risk regime). These results also indicate that increasing signed spillovers are associated with periods of financial stress. The expected duration remaining in intense spillover regimes were less than that of remaining in moderate regimes.

The findings in this chapter have implication for the financial system and could be useful to inform policy makers' and regulators' decision-making processes. For instance, these findings could be useful to design appropriate policies to monitor the financial system to reduce the impact of extreme events, thereby promoting financial stability.

6 Conclusion

6.1 Summary of findings and implications

This thesis was motivated by the recurrence of crises that cause havoc in the global financial system. It aimed to assess vulnerability in global financial networks through identification of causal relationships among different financial markets. Interconnectedness among different markets plays a crucial role in the transmission of shocks across the financial system. Various aspects of vulnerability in the financial markets were studied. The focus of the thesis was global financial markets, with emphasis on Asian markets.

Different approaches were used to assess and detect vulnerabilities across financial markets. Chapter 2 employed combined Granger causality and the DY approach to identify interconnections among different markets. Chapter 3 introduced the SAR model on the CAPM to capture network exposure. Chapter 4 used spillover and contagion methodologies to assess vulnerability in the financial system. Specifically, it applied GHD in VAR to detect spillover and apply portfolio mimicking factor framework using moment conditions to detect contagion. Chapter 5 applied the GHD in VAR with the extension to Markov-switching framework to examine the dynamics of spillover in different states of the market. This chapter presents key findings in line with the objectives of the thesis, earlier outlined in Chapter 1.

O1. Investigate the structure and characteristics of networks among different financial markets

Chapter 2 investigated the structure of networks in financial markets. These markets were categorised into regions representing the global financial system. The findings show the complexity in the structure of the financial system. New links were formed and were others removed from phase to phase. This implies that interconnectedness among financial markets changes over time. The roles of major markets, such as the US and UK were evidenced by their large and stronger interconnections with other markets.

Over time, however, the number of linkages increased between most Asian markets and other regions. We hypothesised that this was because the development of new markets benefits from the support (or existence) of geographically localised hubs or centres that help establish the role of an emerging market within global markets. Conversely, there was also evidence of large markets, such as India, emerging to become more interconnected with global markets without significant use of a geographically based hub. In the Indian case, this may be a consequence of strong historical links to British institutional structures. However, this hypothesis is yet to be empirically tested.

The contribution of gateway or core markets within a region to the development of emerging markets is a strong argument against proposals to develop policies to remove these features from networks–that is, to reduce complexity and increase the randomness of the network. Doing so may have detrimental effects on the development and deepening of emerging markets, which appeared to 'grow' into maturity by establishing their own direct links with non-regional markets through the legitimacy of first transmitting through regional hubs. This is critical for regions with significant untapped financial deepening; a structure that may be beneficial to already developed markets may limit opportunities for those that are emerging.

A core set of markets to support regional financial development may be aided by the formal economic cooperation of strategic players. For example, the results show that while Singapore and Hong Kong played important roles as gatekeepers for many Asian markets, when ASEAN economies were aggregated, their developing role in the world financial markets and as a gatekeeper group of markets was clear.

O2. Examine the emerging role of Asian markets in the global economy

Chapter 2 studied the evolution of the network structure for individual Asian markets in each phase. The findings show that the strength of interconnections for these markets with others changed over time. The evolution of these interconnections presented a brief history of these countries in terms of network structure. These network evolution histories guide policy makers in monitoring these economies with the aim of promoting financial stability.

The recent involvement of Asian markets in the global economy shows the growing importance of these markets in spreading shocks to other markets. The evolution of the financial network over time clearly indicates the growing internationalisation and interconnectedness of Asian markets. We highlighted instances in which this occurred through the interaction of markets with local or regional core or gatekeeper nodes, particularly Hong Kong, Singapore and ASEAN economies.

O3. Assess the degree of network exposure among the global financial markets

Chapter 3 examined vulnerability in the economy through network exposure among financial markets. This objective was achieved by assessing the effects of network exposure on the global economy. Both interconnectedness (captured through connectedness matrix, W) and network intensity parameters (captured using spatial coefficient, ρ) played key roles in assessing network exposure. The findings revealed that both network intensity and interconnectedness among different financial markets increased network exposure.

Additionally, our findings showed that high network intensity was associated with periods of stress. Thus, estimates of network intensity might be used by policy makers to develop policies to monitor the financial system, which would reduce the exposure in global financial network.

O4. Detect the transmission of spillovers and contagion among financial markets with emphasis on Asian economies

Chapter 4 assessed vulnerability in the financial system by detecting spillover and contagion. Quantifying spillovers and contagion between markets is challenging because of the changing nature of volatility in financial markets. The underlying trade and portfolio relationships in the Asian region have grown rapidly and developed since 2000.

Chapter 4 detected evidence of spillovers, contagion interdependence and decoupling for 12 Asian markets, Australia and the US.[1] The findings showed distinct evidence of changes in spillovers between these markets, with increasing evidence of growing effects over the four periods (pre-GFC, GFC, the EDC and most recent periods). The continued effects of the US markets on Asian markets were also apparent. There was a high degree of spillovers from China and the US, both to each other and to other Asian markets. The results also showed strong evidence of both contagion and decoupling effects using the US as the global mimicking factor. Asian markets showed evidence of decoupling from the shocks in the US market during the GFC period. In other words, Asian markets were less influenced by the turmoil in the US markets than would have been anticipated by the degree of spillovers evident in the pre-GFC period. The EDC and the most recent periods also showed signs of change in the transmission of events via the contagion route, although these effects did not return transmissions to pre-GFC levels.

Chapter 4 further considered the possibility that China acts as a source of contagion in

[1] Interdependence implies no statistically significant changes in transmissions between assets (correlation) and decoupling relates to a statistically significant reduction in transmission between assets (correlation).

Asian markets because of its growing importance in the global economy. The findings showed evidence of contagion from China to other Asian markets, especially during the European sovereign debt crisis. It is important to note that this is a prime example of where contagion could be considered positive for recipient markets. During this period of global stress caused by the EDC, China's effects helped sustain higher returns for other markets. This is an instance in which China was not the relevant indicator for the source of global shock in detecting contagion emanating from a crisis. This was further evident when a two-factor specification was used where China and the US represented potentially separable effects on other markets. The intertwining between these two markets was evident in the spillover results, preventing these from being a suitable representation of independently identifiable contagion effects on Asian markets. This resulted in the model's poor empirical characteristics.

O5. Analyse the volatility spillovers among the global financial markets across different economic conditions

Chapter 5 assessed vulnerability in the financial system by detecting signed spillovers across different economic states/regimes. The findings showed that shifts between moderate and intense regime occurred at high probabilities. Additionally, an intense spillover regime was associated with high risk, while moderate spillover regimes were associated with low risk.

The main contribution of this study was to distinguish the impact of signed spillovers under different market conditions. The results showed that periods of financial stress are associated with increasing positive spillovers. This implies that intensity of spillovers increases during periods of financial stress. The results suggest that volatility transmission should be estimated in different regimes to help policy makers and regulators distinguish the intensity of spillovers.

Additionally, assigning signs to the spillovers helped distinguish between 'good' and 'bad' spillover. Our results showed that bad spillovers were associated with intense regime which suggests that bad spillovers are associated with periods of high risk. Moreover, the signed spillovers peaked during periods of financial stress, specifically during the GFC. This would guide policy makers in monitoring the financial system, thereby promoting financial stability.

Chapter 5 also investigated the dynamics of spillover across individual Asian markets. The results showed that individual Asian economies act as channels to transmit shocks.

With economic integration, these markets have become more interconnected with other regions, creating channels for shock transmission and absorption.

This study also showed that both market risk factor and the size of the financial system have negative impacts on shock transmission. With the increasing size of financial markets, the financial system becomes more vulnerable due to increasing spillovers. Volatility transmissions also intensify with increasing market risk.

In assessing the vulnerability in the financial system, this thesis concludes that interconnectedness among financial markets plays a key role in shock transmission across the financial system. These transmissions vary over time and across different markets. Asian markets are growing in importance in transmitting and absorbing shocks to and from other markets.

6.2 Limitations and future research directions

Our endeavours to measure and assess vulnerability in the global financial network were subject to some limitations. Firstly, the single dimension of the financial network considered in this thesis limited our findings. The financial links between economies are certainly more complex than those established simply through equity markets. There is still a major challenge for researchers and policy makers to develop analytically tractable tools that reveal the complexity of the multiple layers of financial interconnectedness between economies through different asset markets and potentially different players. Sovereign bond networks will differ from equity market networks (see Dungey et al., 2019a). Real economy networks such as trade networks, or input-output production networks as in Pesaran and Yang (2016), will be tied to financial networks. However, the weights on the nodes are likely to be quite different, and may involve nodes that are not included in all layers. Further research is required to understand the roles of nodes in different layers of the network. This may be useful in understanding how effective policy interventions may be targeted at nodes that play critical roles in transmitting between layers to contain crises (or even to spread crises in a way that reduces their impact on individual layers and/or nodes). A recent step in this direction can be found in the multi-country or multi-market network analysis of Magkonis and Tsopanakis (2018).

Second, this thesis used BIS quarterly liability data to establish existing linkages in the financial system. This may have limited our findings because there are other channels through which shocks are transmitted in the financial system, including financial transactions, obligations and contracts. By focusing on credit exposures using liability as a proxy, our work was limited in identifying all possible channels of vulnerability in the financial system. Further research could be conducted at the country level by establishing interconnectedness using a combination of different channels to detect vulnerability among individual sectors and cross-border levels.

Thirdly, Chapter 3 of this thesis used a SAR model to assess the impact of network intensity estimates. However, we relied on a homogeneous SAR model, in that the spatial lag vector in the model was assumed to be the same for all institutions/assets. Using a homogeneous SAR model limited our findings. Future research could use a heterogeneous SAR model specification that allows variation in the spatial dependence, variance in the coefficients and variation in the disturbances.

A Appendix

A.1 Chapter 2

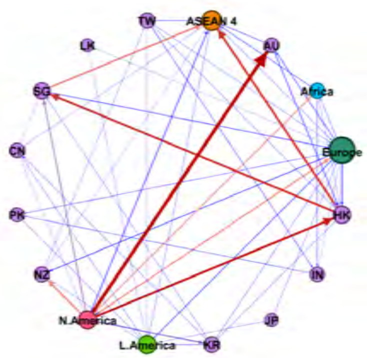
A.1.1 The role of ASEAN markets

Figure A.1 shows the importance of the link between Hong Kong and the association of Southeast Asian nations (ASEAN) markets over the whole period. Each phase diagram shows that this link remains prominent throughout the subsamples. These links primarily run from ASEAN markets to Hong Kong–as previously discussed, this reflects the role of Hong Kong (and Singapore, which is included in the ASEAN sample) in connecting Asian markets to the rest of the world.

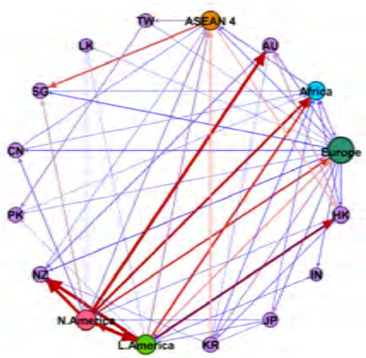
There were transformations of the structure of the network involving ASEAN and Asian markets across the differing phases. These transformations seemed to reflect the increasing development and deepening of the markets dominating the effects of crisis and non-crisis periods. Early in the sample, in Phase 1, there were noticeably fewer links to ASEAN economies than later in the sample. Links were mainly from or to developed markets rather than other developing Asian markets. Notably, Japan as not connected directly to ASEAN in this period. During Phase 2, there was a distinct change–inward links to ASEAN from other Asian markets begin to appear, from China and South Korea. Japan remained directly unconnected.

In Phase 3, post-Asian crisis, the US was clearly central to distribution within the network. Links from other markets continued to develop, with Japan, Taiwan and Pakistan connecting, although South Korea dropped the associations it had during the crisis period of Phase 2. China also connected to the network via its non-Asian connections, but had the role of an end node in this network, a position also occupied by Sri Lanka. In the build-up to the GFC during Phase 4, the network showed ASEAN markets as having stronger links than previously, with a similar group of market to the previous phase. The Indian market, which was previously not directly linked with ASEAN markets, was now present; Pakistan remained relatively isolated.

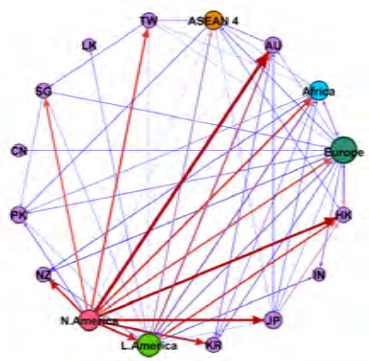
During the GFC itself, Phase 5, the network was dramatically different to than in previous phase. Having subsumed the density of links between European, North American and Latin



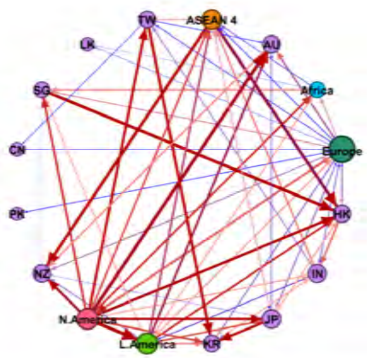
(a) Phase1



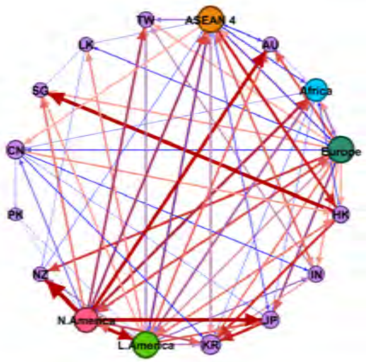
(b) Phase 2



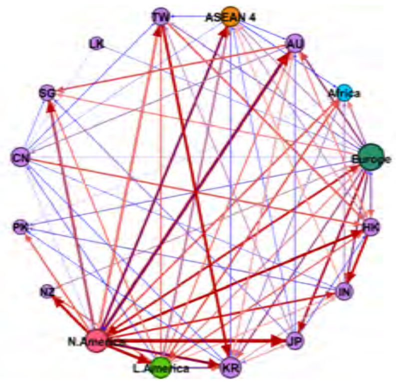
(c) Phase 3



(d) Phase 4



(e) Phase 5



(f) Phase 6

Figure A.1: Evolution of weighted networks with regional groupings highlighting ASEAN and the Asian markets.
Notes: Sample period was 1 March 1995 – 30 December 2016. Regions are colour-coded: Asia (light green), Europe (magenta), North America (dark green), South America (blue), Africa (orange), as defined in Table 2.1. The figure displays the returns-based network of 42 equity markets. Edges were calculated using bivariate Granger causality tests between markets at the 5% level of significance. Edge thickness is proportional to the intensity of the edge strength and is set as: red (strongest), orange (medium) and blue (weakest). Node colour is proportional to the regional grouping while node size is proportional to its degree.

American into regional nodes, it was apparent that during this period there was an important role for the transmission of shocks from the North American markets to ASEAN markets via Japan, less so from Australia than previously, and not at all from New Zealand. The critical paths from the rest of the world to Asian markets changed; Japan had a gatekeeper role that was not evident previously. China was now more strongly linked directly to ASEAN markets and North America, so there were both direct and indirect links between Asian and Chinese markets.

In the final phase, China continued to increase its number of direct links to other nodes in the network, and ASEAN markets were clearly an important hub in terms of the number of linkages coming into the ASEAN node. There were also substantial numbers of weaker links from ASEAN to other Asian markets, such as Japan, South Korea, India, Australia and Hong Kong. ASEAN markets in this final network identified a transition in which they were integrated into the international network in a completely different way than Phase 1 and the subsequent two phases. During the GFC, it appeared that Asian markets had matured to become more clearly interconnected with other major regions, through the hubs of ASEAN, Hong Kong and Singapore, and more directly by links to major regions.

The conclusion from this analysis is that ASEAN markets are part of the bridge between the market regions of Asia, Europe and the Americas. Consequently, there is a role here for ASEAN markets as a core for systemic risk in the Asian region; many links were filtered via ASEAN and Hong Kong markets. Other markets were less clearly hubs for connections with the rest of the world; however, this changed over the last phases as Asian markets became more completely connected to other regions of world markets.

A.2 Chapter 3

A.2.1 Network intensity using alternative weighting matrix

Here, we investigated the role of weighting matrix in estimating network intensity parameters. We worked with the first difference of trade data to construct an alternative weighting matrix. This matrix was then used to estimate network intensity coefficients. Our data comprised quarterly export and import data from the international monetary fund (IMF), world economic outlook (WEO) database for the selected economies. Both indirect and direct trade linkages acted as channels through which shock was transmitted in the financial system. Trade linkages represented high trade exposures in the financial system. For instance, Kali and Reyes (2010) reported that a shock is amplified in the system when financial institutions are more integrated in terms of trade linkages. Asgharian et al. (2013) found that linkages through bilateral trade capture dependencies between stock markets. This is due to feedback effects among financial markets. This suggests that trade concentration is one of the important channels through which shocks spread in the financial system.

In Figure A.2b, we presented the network intensity estimates based on trade weighting matrix. The horizontal red line represents the mean value (0.5698) in the whole sample period while the shaded area is the 95% confident interval. These results showed that higher network intensity estimates were associated with periods when financial systems were under stress. For instance, higher network intensity in 2002 corresponded with the dot-com bubbles while there was sharp decrease in the estimate in 2003. The estimate then fluctuated upwards and decreased just before the global crisis. There was a sharp increase in the estimate during the GFC. The estimates remain higher after the global financial crisis. A network intensity above 65% at the end of the sample period signifies a high risk of collapse when a shock hit the financial system. As can be observed in Figure A.2b, network intensity increased when a shock hit the financial system and decreased in normal periods. This supports our conclusion that a sharp increase in network intensity signals that the financial system is in distress. This observation would help regulators and policy makers monitor these financial institutions.

A.2.2 Comparison of estimates using both liability and trade weights

Figure A.2a depicts the role of the weighting matrix in estimating the network intensity parameter. The horizontal line is the mean value of the estimate obtained using both trade and liability weighting matrix in the whole sample. These results revealed that the trade weighting matrix contributed to the upwards shift of the weighting matrix from 0.5149 − 0.5698. This also implies that the mean value of the estimate is 0.5698 using trade weight matrix and 0.5149 when the liability weighting matrix is used.

The connection matrix played an important role in the estimation of the network intensity parameter. From Figure A.2a, it is clear that although the weighting matrix results in estimates with almost similar trends, their sizes differ in both cases. The network intensity estimates based on trade weights were higher than those obtained using the liability weighting matrix. This suggests that shocks through trade linkages would be more sensitive to the economy compared to those from liability linkages. This supports the fact that the strength of trade linkages increase due to bilateral trade among different markets. The patterns of network intensity

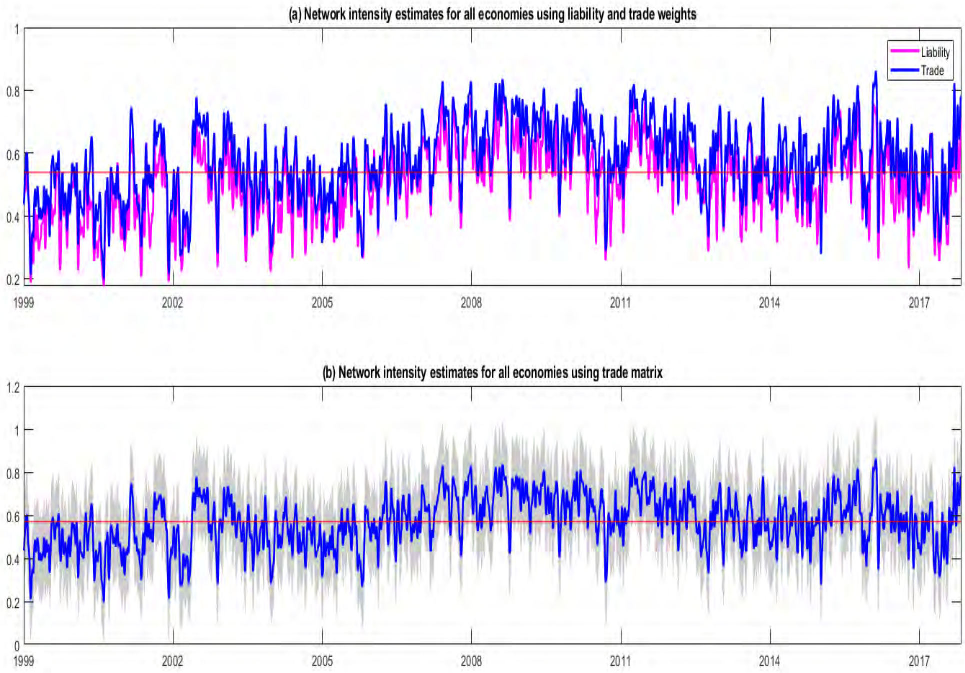


Figure A.2: Network intensity estimates based on trade and liability matrix. The figures compare the network effect using both liability and trade connection matrices for the whole sample period.

estimate also differed at different points in time. For example, the network intensity obtained using trade weights increased before the dot-com bubbles, while network intensity estimated using liability data decreased.

A.2.3 Comparison of MLE with other approaches

Although we used the dynamic MLE approach to estimate the network intensity parameter, we also explored a state-space approach. A state-space model describes the dynamics of a latent state and how the data relate to this state. A general SAR model can be represented in a state-space form with observation and state evolution respectively as:

Observation equation:

$$y_t = C\rho_t W y_t + DX_t + v_t, \quad v_t \sim N(0, V_t) \tag{A.1}$$

State equation:

$$p_t = c_1 + Ap_{t-1} + BX_{t-1} + w_{t-1}, \quad w_{t-1} \sim N(0, W_{t-1}) \quad \text{and} \quad t = 1, 2, ..., T \tag{A.2}$$

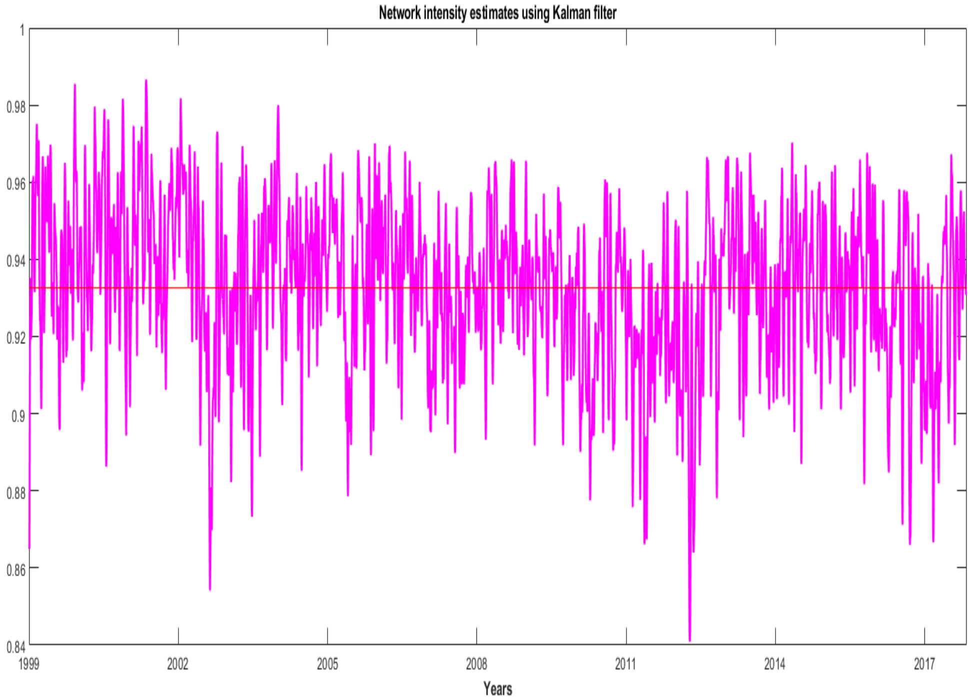


Figure A.3: Network intensity estimates using Kalman filter

where A_t, B_t and D_t are the input variables and C_t is the state loading matrix. v_t and w_t are measurement and state space process errors respectively, X_t is the exogenous variables. The observation equation can be expressed in matrix form as

$$\begin{bmatrix} X_t \\ y_t \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ D_t & C_t \end{bmatrix} \begin{bmatrix} X_t \\ \rho_t W y_t \end{bmatrix} + \begin{bmatrix} 0 \\ v_t \end{bmatrix} \tag{A.3}$$

while the state equation can be represented as

$$\begin{bmatrix} X_t \\ p_t \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ B_{t-1} & A_{t-1} \end{bmatrix} \begin{bmatrix} w_{t-1} \\ p_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ w_{t-1} \end{bmatrix} \tag{A.4}$$

Figure A.3 shows the network intensity estimates obtained using a Kalman filter. These estimates support our previous findings in Figure 3.9a, which showed that the network intensity remained higher during periods of stress. This explains the high exposure of financial markets during difficult times. Caution is required to correctly monitor markets during periods of stress, which correspond with increased fragility in the financial system (Sun and Chan-Lau, 2017).

A.2.4 Dynamics of network intensity parameter

We simulated 4,956 daily data (the estimate choice is based on the number of sample size in our analysis) using different specifications of the spatial coefficient. These patterns are similar to Brownlees and Engle (2016) and follow:

- constant: $\rho_t = 0.5$
- sine: $\rho_t == 0.5 + 0.4 * cos(2 * pi * k/200)$
- fast sine: $\rho_t = 0.5 + 0.4 * cos(2 * pi * k/20)$
- step: $\rho_t = 0.9 - 0.5 * (k > 500)$

All these specifications give different patterns of the network intensity parameter. Using these different specifications will help to investigate whether the initial values of the network intensity parameter matter in the estimation. Figure A.4 shows these forms of network intensity parameters. The results shows that network intensity parameters have different forms of changes. The constant shows a constant trend, Sine shows exhibit gradual change, and the fast sine has rapid change while step changes in different steps.

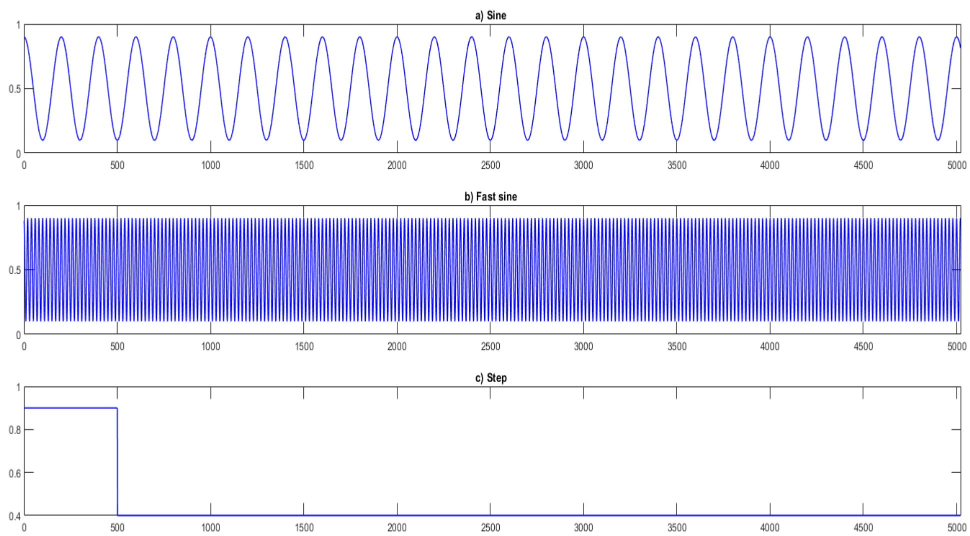


Figure A.4: Simulated network intensity dynamics

A.3 Chapter 5

A.3.1 Static signed spillovers at each phase

Tables A.1 to A.4 presented the static signed spillover at each phase. These results correspond to the signed spillovers in Regime 2 (associated with intense spillover). From these tables, it is evident that the signed spillover estimates vary at each phase with high variation in crises. The implication of this is that more bad spillovers were transmitted during the GFC followed by the EDC, with total spillover being 51.47 and 5.12 respectively. As a result, the financial system was exposed to different shocks over time which may have had adverse effects on financial stability.

The static spillover results were limited due to increasing variability in the financial market. For this reason, we investigated how the signed spillover changed over time. This would help investors' and policy makers' decision-making processes by increasing understanding of the changing nature of vulnerability in the financial system.

Table A.1: Average signed spillovers under Regime 2 during the pre-crisis period

	AT	BE	FR	DE	GR	HU	IE	NL	NO	PT	ES	CH	TR	GB	BR	CL	MX	US	AU	CN	IN	ID	JP	HK	MY	NZ	PH	SG	KR	LK	TH	TW	Cont. FROM
AT	0.00	0.49	1.64	1.16	0.69	0.06	0.67	0.70	0.86	0.44	1.66	0.49	-0.48	1.55	0.54	0.75	0.24	0.68	0.17	0.01	-0.36	-0.80	-0.36	-0.38	-1.60	-0.21	-1.48	0.05	-1.04	-0.80	-0.56	-0.59	0.13
BE	-0.16	0.00	-0.97	-0.96	-0.53	-0.06	-0.26	-0.65	-0.38	-0.28	-0.86	-0.56	0.35	-0.58	-0.59	-0.41	-0.23	-0.19	-0.08	-0.01	0.14	0.33	0.18	0.13	0.58	0.08	0.59	-0.02	0.35	0.42	0.21	0.34	-0.13
FR	-0.15	-0.54	0.00	0.52	-0.23	-0.01	-0.08	-0.35	-0.58	-0.06	-1.56	0.10	0.27	-0.89	-0.15	0.20	0.13	-0.19	-0.23	-0.01	0.15	0.29	0.26	0.10	1.15	0.08	0.59	-0.01	0.59	-0.05	0.13	0.12	-0.01
DE	-0.18	-0.06	0.00	0.00	-0.25	0.05	0.12	0.08	0.36	-0.02	1.18	0.10	-0.21	0.88	0.51	-0.52	0.02	0.23	0.14	0.01	-0.16	0.35	0.00	-0.12	-0.53	-0.08	0.03	0.01	-0.22	0.39	0.09	0.00	0.07
GR	-0.50	-2.90	-2.51	-2.56	0.00	-0.29	-1.35	-2.05	-1.76	-1.31	-2.45	-1.69	1.01	-2.27	-1.13	-1.02	-0.75	-0.61	-0.23	-0.03	0.55	1.45	0.39	0.57	2.24	0.22	1.51	-0.06	1.13	1.37	0.74	0.89	-0.42
HU	-0.11	-0.09	-0.43	-1.46	-0.68	0.00	-0.18	-0.82	-0.42	-0.17	-0.70	-0.35	0.32	-0.72	-0.83	-0.42	-0.43	-0.28	-0.07	-0.01	0.18	0.55	0.18	0.01	0.27	0.08	0.57	-0.03	0.40	0.32	0.26	0.54	-0.14
IE	-0.06	-0.91	-0.96	-0.31	-0.16	-0.02	0.00	-0.57	-0.22	-0.29	-0.68	-0.47	0.26	-0.42	0.00	-0.22	-0.18	-0.29	-0.10	-0.01	0.15	0.33	0.10	0.40	1.32	0.10	0.42	-0.03	0.55	0.48	0.30	0.26	-0.04
NL	0.07	-1.58	-0.28	-0.49	-0.34	-0.08	-0.09	0.00	0.39	0.15	0.18	-0.41	0.02	-0.53	-0.31	0.28	-0.16	-0.06	0.12	0.00	0.03	-0.12	-0.01	0.08	0.04	0.01	0.06	0.00	0.13	0.06	-0.09	0.20	-0.08
NO	-0.60	-3.59	-3.45	-2.54	-1.71	-0.20	-0.88	-1.34	0.00	-1.59	-4.05	-1.32	1.34	-2.57	-1.47	-1.49	-0.70	-0.97	-0.33	-0.03	0.67	1.69	0.54	0.40	2.77	0.32	2.05	-0.08	1.87	1.53	1.03	0.79	-0.44
PT	-0.42	-3.03	-2.38	-1.57	-1.04	-0.12	-0.94	-1.31	-1.17	0.00	-2.95	-0.82	0.67	-1.82	-0.82	-0.86	-0.24	-0.62	-0.34	-0.03	0.60	1.29	0.41	0.60	1.81	0.20	1.30	-0.05	1.11	0.90	0.65	0.53	-0.33
ES	-0.21	-1.70	-1.86	-0.52	-0.49	-0.06	-0.53	-0.39	-1.09	-0.53	0.00	-0.34	0.42	-1.12	-0.36	-0.81	-0.12	-0.54	-0.16	-0.01	0.31	0.29	0.14	0.32	0.88	0.20	1.56	-0.05	1.11	0.62	0.44	0.43	-0.13
CH	-0.08	0.63	-0.22	-0.37	-0.44	-0.07	-0.50	-0.27	-0.23	-0.10	-0.15	0.00	0.13	0.38	-0.53	0.18	-0.09	0.29	-0.04	0.00	0.02	0.40	-0.10	0.04	0.10	-0.04	-0.84	0.00	-0.27	0.21	0.06	0.19	-0.05
TR	-0.64	-4.22	-3.60	-2.89	-2.52	-0.26	-0.92	-2.46	-2.21	-1.69	-3.66	-1.61	0.00	-4.15	-2.01	-1.52	-0.54	-1.27	-0.44	-0.04	0.76	2.02	0.72	0.57	3.07	0.32	2.81	-0.10	2.19	1.84	1.09	1.33	-0.63
GB	-1.46	-9.06	-8.82	-7.15	-5.47	-0.58	-2.80	-4.95	-5.21	-3.75	-9.00	-4.02	3.31	0.00	-3.53	-3.29	-1.46	-2.73	-1.01	-0.08	1.83	4.47	1.60	1.70	7.00	0.81	5.75	-0.22	5.08	4.11	2.50	3.03	-1.04
BR	-0.67	-3.00	-2.74	-3.24	-2.54	-0.19	-0.96	-2.29	-1.72	-1.19	-2.69	-1.63	1.07	-2.67	0.00	-0.91	-0.42	-0.72	-0.36	-0.02	0.54	1.64	0.47	0.53	1.79	0.23	1.76	-0.07	1.31	1.45	0.88	1.30	-0.47
CL	-0.48	-3.08	-3.16	-2.51	-1.57	-0.19	-0.94	-1.63	-2.07	-1.43	-3.10	-1.70	1.11	-2.38	-1.40	0.00	-0.71	-0.66	-0.31	-0.03	0.64	1.71	0.45	0.44	2.38	0.26	1.27	-0.07	1.52	1.43	0.89	0.83	-0.45
MX	-0.49	-2.53	-2.97	-2.21	-1.22	-0.17	-0.59	-1.56	-0.97	-0.92	-2.51	-1.35	0.73	-1.74	-0.94	-0.51	0.00	-0.77	-0.29	-0.02	0.42	1.45	0.39	0.43	1.45	0.21	1.04	-0.06	1.41	1.28	0.64	0.82	-0.36
US	-0.25	-1.87	-2.02	-1.03	-0.71	-0.08	-0.44	-1.02	-1.12	-0.45	-2.09	-0.61	0.57	-1.11	-0.50	-0.56	-0.22	0.00	-0.14	-0.01	0.36	0.70	0.31	0.29	1.21	0.18	2.11	-0.07	1.36	0.96	0.54	0.65	-0.16
AU	-0.62	-3.40	-3.57	-3.45	-2.47	-0.22	-1.52	-2.28	-2.22	-1.79	-3.69	-1.64	1.23	-3.25	-1.62	-1.15	-0.59	-1.01	0.00	-0.03	0.72	1.85	0.61	0.76	2.87	0.30	1.93	-0.08	1.70	1.39	0.96	1.20	-0.60
CN	-1.00	-5.49	-5.08	-4.67	-3.62	-0.38	-1.49	-3.36	-2.87	-2.11	-5.01	-2.91	2.54	-4.95	-3.01	-1.90	-1.00	-1.47	-0.65	0.00	1.10	2.62	0.89	0.93	3.97	0.46	3.19	-0.12	2.85	2.59	1.36	1.81	-0.84
IN	-0.12	-0.85	-1.05	-0.23	-0.49	-0.04	-0.40	-0.04	-0.55	-0.42	-1.21	-0.23	0.24	-0.41	-0.37	-0.50	0.10	-0.30	-0.16	-0.01	0.00	0.97	0.18	0.30	1.23	0.13	0.74	-0.03	0.68	0.44	0.23	0.30	-0.06
ID	-0.15	-0.76	-0.90	-0.18	-0.24	-0.06	-0.19	-0.40	-0.29	-0.46	-0.80	-0.16	0.14	-0.63	-0.31	0.00	-0.01	-0.29	-0.10	-0.01	0.16	0.00	0.13	0.23	0.38	0.01	0.54	-0.02	0.58	0.35	0.44	0.41	-0.08
JP	-0.18	-1.19	-0.44	-0.93	-0.28	-0.03	-0.05	-0.76	-0.94	-0.52	-1.38	-0.26	0.40	-0.27	-0.12	-0.68	-0.02	-0.17	-0.07	-0.01	0.05	0.20	0.00	0.03	0.33	0.07	0.44	-0.01	0.32	0.19	0.20	-0.10	-0.19
HK	-0.27	-2.47	-2.45	-1.63	-0.91	-0.10	-0.63	-1.45	-1.15	-1.08	-1.76	-1.03	0.95	-2.28	-0.36	-0.77	-0.52	-0.89	-0.28	-0.03	0.37	1.07	0.51	0.00	2.11	0.21	1.72	-0.05	1.40	0.99	0.65	0.80	-0.29
MY	-0.19	-0.74	-0.62	-0.40	-0.22	-0.05	-0.14	-0.04	-0.32	-0.27	-0.74	-0.32	0.09	0.08	-0.49	-0.01	-0.04	-0.18	-0.11	-0.01	0.12	0.33	0.05	0.14	0.00	0.13	0.45	-0.02	0.28	0.39	0.16	0.09	-0.08
NZ	-0.64	-3.99	-4.25	-3.11	-2.01	-0.23	-1.25	-1.93	-2.06	-1.64	-4.20	-1.66	1.38	-2.69	-1.59	-1.54	-0.55	-1.07	-0.44	-0.04	0.69	1.93	0.67	0.65	2.84	0.00	2.26	-0.09	2.07	1.71	1.03	1.12	-0.58
PH	-0.09	-0.31	-0.47	-0.37	-0.48	-0.05	-0.11	-0.45	-0.47	-0.01	-0.18	-0.80	0.30	-0.77	-0.41	-0.36	-0.05	-0.25	-0.04	-0.01	0.06	0.23	0.10	0.02	0.52	0.02	0.00	-0.01	0.21	0.21	0.16	0.08	-0.12
SG	0.24	1.30	0.41	0.79	0.63	0.05	-0.30	0.66	0.20	0.40	0.30	0.24	-0.19	0.68	0.06	0.11	0.33	0.01	-0.01	0.01	0.11	0.27	-0.02	0.02	0.13	0.05	0.30	0.00	-0.03	-0.30	0.12	0.02	0.21
KR	-0.19	-1.56	-1.59	-0.91	-1.16	-0.08	-0.32	-0.83	-0.92	-0.40	-1.51	-0.55	0.66	-1.39	-0.65	-0.58	-0.24	-0.53	-0.21	-0.01	0.27	0.53	0.27	0.24	1.01	0.16	1.09	-0.04	0.00	0.97	0.53	0.77	-0.22
LK	-0.11	-0.85	-0.71	-0.29	-0.38	-0.05	-0.17	-0.25	-0.51	-0.37	-0.98	-0.27	0.26	-0.50	-0.39	-0.47	-0.07	-0.10	-0.07	-0.01	0.17	0.42	0.08	0.08	0.85	0.03	0.42	-0.02	0.54	0.00	0.19	0.18	-0.10
TH	-0.41	-2.70	-3.06	-2.01	-1.80	-0.17	-0.91	-1.64	-1.61	-1.32	-2.99	-1.51	1.20	-2.95	-0.90	-1.00	-0.46	-0.79	-0.36	-0.03	0.77	1.52	0.42	0.70	2.47	0.28	1.54	-0.06	1.40	1.57	0.00	1.01	-0.43
TW	-0.30	-1.37	-1.56	-1.45	-1.08	-0.09	-0.47	-0.98	-0.91	-0.68	-1.39	-0.73	0.66	-1.27	-0.59	-0.33	-0.21	-0.59	-0.19	-0.01	0.27	0.99	0.33	0.30	1.39	0.12	1.26	-0.04	0.93	0.92	0.53	0.00	-0.21
Cont. TO	-0.33	-1.92	-1.88	-1.47	-1.05	-0.12	-0.58	-1.08	-1.00	-0.75	-1.84	-0.87	0.65	-1.27	-0.76	-0.63	-0.29	-0.51	-0.20	-0.02	0.37	0.97	0.31	0.33	1.44	0.16	1.16	-0.05	0.99	0.87	0.51	0.61	**-8.28**

The sample period is 4 January 1999 – 14 September 2008. The right column (Contr. FROM) represents the average contributions from other economies and the bottom row (Contr. TO) gives the average contributions to other economies. The bold bottom-right element is the total spillover (average 'FROM' or average 'TO').

Table A.2: Average signed spillovers under Regime 2 during the crisis period

	AT	BE	FR	DE	GR	HU	IE	NL	NO	PT	ES	CH	TR	GB	BR	CL	MX	US	AU	CN	IN	ID	JP	HK	MY	NZ	PH	SG	KR	LK	TH	TW	Cont. FROM
AT	0.00	-2.01	-5.44	-3.63	0.27	-1.66	-2.06	-3.28	-2.68	-0.11	-4.18	-2.30	0.41	1.33	0.59	0.59	0.48	-0.23	-1.63	0.70	-1.61	-0.38	-2.71	-2.23	-0.13	2.34	-3.97	-1.53	-1.65	0.29	1.09	0.75	-1.08
BE	2.72	0.00	3.20	2.97	-0.17	1.90	0.82	3.04	1.18	0.07	2.14	2.51	-0.30	-0.51	-0.63	-0.32	-0.42	0.01	0.74	-0.65	0.66	0.18	1.30	0.79	0.08	-0.95	1.59	0.61	0.60	-0.13	-0.40	-0.45	0.69
FR	2.48	2.12	0.00	-1.51	-0.11	0.10	0.28	1.67	1.79	0.04	3.88	-0.37	-0.23	-0.75	-0.16	0.17	0.17	-0.01	2.24	-1.31	0.68	0.16	1.82	0.69	-0.02	-0.92	1.60	0.31	0.92	-0.14	-0.22	-0.10	0.48
DE	3.67	0.08	-0.09	0.00	-0.01	-1.50	-0.39	-0.43	-1.13	-0.02	-2.94	-0.49	0.18	0.74	0.55	-0.43	0.07	-0.03	-1.32	0.56	-0.69	-0.13	-0.27	-0.78	-0.07	0.88	-0.13	-0.07	-0.46	0.14	-0.25	-0.10	-0.15
GR	8.73	10.94	8.31	7.98	0.00	8.52	4.11	9.55	5.38	0.27	6.15	7.56	-0.87	-1.96	-1.22	-0.80	-1.35	0.01	2.25	-2.05	2.41	0.59	3.11	3.33	0.22	-2.49	4.23	1.51	1.95	-0.43	-1.43	-1.13	2.61
HU	1.83	0.45	1.49	4.49	-0.20	0.00	0.57	3.80	1.27	0.05	1.75	1.62	-0.27	-0.62	-0.89	-0.33	-0.73	0.11	0.68	-0.50	0.79	0.18	1.31	0.27	0.12	-0.87	1.51	0.71	0.66	-0.13	-0.51	-0.78	0.56
IE	0.92	3.42	3.16	1.01	-0.09	0.43	0.00	2.65	0.71	0.06	1.72	2.10	-0.22	-0.38	-0.01	-0.17	-0.33	0.08	0.95	-0.52	0.68	0.17	0.85	2.09	-0.04	-1.20	1.19	0.71	0.86	-0.12	-0.59	-0.32	0.62
NL	-1.37	5.70	0.86	1.49	-0.08	2.46	0.27	0.00	-1.16	-0.02	-0.47	1.79	-0.02	-0.42	-0.33	0.23	-0.24	0.07	-1.18	0.14	0.08	-0.02	-0.09	0.33	-0.02	-0.17	0.16	-0.13	0.14	0.00	0.19	-0.31	0.25
NO	10.24	13.57	11.41	7.97	-0.60	5.68	2.78	6.32	0.00	0.32	10.12	6.03	-1.16	-2.25	-1.60	-1.17	-1.31	0.18	3.13	-2.44	2.98	0.73	4.22	2.67	0.26	-3.60	5.68	2.17	2.98	-0.54	-2.00	-0.90	2.56
PT	7.27	11.37	7.85	4.94	-0.39	3.22	2.90	6.10	3.60	0.00	7.35	3.75	-0.58	-1.58	-0.89	-0.68	-0.51	0.08	3.26	-2.13	2.52	0.48	3.10	3.33	0.19	-2.19	3.64	1.25	1.83	-0.36	-1.26	-0.61	2.09
ES	3.45	6.39	6.12	1.68	-0.21	1.72	1.65	1.83	3.33	0.12	0.00	1.59	-0.36	-0.98	-0.39	-0.63	-0.28	0.15	1.57	-0.51	1.39	0.33	1.31	1.87	0.20	-2.33	4.11	1.37	1.67	-0.23	-0.85	-0.54	1.08
CH	1.47	-2.29	0.72	1.14	-0.10	2.26	1.46	1.23	0.66	0.01	0.37	0.00	-0.11	0.30	-0.56	0.14	-0.14	-0.26	0.37	0.40	0.11	0.03	-0.56	0.20	0.01	0.45	-2.01	0.01	-0.32	-0.01	-0.12	-0.29	0.14
TR	10.90	15.97	11.97	9.11	-0.83	7.59	2.94	11.50	6.82	0.38	9.19	7.34	0.00	-3.55	-2.17	-1.18	-1.09	0.29	4.23	-2.52	3.43	0.90	5.51	3.68	0.38	-3.51	7.68	2.51	3.54	-0.67	-2.07	-1.67	3.33
GB	24.79	34.31	29.17	22.41	-1.80	16.52	8.75	23.13	16.02	0.82	22.54	18.24	-2.84	0.00	-3.84	-2.56	-2.82	0.58	9.74	-6.11	8.11	1.94	12.27	10.12	0.80	-9.00	15.85	5.65	8.07	-1.45	-4.77	-3.86	7.84
BR	11.88	11.38	9.10	10.07	-0.75	5.59	3.00	10.61	5.28	0.25	6.75	7.31	-0.93	-2.28	0.00	-0.70	-0.83	0.07	3.51	-1.49	2.42	0.63	3.64	3.20	0.33	-2.57	4.87	1.75	2.18	-0.47	-1.70	-1.76	2.82
CL	8.19	11.70	10.46	7.88	-0.55	5.46	2.95	7.64	6.32	0.31	7.76	7.63	-0.95	-2.06	-1.52	0.00	-1.30	-0.03	2.96	-2.33	2.81	0.67	3.59	2.79	0.27	-2.90	3.74	1.83	2.50	-0.49	-1.72	-0.98	2.58
MX	8.58	9.59	9.76	6.89	-0.43	4.83	1.88	7.29	3.02	0.19	6.29	6.07	-0.63	-1.52	-1.02	-0.38	0.00	0.21	2.78	-1.91	1.93	0.51	3.03	2.56	0.25	-2.35	3.04	1.50	2.21	-0.38	-1.23	-1.04	2.24
US	4.25	7.04	6.61	3.23	-0.26	2.13	1.38	4.72	3.44	0.11	5.21	2.79	-0.49	-0.98	-0.54	-0.43	-0.45	0.00	1.38	-0.91	1.61	0.38	2.36	1.79	0.18	-2.06	5.47	1.97	2.03	-0.27	-1.04	-0.86	1.56
AU	10.73	12.91	11.80	10.77	-0.78	6.21	4.67	10.64	6.80	0.38	9.23	7.41	-1.06	-2.79	-1.76	-0.90	-1.13	0.17	0.00	-2.45	3.20	0.77	4.73	4.43	0.31	-3.29	5.45	2.08	2.82	-0.57	-1.83	-1.55	3.04
CN	17.10	20.87	16.86	14.69	-1.20	11.01	4.71	15.74	8.88	0.49	12.58	13.17	-2.21	-4.29	-3.26	-1.49	-1.92	0.14	6.24	0.00	4.92	1.27	7.08	5.74	0.60	-5.04	8.95	3.13	4.67	-0.95	-2.54	-2.23	4.80
IN	1.85	3.35	3.49	0.80	-0.19	1.03	1.25	0.26	1.72	0.10	3.02	1.11	-0.20	-0.38	-0.41	-0.38	0.10	0.02	1.55	-0.96	0.00	0.27	1.46	1.69	0.08	-1.51	2.06	0.90	1.11	-0.21	-0.41	-0.35	0.69
ID	2.49	2.91	2.97	0.61	-0.11	1.68	0.62	1.87	0.92	0.10	2.00	0.76	-0.12	-0.55	-0.33	0.02	-0.07	0.07	1.00	-0.39	0.71	0.00	1.07	1.29	0.12	0.01	1.51	0.53	0.87	-0.13	-0.90	-0.57	0.65
JP	3.19	4.42	1.49	2.89	-0.11	0.88	0.17	3.48	2.81	0.09	3.44	1.20	-0.35	-0.25	-0.13	-0.56	-0.07	0.03	0.70	-0.56	0.32	0.13	0.00	0.29	0.09	-0.79	1.21	0.24	0.53	-0.12	-0.39	0.21	0.76
HK	4.26	9.38	8.12	5.16	-0.38	2.82	1.99	6.77	3.58	0.25	4.47	4.72	-0.82	-1.97	-0.41	-0.59	-0.99	0.21	2.66	-1.88	1.77	0.55	3.91	0.00	0.23	-2.26	4.74	1.23	2.30	-0.43	-1.23	-1.00	1.79
MY	3.31	2.79	2.04	1.25	-0.09	1.48	0.46	0.21	1.01	0.06	1.85	1.42	-0.07	0.03	-0.53	0.00	-0.10	0.03	1.04	-0.41	0.56	0.14	0.52	0.80	0.00	-1.52	1.23	0.61	0.50	-0.11	-0.29	-0.07	0.57
NZ	11.04	15.10	14.00	9.77	-0.70	6.67	3.89	9.06	6.36	0.35	10.50	7.51	-1.19	-2.35	-1.72	-1.21	-1.07	0.19	4.30	-2.87	3.10	0.81	5.11	3.96	0.35	0.00	6.29	2.36	3.33	-0.59	-1.97	-1.38	3.41
PH	1.43	1.24	1.57	1.18	-0.16	1.62	0.38	2.11	1.44	0.03	0.47	3.53	-0.26	-0.65	-0.44	-0.28	-0.11	0.09	0.34	-0.29	0.34	0.15	0.78	0.26	0.06	-0.21	0.00	0.27	0.39	-0.11	-0.30	-0.05	0.46
SG	-4.52	-4.72	-1.32	-2.45	0.15	-1.65	0.88	-3.04	-0.61	-0.06	-0.74	-1.09	0.17	0.57	0.06	0.09	0.55	0.01	0.08	0.86	0.40	-0.02	-0.16	0.12	-0.02	-0.68	0.70	0.00	-0.05	0.02	-0.27	-0.05	-0.52
KR	3.04	5.92	5.27	2.89	-0.36	2.15	1.03	3.87	2.83	0.10	3.78	2.51	-0.57	-1.20	-0.70	-0.45	-0.46	0.14	2.02	-0.76	1.23	0.34	2.09	1.51	0.18	-1.75	2.99	1.01	0.00	-0.27	-1.04	-1.06	1.13
LK	1.88	3.19	2.32	0.93	-0.13	1.42	0.55	1.17	1.56	0.07	2.43	1.23	-0.23	-0.43	-0.42	-0.36	-0.14	-0.05	0.65	-0.39	0.73	0.15	0.67	0.54	0.01	-0.33	1.15	0.51	0.79	0.00	-0.35	-0.21	0.59
TH	6.72	10.30	10.13	6.35	-0.61	4.89	2.88	7.69	4.98	0.29	7.50	6.80	-1.03	-2.53	-0.98	-0.78	-0.91	0.03	3.54	-2.14	3.30	0.69	3.47	4.08	0.31	-3.07	4.43	1.55	2.41	-0.51	0.00	-1.26	2.45
TW	5.27	5.23	5.17	4.52	-0.35	2.42	1.48	4.56	2.81	0.15	3.51	3.33	-0.57	-1.10	-0.64	-0.25	-0.43	0.19	1.80	-0.66	1.24	0.36	2.48	1.78	0.12	-1.24	3.40	1.20	1.48	-0.26	-1.03	0.00	1.44
Cont. TO	5.56	7.27	6.21	4.61	-0.35	3.37	1.82	5.05	3.09	0.16	4.61	3.96	-0.56	-1.10	-0.82	-0.49	-0.56	0.08	1.92	-1.14	1.63	0.41	2.41	1.97	0.17	-1.72	3.20	1.18	1.59	-0.30	-0.98	-0.77	**51.47**

The sample period is 15 September 2008 – 31 March 2010. The right column (Contr. FROM) represents the average contributions from other economies and the bottom row (Contr. TO) gives the average contributions to other economies. The bold bottom-right element is the total spillover (average 'FROM' or average 'TO').

Table A.3: Average signed spillovers under regime 2 during the European sovereign debt crisis period

	AT	BE	FR	DE	GR	HU	IE	NL	NO	PT	ES	CH	TR	GB	BR	CL	MX	US	AU	CN	IN	ID	JP	HK	MY	NZ	PH	SG	KR	LK	TH	TW	Cont. FROM
AT	0.00	-0.66	-1.67	-1.15	-0.80	-0.23	-0.31	-0.68	-0.59	-0.43	-2.06	-0.32	0.42	-1.00	-0.10	-0.31	0.32	-1.00	0.12	0.25	0.24	1.09	0.38	0.84	2.06	0.56	2.15	-0.28	1.18	-0.69	0.27	1.21	-0.04
BE	0.14	0.00	0.96	0.89	0.62	0.16	0.13	0.55	0.27	0.28	1.05	0.29	-0.31	0.38	0.14	0.18	-0.28	0.31	-0.05	-0.20	-0.10	-0.45	-0.18	-0.28	-0.74	-0.23	-0.85	0.12	-0.40	0.35	-0.11	-0.70	0.06
FR	0.14	0.63	0.00	-0.36	0.26	0.07	0.07	0.32	0.37	0.06	1.87	0.00	-0.24	0.57	0.01	-0.15	0.09	0.31	-0.18	-0.36	-0.10	-0.40	-0.25	-0.22	-1.46	-0.24	-0.85	0.06	-0.67	0.03	-0.09	-0.24	-0.03
DE	0.03	0.00	-0.09	0.00	0.31	-0.13	-0.07	-0.13	-0.25	0.02	-1.43	-0.10	0.18	-0.55	-0.13	0.30	0.06	-0.35	0.11	0.17	0.10	-0.35	0.06	0.28	0.69	0.22	0.00	-0.01	0.26	0.23	0.03	-0.01	-0.02
GR	0.45	3.32	2.54	2.43	0.00	0.63	0.58	1.76	1.13	1.28	3.04	0.90	-0.89	1.46	0.24	0.42	-0.91	0.98	-0.16	-0.63	-0.36	-1.93	-0.44	-1.25	-2.88	-0.64	-2.23	0.28	-1.28	1.15	-0.38	-1.84	0.21
HU	0.11	0.16	0.47	1.31	0.80	0.00	0.09	0.68	0.28	0.16	0.86	0.18	-0.28	0.47	0.22	0.19	-0.48	0.42	-0.05	-0.15	-0.12	-0.71	-0.18	-0.04	-0.35	-0.21	-0.82	0.13	-0.46	0.28	-0.12	-1.14	0.05
IE	0.09	1.04	0.95	0.35	0.18	0.09	0.00	0.49	0.19	0.28	0.85	0.26	-0.22	0.27	-0.03	0.08	-0.22	0.44	-0.08	-0.17	-0.10	-0.45	-0.13	-0.87	-1.69	-0.28	-0.62	0.13	-0.63	0.39	-0.13	-0.53	0.00
NL	-0.03	1.72	0.26	0.42	0.41	0.12	0.03	0.00	-0.20	-0.13	-0.20	0.17	-0.02	0.33	0.09	-0.14	-0.17	0.08	0.10	0.04	-0.02	0.15	0.01	-0.16	-0.05	-0.01	-0.10	-0.03	-0.15	0.04	0.03	-0.44	0.07
NO	0.55	4.14	3.46	2.47	1.99	0.56	0.46	1.28	0.00	1.57	4.95	0.80	-1.19	1.66	0.32	0.63	-0.87	1.50	-0.23	-0.76	-0.45	-2.26	-0.60	-0.88	-3.56	-0.90	-3.01	0.41	-2.12	1.30	-0.50	-1.62	0.28
PT	0.39	3.45	2.38	1.56	1.21	0.35	0.43	1.16	0.79	0.00	3.60	0.50	-0.59	1.17	0.16	0.34	-0.36	0.96	-0.24	-0.64	-0.39	-1.70	-0.43	-1.29	-2.33	-0.56	-1.91	0.24	-1.25	0.79	-0.32	-1.07	0.20
ES	0.23	1.98	1.83	0.59	0.56	0.21	0.25	0.44	0.68	0.52	0.00	0.25	-0.36	0.73	0.06	0.36	-0.18	0.81	-0.12	-0.19	-0.21	-0.47	-0.20	-0.70	-1.15	-0.54	-2.25	0.27	-1.26	0.54	-0.22	-0.88	0.05
CH	0.04	-0.67	0.20	0.31	0.52	0.12	0.18	0.20	0.13	0.09	0.17	0.00	-0.12	-0.24	0.16	-0.09	-0.10	-0.37	-0.03	0.10	-0.02	-0.48	0.07	-0.08	-0.13	0.08	1.17	0.01	0.31	0.15	-0.03	-0.40	0.04
TR	0.63	4.85	3.67	2.85	2.94	0.71	0.50	2.18	1.47	1.65	4.54	0.95	0.00	2.68	0.45	0.61	-0.76	1.94	-0.31	-0.80	-0.51	-2.71	-0.78	-1.27	-3.96	-0.94	-4.11	0.47	-2.49	1.58	-0.58	-2.77	0.40
GB	1.41	10.48	8.89	6.93	6.38	1.55	1.36	4.47	3.42	3.66	11.10	2.32	-2.93	0.00	0.72	1.32	-1.93	4.18	-0.73	-1.91	-1.22	-5.98	-1.72	-3.70	-9.01	-2.28	-8.43	1.07	-5.75	3.50	-1.29	-6.29	0.61
BR	0.56	3.44	2.76	3.02	2.98	0.50	0.45	1.94	1.11	1.16	3.33	0.89	-0.95	1.71	0.00	0.35	-0.59	1.14	-0.26	-0.49	-0.36	-2.17	-0.51	-1.17	-2.32	-0.66	-2.59	0.34	-1.48	1.22	-0.43	-2.70	0.32
CL	0.47	3.55	3.16	2.42	1.83	0.52	0.46	1.48	1.31	1.40	3.81	0.93	-0.98	1.53	0.31	0.00	-0.87	1.07	-0.22	-0.72	-0.43	-2.25	-0.51	-0.97	-3.06	-0.75	-1.91	0.34	-1.72	1.22	-0.45	-1.71	0.29
MX	0.42	2.90	2.88	2.08	1.42	0.42	0.30	1.34	0.69	0.90	3.07	0.72	-0.64	1.13	0.20	0.17	0.00	1.15	-0.22	-0.57	-0.29	-1.89	-0.43	-0.93	-1.87	-0.59	-1.57	0.28	-1.61	1.07	-0.33	-1.72	0.27
US	0.27	2.15	1.99	1.05	0.82	0.25	0.23	0.93	0.72	0.44	2.55	0.38	-0.50	0.73	0.08	0.22	-0.30	0.00	-0.10	-0.30	-0.25	-0.97	-0.33	-0.64	-1.56	-0.50	-3.02	0.36	-1.55	0.79	-0.27	-1.36	0.07
AU	0.58	3.93	3.58	3.26	2.88	0.59	0.68	2.00	1.43	1.74	4.54	0.95	-1.08	2.08	0.36	0.44	-0.79	1.55	0.00	-0.77	-0.48	-2.47	-0.67	-1.66	-3.70	-0.85	-2.86	0.39	-1.93	1.22	-0.50	-2.49	0.37
CN	0.94	6.37	5.19	4.52	4.22	1.02	0.77	3.01	1.95	2.06	6.23	1.63	-2.27	3.17	0.67	0.74	-1.32	2.32	-0.47	0.00	-0.73	-3.56	-1.01	-2.04	-5.13	-1.32	-4.70	0.59	-3.21	2.22	-0.76	-3.75	0.54
IN	0.16	0.99	1.08	0.31	0.57	0.16	0.19	0.16	0.40	0.42	1.50	0.18	-0.20	0.28	0.07	0.21	0.04	0.48	-0.12	-0.30	0.00	-1.24	-0.21	-0.65	-1.58	-0.37	-1.09	0.17	-0.78	0.40	-0.15	-0.62	0.01
ID	0.14	0.89	0.90	0.24	0.28	0.16	0.11	0.38	0.23	0.45	0.99	0.12	-0.12	0.40	0.06	-0.04	-0.05	0.43	-0.08	-0.13	-0.10	0.00	-0.15	-0.50	-0.50	-0.06	-0.80	0.10	-0.65	0.31	-0.18	-0.87	0.06
JP	0.14	1.31	0.47	0.86	0.32	0.10	0.05	0.61	0.53	0.50	1.63	0.15	-0.36	0.18	0.00	0.32	-0.06	0.27	-0.05	-0.17	-0.04	-0.28	0.00	-0.07	-0.44	-0.19	-0.64	0.05	-0.36	0.18	-0.10	0.23	0.16
HK	0.33	2.86	2.50	1.66	1.05	0.36	0.34	1.32	0.82	1.05	2.23	0.62	-0.84	1.46	0.00	0.28	-0.66	1.35	-0.21	-0.60	-0.24	-1.46	-0.55	0.00	-2.71	-0.60	-2.52	0.23	-1.59	0.88	-0.35	-1.66	0.17
MY	0.14	0.84	0.63	0.40	0.25	0.12	0.08	0.09	0.22	0.27	0.90	0.18	-0.07	-0.03	0.12	-0.02	-0.06	0.27	-0.08	-0.13	-0.08	-0.44	-0.08	-0.30	0.00	-0.33	-0.66	0.11	-0.32	0.32	-0.09	-0.18	0.07
NZ	0.60	4.58	4.19	2.99	2.34	0.64	0.59	1.76	1.37	1.60	5.14	0.96	-1.22	1.74	0.33	0.64	-0.75	1.66	-0.33	-0.88	-0.45	-2.57	-0.72	-1.43	-3.65	0.00	-3.33	0.44	-2.35	1.46	-0.54	-2.32	0.39
PH	0.09	0.40	0.51	0.38	0.56	0.14	0.07	0.41	0.29	0.01	0.26	0.37	-0.27	0.49	0.09	0.16	-0.10	0.37	-0.02	-0.10	-0.04	-0.33	-0.11	-0.05	-0.67	-0.09	0.00	0.05	-0.23	0.20	-0.09	-0.17	0.08
SG	-0.13	-1.39	-0.37	-0.67	-0.74	-0.09	0.10	-0.49	-0.11	-0.39	-0.34	-0.10	0.18	-0.42	0.00	-0.05	0.36	-0.02	-0.01	0.22	-0.08	-0.30	0.02	-0.06	-0.17	-0.12	-0.42	0.00	0.03	-0.22	-0.02	-0.03	-0.18
KR	0.21	1.81	1.60	0.93	1.35	0.24	0.18	0.76	0.61	0.39	1.86	0.33	-0.59	0.89	0.14	0.23	-0.32	0.80	-0.15	-0.26	-0.18	-0.75	-0.30	-0.53	-1.30	-0.44	-1.60	0.19	0.00	0.80	-0.26	-1.61	0.16
LK	0.11	0.97	0.71	0.31	0.44	0.13	0.09	0.24	0.31	0.36	1.18	0.16	-0.23	0.32	0.09	0.22	-0.10	0.17	-0.05	-0.12	-0.11	-0.55	-0.10	-0.18	-1.08	-0.11	-0.61	0.10	-0.61	0.00	-0.10	-0.38	0.05
TH	0.45	3.17	3.10	2.02	2.09	0.51	0.46	1.51	1.10	1.29	3.70	0.86	-1.06	1.88	0.14	0.38	-0.63	1.25	-0.27	-0.68	-0.51	-2.05	-0.51	-1.53	-3.18	-0.79	-2.29	0.30	-1.59	1.32	0.00	-2.08	0.26
TW	0.28	1.60	1.57	1.39	1.26	0.25	0.23	0.86	0.60	0.66	1.73	0.42	-0.59	0.82	0.12	0.10	-0.29	0.88	-0.13	-0.23	-0.18	-1.30	-0.34	-0.65	-1.79	-0.34	-1.84	0.23	-1.06	0.76	-0.26	0.00	0.15
Cont. TO	0.31	2.21	1.88	1.43	1.23	0.32	0.28	0.97	0.66	0.73	2.27	0.50	-0.57	0.82	0.16	0.25	-0.38	0.79	-0.14	-0.36	-0.24	-1.29	-0.34	-0.72	-1.85	-0.44	-1.70	0.22	-1.12	0.74	-0.26	-1.25	**5.12**

The sample period is 1 April 2010 – 21 November 2013. The right column (Contr. FROM) represents the average contributions from other economies and the bottom row (Contr. TO) gives the average contributions to other economies. The bold bottom-right element is the total spillover (average 'FROM' or average 'TO').

Table A.4: Average signed spillovers under Regime 2 in the most recent period

	AT	BE	FR	DE	GR	HU	IE	NL	NO	PT	ES	CH	TR	GB	BR	CL	MX	US	AU	CN	IN	ID	JP	HK	MY	NZ	PH	SG	KR	LK	TH	TW	Cont. FROM
AT	0.00	-0.08	-0.68	-0.57	-0.98	0.56	-0.60	-0.07	-0.63	-0.63	-0.74	-0.17	0.60	-3.11	-1.28	-1.51	-0.91	-0.65	0.09	-0.44	1.17	1.08	1.37	0.93	1.92	-0.68	2.98	0.56	1.95	2.30	0.74	0.12	0.08
BE	-0.65	0.00	0.41	0.49	0.75	-0.62	0.23	0.07	0.27	0.41	0.37	0.23	-0.42	1.16	1.42	0.83	0.88	0.19	-0.04	0.40	-0.47	-0.44	-0.67	-0.32	-0.70	0.27	-1.18	-0.22	-0.67	-1.22	-0.27	-0.05	0.01
FR	-0.59	0.07	0.00	-0.32	0.33	-0.04	0.04	0.06	0.45	0.08	0.72	-0.06	-0.33	1.80	0.34	-0.46	-0.49	0.19	-0.13	0.79	-0.50	-0.39	-0.99	-0.26	-1.39	0.27	-1.17	-0.08	-1.10	0.17	-0.16	-0.07	-0.10
DE	-0.99	0.02	0.04	0.00	0.34	0.49	-0.09	0.00	-0.27	0.04	-0.53	-0.01	0.26	-1.80	-1.23	1.12	-0.08	-0.22	0.07	-0.34	0.51	-0.49	0.00	0.30	0.65	-0.25	-0.08	-0.02	0.42	-1.19	-0.16	0.06	-0.11
GR	-2.10	0.35	1.03	1.28	0.00	-2.79	1.23	0.20	1.33	1.89	1.09	0.69	-1.24	4.56	2.69	2.05	2.86	0.61	-0.13	1.26	-1.76	-1.96	-1.47	-1.38	-2.70	0.68	-3.02	-0.50	-2.16	-3.95	-0.97	-0.19	-0.08
HU	-0.42	0.01	0.18	0.76	0.97	0.00	0.15	0.09	0.31	0.23	0.30	0.16	-0.39	1.46	2.02	0.86	1.63	0.27	-0.04	0.30	-0.59	-0.74	-0.70	-0.07	-0.33	0.24	-1.13	-0.27	-0.76	-0.91	-0.35	-0.04	0.10
IE	-0.19	0.12	0.40	0.13	0.22	-0.15	0.00	0.06	0.12	0.43	0.31	0.19	-0.33	0.82	-0.03	0.44	0.67	0.28	-0.05	0.32	-0.49	-0.44	-0.38	-0.92	-1.59	0.35	-0.83	-0.26	-1.03	-1.40	-0.40	-0.06	-0.12
NL	0.32	0.18	0.11	0.26	0.48	-0.79	0.10	0.00	-0.34	-0.24	-0.11	0.17	-0.01	1.14	0.76	-0.59	0.59	0.06	0.07	-0.09	-0.08	0.16	0.06	-0.16	-0.04	0.05	-0.12	0.05	-0.23	-0.18	0.13	0.02	0.05
NO	-2.45	0.41	1.43	1.27	2.43	-1.87	0.72	0.13	0.00	2.30	1.84	0.47	-1.64	5.16	3.51	3.02	2.66	0.95	-0.17	1.50	-2.16	-2.28	-2.03	-1.04	-3.34	1.02	-4.09	-0.75	-3.51	-4.38	-1.35	-0.25	-0.08
PT	-1.76	0.38	0.99	0.77	1.48	-1.07	0.84	0.13	0.85	0.00	1.32	0.28	-0.84	3.66	1.95	1.72	0.93	0.60	-0.19	1.30	-1.91	-1.75	-1.54	-1.41	-2.19	0.60	-2.58	-0.42	-2.09	-2.58	-0.86	-0.17	-0.11
ES	-0.83	0.15	0.79	0.23	0.69	-0.58	0.46	0.00	0.85	0.76	0.00	0.11	-0.52	2.24	0.83	1.64	0.46	0.52	-0.08	0.32	-1.01	-0.36	-0.55	-0.78	-1.07	0.69	-3.14	-0.53	-2.06	-1.78	-0.57	-0.11	-0.10
CH	-0.37	-0.08	0.10	0.21	0.61	-0.73	0.50	0.05	0.19	0.15	0.07	0.00	-0.16	-0.80	1.31	-0.37	0.33	-0.26	-0.02	-0.24	-0.07	-0.55	0.37	-0.08	-0.11	-0.15	1.71	-0.01	0.47	-0.61	-0.08	0.00	0.04
TR	-2.59	0.50	1.49	1.43	3.57	-2.49	0.73	0.25	1.63	2.44	1.64	0.62	0.00	8.42	4.81	3.04	2.09	1.23	-0.24	1.55	-2.46	-2.72	-2.71	-1.46	-3.71	0.96	-5.63	-0.86	-4.12	-5.28	-1.41	-0.28	0.01
GB	-5.91	1.01	3.64	3.56	7.73	-5.43	2.39	0.47	3.90	5.41	4.02	1.54	-4.08	0.00	8.39	6.59	5.58	2.66	-0.53	3.75	-5.92	-6.00	-6.06	-4.14	-8.45	2.52	-11.50	-1.96	-9.52	-11.78	-3.25	-0.61	-0.69
BR	-2.91	0.36	1.15	1.67	3.58	-1.83	0.84	0.25	1.29	1.72	1.19	0.67	-1.31	5.40	0.00	1.80	1.63	0.71	-0.19	0.92	-1.74	-2.21	-1.77	-1.30	-2.17	0.71	-3.53	-0.62	-2.49	-4.17	-1.15	-0.17	-0.11
CL	-1.94	0.34	1.32	1.27	2.23	-1.80	0.80	0.15	1.59	2.08	1.39	0.69	-1.36	4.78	3.35	0.00	2.70	0.65	-0.17	1.43	-2.05	-2.30	-1.70	-1.10	-2.87	0.81	-2.53	-0.62	-2.87	-4.10	-1.17	-0.22	-0.04
MX	-2.08	0.27	1.28	1.13	1.74	-1.58	0.48	0.19	0.67	1.32	1.14	0.56	-0.90	3.49	2.24	0.98	0.00	0.74	-0.14	1.16	-1.37	-1.96	-1.46	-1.05	-1.76	0.67	-2.08	-0.52	-2.63	-3.70	-0.84	-0.16	-0.13
US	-1.01	0.21	0.86	0.48	1.00	-0.71	0.36	0.08	0.85	0.64	0.94	0.22	-0.71	2.20	1.17	1.11	0.84	0.00	-0.07	0.56	-1.17	-0.94	-1.17	-0.73	-1.46	0.59	-4.23	-0.76	-2.51	-2.79	-0.71	-0.12	-0.22
AU	-2.58	0.41	1.49	1.77	3.49	-2.03	1.37	0.23	1.68	2.61	1.66	0.62	-1.52	6.59	3.88	2.29	2.27	0.98	0.00	1.51	-2.33	-2.50	-2.31	-1.83	-3.46	0.91	-3.85	-0.70	-3.22	-3.98	-1.25	-0.24	0.06
CN	-4.09	0.63	2.08	2.33	5.13	-3.61	1.22	0.31	2.07	3.04	2.22	1.15	-3.09	10.00	7.22	3.78	3.84	1.45	-0.34	0.00	-3.54	-3.52	-3.39	-2.31	-4.81	1.37	-6.36	-1.03	-5.37	-7.43	-1.75	-0.41	-0.10
IN	-0.41	0.09	0.43	0.09	0.70	-0.36	0.35	-0.01	0.39	0.61	0.51	0.09	-0.30	0.73	0.88	1.01	-0.37	0.30	-0.08	0.59	0.00	-1.30	-0.67	-0.70	-1.48	0.44	-1.47	-0.33	-1.28	-1.27	-0.28	-0.09	-0.10
ID	-0.59	0.07	0.37	0.07	0.35	-0.56	0.16	0.03	0.19	0.66	0.35	0.05	-0.18	1.27	0.72	-0.05	0.05	0.28	-0.05	0.24	-0.51	0.00	-0.50	-0.54	-0.47	-0.04	-1.08	-0.18	-1.08	-1.01	-0.58	-0.05	-0.08
JP	-0.78	0.18	0.18	0.48	0.39	-0.29	0.01	0.11	0.78	0.76	0.65	0.11	-0.48	0.52	0.26	1.42	0.08	0.17	-0.05	0.35	-0.19	-0.26	0.00	-0.11	-0.41	0.23	-0.88	-0.07	-0.61	-0.52	-0.27	-0.07	0.05
HK	-0.94	0.31	1.01	0.77	1.31	-0.94	0.49	0.12	0.79	1.56	0.79	0.37	-1.18	4.59	0.81	1.53	1.99	0.86	-0.13	1.17	-1.22	-1.43	-1.95	0.00	-2.53	0.61	-3.43	-0.37	-2.63	-2.83	-0.85	-0.19	-0.05
MY	-0.81	0.09	0.26	0.18	0.32	-0.48	0.11	-0.01	0.23	0.40	0.33	0.12	-0.11	-0.23	1.19	0.00	0.14	0.17	-0.05	0.26	-0.40	-0.45	-0.20	-0.33	0.00	0.47	-0.88	-0.22	-0.53	-1.14	-0.20	-0.05	-0.06
NZ	-2.63	0.48	1.79	1.56	2.86	-2.19	1.08	0.17	1.52	2.38	1.89	0.63	-1.70	5.36	3.78	3.10	2.10	1.05	-0.23	1.76	-2.23	-2.60	-2.52	-1.61	-3.43	0.00	-4.52	-0.81	-3.88	-4.93	-1.35	-0.26	-0.11
PH	-0.32	0.02	0.18	0.16	0.69	-0.53	0.08	0.03	0.36	0.00	0.07	0.36	-0.36	1.58	0.99	0.73	0.19	0.24	-0.01	0.18	-0.21	-0.31	-0.36	-0.08	-0.63	0.04	0.00	-0.07	-0.41	-0.60	-0.21	-0.06	0.05
SG	1.15	-0.21	-0.18	-0.42	-0.89	0.53	0.31	-0.09	-0.16	-0.58	-0.15	-0.11	0.23	-1.45	-0.15	-0.23	-1.26	-0.01	0.00	-0.52	-0.34	-0.37	0.09	-0.04	-0.15	0.23	-0.62	0.00	0.06	0.88	-0.17	0.01	-0.14
KR	-0.70	0.18	0.65	0.44	1.63	-0.71	0.25	0.07	0.68	0.56	0.68	0.20	-0.81	2.80	1.53	1.16	0.90	0.51	-0.13	0.47	-0.87	-0.70	-1.02	-0.60	-1.22	0.50	-2.19	-0.35	0.00	-2.79	-0.69	-0.09	0.01
LK	-0.45	0.09	0.29	0.13	0.54	-0.47	0.14	0.03	0.40	0.53	0.44	0.10	-0.32	1.00	0.93	0.95	0.25	0.10	-0.03	0.24	-0.55	-0.57	-0.29	-0.21	-1.02	0.08	-0.83	-0.19	-1.00	0.00	-0.24	-0.05	0.00
TH	-1.55	0.30	1.27	0.97	2.54	-1.61	0.76	0.14	1.16	1.92	1.33	0.59	-1.49	5.97	2.11	1.99	1.76	0.77	-0.19	1.32	-2.46	-2.04	-1.58	-1.68	-2.98	0.85	-3.06	-0.49	-2.66	-4.51	0.00	-0.23	-0.02
TW	-1.27	0.14	0.65	0.73	1.53	-0.80	0.40	0.10	0.69	0.99	0.62	0.28	-0.81	2.56	1.40	0.63	0.81	0.57	-0.10	0.41	-0.87	-1.34	-1.26	-0.73	-1.67	0.33	-2.53	-0.43	-1.74	-2.64	-0.69	0.00	-0.13
Cont. TO	-1.33	0.22	0.78	0.73	1.49	-1.11	0.50	0.10	0.74	1.08	0.82	0.34	-0.80	2.56	1.81	1.27	1.10	0.50	-0.11	0.70	-1.18	-1.30	-1.17	-0.81	-1.74	0.48	-2.31	-0.41	-1.85	-2.51	-0.67	-0.13	**-2.18**

The sample period is 22 November 2013 – 31 December 2017. The right column (Contr. FROM) represents the average contributions from other economies and the bottom row (Contr. TO) gives the average contributions to other economies. The bold bottom-right element is the total spillover (average 'FROM' or average 'TO').

Bibliography

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*, 105(2):564–608.

ADB (2017). The era of financial interconnectedness: How can Asia strengthen financial resilience? Asian Economic Integration Report 2017.

Affinito, M. and Pozzolo, A. F. (2017). The interbank network across the global financial crisis: Evidence from Italy. *Journal of Banking & Finance*, 80:90–107.

Agénor, P.-R. (2003). Benefits and costs of international financial integration: Theory and facts. *World Economy*, 26(8):1089–1118.

Agénor, P.-R. (2013). International financial integration: Benefits, costs and policy challenges. *International Finance: A Survey*, page 110.

Agénor, P.-R., Kharroubi, E., Gambacorta, L., Lombardo, G., and Pereira da Silva, L. A. (2017). The international dimensions of macroprudential policies. BIS Working Papers No. 643.

Aizenman, J., Jinjarak, Y., Lee, M., and Park, D. (2016a). Developing countries' financial vulnerability to the Eurozone crisis: An event study of equity and bond markets. *Journal of Economic Policy Reform*, 19(1):1–19.

Aizenman, J., Jinjarak, Y., and Park, D. (2015). Financial development and output growth in developing Asia and Latin America: A comparative sectoral analysis. NBER Working Paper No. 20917.

Aizenman, J., Jinjarak, Y., and Park, D. (2016b). Fundamentals and sovereign risk of emerging markets. *Pacific Economic Review*, 21(2):151–177.

Alexeev, V. and Dungey, M. (2015). Equity portfolio diversification with high frequency data. *Quantitative Finance*, 15(7):1205–1215.

Allen, F. and Babus, A. (2009). Networks in finance. *The Network Challenge: Strategy, Profit and Risk in an Interlinked World*, 367–382.

Allen, F. and Gale, D. (2000). Financial contagion. *Journal of Political Economy*, 108(1):1–33.

Allen, F. and Gale, D. (2004). Competition and financial stability. *Journal of Money, Credit and Banking*, pages 453–480.

Allen, W. A. and Wood, G. (2006). Defining and achieving financial stability. *Journal of Financial Stability*, 2(2):152–172.

Alter, A. and Beyer, A. (2014). The dynamics of spillover effects during the European sovereign debt turmoil. *Journal of Banking & Finance*, 42:134–153.

Amini, H., Cont, R., and Minca, A. (2016). Resilience to contagion in financial networks. *Mathematical Finance*, 26(2):329–365.

Andersen, T. G. and Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*, pages 885–905.

Andersen, T. G., Bollerslev, T., Christoffersen, P. F., and Diebold, F. X. (2006). Volatility and correlation forecasting. *Handbook of economic forecasting*, 1:777–878.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Ebens, H. (2001). The distribution of realised stock return volatility. *Journal of Financial Economics*, 61(1):43–76.

Anselin, L. (1988). *Spatial econometrics: Methods and models.* The Netherlands: Kluwer Academic Publishers.

Antonakakis, N., Chatziantoniou, I., and Filis, G. (2013). Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. *Economics Letters*, 120(1):87–92.

Apostolakis, G. and Papadopoulos, A. P. (2014). Financial stress spillovers in advanced economies. *Journal of International Financial Markets, Institutions and Money*, 32:128–149.

Areal, N. M. and Taylor, S. J. (2002). The realised volatility of FTSE-100 futures prices. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, 22(7):627–648.

Arnold, M., Stahlberg, S., and Wied, D. (2013). Modeling different kinds of spatial dependence in stock returns. *Empirical Economics*, 44(2):761–774.

Arslanalp, S., Liao, W., Piao, S., and Seneviratne, M. (2016). China's growing influence on Asian financial markets. IMF Working Paper WP/16/173.

Asgharian, H., Hess, W., and Liu, L. (2013). A spatial analysis of international stock market linkages. *Journal of Banking & Finance*, 37(12):4738–4754.

Avdjiev, S., Bruno, V., Koch, C., and Shin, H. S. (2019). The dollar exchange rate as a global risk factor: Evidence from investment. *IMF Economic Review*, 67(1):151–173.

Baele, L. (2005). Volatility spillover effects in European equity markets. *Journal of Financial and Quantitative Analysis*, 40(2):373–401.

Bali, T. G. and Cakici, N. (2008). Idiosyncratic volatility and the cross section of expected returns. *Journal of Financial and Quantitative Analysis*, 43(1):29–58.

Bali, T. G. and Cakici, N. (2010). World market risk, country-specific risk and expected returns in international stock markets. *Journal of Banking & Finance*, 34(6):1152–1165.

Balli, F., Balli, H. O., Louis, R. J., and Vo, T. K. (2015a). The transmission of market shocks and bilateral linkages: Evidence from emerging economies. *International Review of Financial Analysis*, 42:349–357.

Balli, F., Hajhoj, H. R., Basher, S. A., and Ghassan, H. B. (2015b). An analysis of returns and volatility spillovers and their determinants in emerging Asian and middle Eastern countries. *International Review of Economics & Finance*, 39:311–325.

Battiston, S. and Caldarelli, G. (2013). Systemic risk in financial networks. *Journal of Financial Management, Markets and Institutions*, 1(2):129–154.

Battiston, S., Gatti, D. D., Gallegati, M., Greenwald, B., and Stiglitz, J. E. (2012). Liaisons dangereuses: Increasing connectivity, risk sharing and systemic risk. *Journal of Economic Dynamics and Control*, 36(8):1121–1141.

Baur, D. and Schulze, N. (2005). Coexceedances in financial markets−a quantile regression analysis of contagion. *Emerging Markets Review*, 6(1):21–43.

Baur, D. G. and Fry, R. A. (2009). Multivariate contagion and interdependence. *Journal of Asian Economics*, 20(4):353–366.

Beaino, G.-C., Lombardi, D., and Siklos, P. L. (2019). The transmission of financial shocks on a global scale: Some new empirical evidence. *Emerging Markets Finance and Trade*, 55(7):1634–1655.

Beirne, J., Caporale, G. M., Schulze-Ghattas, M., and Spagnolo, N. (2010). Global and regional spillovers in emerging stock markets: A multivariate GARCH-in-mean analysis. *Emerging Markets Review*, 11(3):250–260.

Bekaert, G. and Harvey, C. R. (2017). Emerging equity markets in a globalising world. Available at SSRN 2344817.

Belke, A. and Gros, D. (2016). On the shock-absorbing properties of a banking union: Europe compared with the United States. *Comparative Economic Studies*, 58(3):359–386.

BenSaïda, A. (2018). The contagion effect in european sovereign debt markets: A regime-switching vine copula approach. *International Review of Financial Analysis*, 58:153–165.

Białkowski, J. d. and Serwa, D. (2005). Financial contagion, spillovers and causality in the Markov switching framework. *Quantitative Finance*, 5(1):123–131.

Billio, M., Caporin, M., Panzica, R., and Pelizzon, L. (2015). Network connectivity and systematic risk. Working Paper.

Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3):535–559.

Black, L., Correa, R., Huang, X., and Zhou, H. (2016). The systemic risk of European banks during the financial and sovereign debt crises. *Journal of Banking & Finance*, 63:107–125.

Blasques, F., Koopman, S. J., Lucas, A., and Schaumburg, J. (2016). Spillover dynamics for systemic risk measurement using spatial financial time series models. *Journal of Econometrics*, 195(2):211–223.

Bollen, B. and Inder, B. (2002). Estimating daily volatility in financial markets utilising intraday data. *Journal of Empirical Finance*, 9(5):551–562.

Bollerslev, T., Osterrieder, D., Sizova, N., and Tauchen, G. (2013). Risk and return: Long-run relations, fractional cointegration and return predictability. *Journal of Financial Economics*, 108(2):409–424.

Bonacich, P. (1972). Factoring and weighting approaches to status scores and clique identification. *Journal of Mathematical Sociology*, 2(1):113–120.

Botman, D. P., Carvalho Filho, I. E., and Lam, M. R. W. (2013). The curious case of the yen as a safe haven currency: A forensic analysis. IMF Working Paper WP/13/228.

Brownlees, C. and Engle, R. F. (2016). SRISK: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies*, 30(1):48–79.

Bruno, V. and Shin, H. S. (2014). Cross-border banking and global liquidity. *The Review of Economic Studies*, 82(2):535–564.

Busetti, F. and Harvey, A. (2010). When is a copula constant? A test for changing relationships. *Journal of Financial Econometrics*, 9(1):106–131.

Campbell, J. Y., Lettau, M., Malkiel, B. G., and Xu, Y. (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *The Journal of Finance*, 56(1):1–43.

Cao, Y., Gregory-Smith, I., and Montagnoli, A. (2017). Transmission of liquidity shocks: Evidence on cross-border bank ownership linkages. *Journal of International Financial Markets, Institutions and Money*.

Caporin, M., Pelizzon, L., Ravazzolo, F., and Rigobon, R. (2018). Measuring sovereign contagion in Europe. *Journal of Financial Stability*, 34:150–181.

Casarin, R., Sartore, D., and Tronzano, M. (2018). A Bayesian Markov-switching correlation model for contagion analysis on exchange rate markets. *Journal of Business & Economic Statistics*, 36(1):101–114.

Catania, L. and Billé, A. G. (2017). Dynamic spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Applied Econometrics*, 32(6):1178–1196.

Cavicchioli, M. (2014). Analysis of the likelihood function for Markov-switching VAR (CH) models. *Journal of Time Series Analysis*, 35(6):624–639.

Chan-Lau, J. A., Liu, E. X., and Schmittmann, J. M. (2015). Equity returns in the banking sector in the wake of the great recession and the European sovereign debt crisis. *Journal of Financial Stability*, 16:164–172.

Chen, P. and Semmler, W. (2018). Financial stress, regime switching and spillover effects: Evidence from a multi-regime global VAR model. *Journal of Economic Dynamics and Control*, 91:318–348.

Chevallier, J., Nguyen, D. K., Siverskog, J., and Uddin, G. S. (2018). Market integration and financial linkages among stock markets in Pacific Basin countries. *Journal of Empirical Finance*, 46:77–92.

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

Chiang, T. C., Qiao, Z., and Wong, W.-K. (2011). A Markov regime-switching model of stock return volatility: Evidence from Chinese markets. *Nonlinear Financial Econometrics: Markov Switching Models, Persistence and Nonlinear Cointegration*, pages 49–73.

Chinazzi, M., Fagiolo, G., Reyes, J. A., and Schiavo, S. (2013). Post-mortem examination of the international financial network. *Journal of Economic Dynamics and Control*, 37(8):1692–1713.

Chou, R. Y., Chou, H., and Liu, N. (2010). Range volatility models and their applications in finance. In *Handbook of quantitative finance and risk management*, pages 1273–1281. Springer.

Chow, H. K. (2017). Volatility spillovers and linkages in Asian stock markets. *Emerging Markets Finance and Trade*, 53(12):2770–2781.

Chowdhury, B., Dungey, M., Kangogo, M., Sayeed, M. A., and Volkov, V. (2019). The changing network of financial market linkages: The Asian experience. *International Review of Financial Analysis*.

Chu, C.-S. J., Santoni, G. J., and Liu, T. (1996). Stock market volatility and regime shifts in returns. *Information Sciences*, 94(1-4):179–190.

Cimini, R. (2015). Eurozone network "connectedness" after fiscal year 2008. *Finance Research Letters*, 14:160–166.

Claessens, S. and Forbes, K. (2013). *International financial contagion*. Springer Science & Business Media.

Cohen-Cole, E., Patacchini, E., and Zenou, Y. (2012). Systemic risk and network formation in the interbank market. CAREFIN Research Paper No. 25/2010.

Corsi, F., Mittnik, S., Pigorsch, C., and Pigorsch, U. (2008). The volatility of realised volatility. *Econometric Reviews*, 27(1-3):46–78.

De Bruyckere, V., Gerhardt, M., Schepens, G., and Vander Vennet, R. (2013). Bank/sovereign risk spillovers in the European debt crisis. *Journal of Banking & Finance*, 37(12):4793–4809.

Degiannakis, S., Filis, G., and Hassani, H. (2018). Forecasting global stock market implied volatility indices. *Journal of Empirical Finance*, 46:111–129.

Demirer, M., Diebold, F. X., Liu, L., and Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics*, 33(1):1–15.

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

Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1):57–66.

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

Diebold, F. X. and Yilmaz, K. (2015). Trans-Atlantic equity volatility connectedness: US and European financial institutions, $2004 - 2014$. *Journal of Financial Econometrics*, 14(1):81–127.

Dufrénot, G. and Keddad, B. (2014). Spillover effects of the 2008 global financial crisis on the volatility of the Indian equity markets: Coupling or uncoupling? A study on sector-based data. *International Review of Financial Analysis*, 33:17–32.

Dungey, M., Fry, R., González-Hermosillo, B., and Martin, V. L. (2005). Empirical modelling of contagion: A review of methodologies. *Quantitative Finance*, 5(1):9–24.

Dungey, M., Fry, R., and Martin, V. L. (2004). Currency market contagion in the Asia-Pacific region. *Australian Economic Papers*, 43(4):379–395.

Dungey, M., Fry, R., and Martin, V. L. (2006). Correlation, contagion and Asian evidence. *Asian Economic Papers*, 5(2):32–72.

Dungey, M., Harvey, J., and Volkov, V. (2019a). The changing international network of sovereign debt and financial institutions. *Journal of International Financial Markets, Institutions and Money*, 60:149–168.

Dungey, M., Kangogo, M., and Volkov, V. (2019b). Changing vulnerability in Asia: Contagion and systemic risk. ADB Economics Working Paper Series No. 583.

Dungey, M., Khan, F., and Raghavan, M. (2018a). International trade and the transmission of shocks: The case of ASEAN-4 and NIE-4 economies. *Economic Modelling*, 72:109–121.

Dungey, M., Luciani, M., and Veredas, D. (2012). Ranking systemically important financial institutions. Tinbergen Institute Discussion Paper.

Dungey, M., Luciani, M., and Veredas, D. (2013). Googling SIFIs. *Systemic Risk: Liquidity Risk, Governance and Financial Stability, Forthcoming.*

Dungey, M., Milunovich, G., Thorp, S., and Yang, M. (2015). Endogenous crisis dating and contagion using smooth transition structural GARCH. *Journal of Banking & Finance*, 58:71–79.

Dungey, M. and Renault, E. (2018). Identifying contagion. *Journal of Applied Econometrics*, 33(2):227–250.

Dungey, M. and Tambakis, D. (2005). *Identifying international financial contagion: progress and challenges.* Oxford University Press.

Dungey, M. and Zhumabekova, D. (2001). Testing for contagion using correlations: Some words of caution. Federal Reserve Bank of San Francisco.

Dungey, M. H., Harvey, J., Siklos, P. L., and Volkov, V. (2018b). Signed spillover effects building on historical decompositions. Tasmanian School of Business and Economics Discussion Paper Series No. 2017-11.

Eder, A. and Keiler, S. (2015). CDS spreads and contagion amongst systemically important financial institutions- A spatial econometric approach. *International Journal of Finance & Economics*, 20(4):291–309.

Edwards, S. et al. (1998). Interest rate volatility, contagion and convergence: An empirical investigation of the cases of Argentina, Chile and Mexico. *Journal of Applied Economics*, 1(1):55–86.

Elekdag, S., Rungcharoenkitkul, M. P., and Wu, M. Y. (2012). The evolution of Asian financial linkages: Key determinants and the role of policy. IMF Working Paper WP/12/262.

Elhorst, J. P. (2010). Applied spatial econometrics: Raising the bar. *Spatial Economic Analysis*, 5(1):9–28.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalised autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3):339–350.

Fackler, J. S. and McMillin, W. D. (1998). Historical decomposition of aggregate demand and supply shocks in a small macro model. *Southern Economic Journal*, pages 648–664.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fernandez, V. (2011). Spatial linkages in international financial markets. *Quantitative Finance*, 11(2):237–245.

Finta, M. A., Frijns, B., and Tourani-Rad, A. (2017). Contemporaneous spillover effects between the us and the uk equity markets. *Financial Review*, 52(1):145–166.

Flood, R. P. and Garber, P. M. (1984). Collapsing exchange-rate regimes: Some linear examples. *Journal of International Economics*, 17(1-2):1–13.

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

Frankel, J. A. and Rose, A. K. (1996). Currency crashes in emerging markets: An empirical treatment. *Journal of international Economics*, 41(3-4):351–366.

Fukuda, S.-i. and Tanaka, M. (2017). The impacts of emerging Asia on global financial markets. *Emerging Markets Finance and Trade*, 53(12):2725–2743.

Gai, P. and Kapadia, S. (2010). Contagion in financial networks. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 466(2120):2401–2423.

Gallo, G. M. and Otranto, E. (2008). Volatility spillovers, interdependence and comovements: A Markov switching approach. *Computational Statistics & Data Analysis*, 52(6):3011–3026.

Garman, M. B. and Klass, M. J. (1980). On the estimation of security price volatilities from historical data. *Journal of business*, pages 67–78.

Gębka, B. and Serwa, D. (2006). Are financial spillovers stable across regimes?: Evidence from the 1997 asian crisis. *Journal of International Financial Markets, Institutions and Money*, 16(4):301–317.

Geraci, M. V. and Gnabo, J.-Y. (2018). Measuring interconnectedness between financial institutions with Bayesian time-varying vector autoregressions. *Journal of Financial and Quantitative Analysis*, 53(3):1371–1390.

Giannetti, M. and Laeven, L. (2015). Local ownership, crises and asset prices: Evidence from US mutual funds. *Review of Finance*, 20(3):947–978.

Giraitis, L., Kapetanios, G., Wetherilt, A., and Žikeš, F. (2016). Estimating the dynamics and persistence of financial networks, with an application to the Sterling money market. *Journal of Applied Econometrics*, 31(1):58–84.

Giudici, P. and Spelta, A. (2016). Graphical network models for international financial flows. *Journal of Business & Economic Statistics*, 34(1):128–138.

Glasserman, P. and Young, H. P. (2015). How likely is contagion in financial networks? *Journal of Banking & Finance*, 50:383–399.

Glasserman, P. and Young, H. P. (2016). Contagion in financial networks. *Journal of Economic Literature*, 54(3):779–831.

Gofman, M. (2017). Efficiency and stability of a financial architecture with too-interconnected-to-fail institutions. *Journal of Financial Economics*, 124(1):113–146.

González-Páramo, J. M. (2010). Globalisation, international financial integration and the financial crisis–the future of european and international financial market regulation and supervision. *Discurso en el Institute of International and European Affairs, Dublin.*

Goodhart, C. A. E., Goodhart, C., Lu, D., et al. (2003). *Intervention to save H ong K ong: The authorities' counter-speculation in financial markets*. Oxford University Press on Demand.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, pages 424–438.

Granger, C. W., Huangb, B.-N., and Yang, C.-W. (2000). A bivariate causality between stock prices and exchange rates: Evidence from recent Asianflu. *The Quarterly Review of Economics and Finance*, 40(3):337–354.

Grobys, K. (2015). Are volatility spillovers between currency and equity market driven by economic states? evidence from the us economy. *Economics Letters*, 127:72–75.

Guimarães-Filho, R. and Hong, G. H. (2016). Dynamic connectedness of Asian equity markets. IMF Working Paper WP/16/57.

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

Haldane, A. (2009). Rethinking the financial network. Speech delivered at the Financial Students Association, 28 April 2009, Amsterdam.

Hamilton, J. D. (1994). *Time series analysis*. Princeton University Press, New Jersey.

Harvey, C. R. (1995). Predictable risk and returns in emerging markets. *The Review of Financial Studies*, 8(3):773–816.

Henry, O. T. (2009). Regime switching in the relationship between equity returns and short-term interest rates in the UK. *Journal of Banking & Finance*, 33(2):405–414.

Herwartz, H. and Lütkepohl, H. (2014). Structural vector autoregressions with Markov switching: Combining conventional with statistical identification of shocks. *Journal of Econometrics*, 183(1):104–116.

Hu, T., Hu, L., and Ning, L. (2018). Return and volatility spillovers in the Asia-Pacific information technology stock markets. Presented at the 2018 IEEE International Symposium on Innovation and Entrepreneurship (TEMS-ISIE).

Hueng, C. J. and Yau, R. (2013). Country-specific idiosyncratic risk and global equity index returns. *International Review of Economics & Finance*, 25:326–337.

Hung, N. T. (2019). Return and volatility spillover across equity markets between China and Southeast Asian countries. *Journal of Economics, Finance and Administrative Science*.

Hüser, A.-C. (2015). Too interconnected to fail: A survey of the interbank networks literature. SAFE Working Paper No. 91.

Hwang, E., Min, H.-G., Kim, B.-H., and Kim, H. (2013). Determinants of stock market co-movements among US and emerging economies during the US financial crisis. *Economic Modelling*, 35:338–348.

Ji, Q., Bouri, E., Lau, C. K. M., and Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis*, 63:257–272.

Ji, Q., Bouri, E., and Roubaud, D. (2018a). Dynamic network of implied volatility transmission among US equities, strategic commodities and BRICS equities. *International Review of Financial Analysis*, 57:1–12.

Ji, Q., Geng, J.-B., and Tiwari, A. K. (2018b). Information spillovers and connectedness networks in the oil and gas markets. *Energy Economics*, 75:71–84.

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

Kaminsky, G. L. and Reinhart, C. (2003). The center and the periphery: The globalisation of financial turmoil. NBER Working Paper No. 9479.

Kaminsky, G. L. and Reinhart, C. M. (2002). Financial markets in times of stress. *Journal of Development Economics*, 69(2):451–470.

Kanas, A. (2005). Regime linkages between the Mexican currency market and emerging equity markets. *Economic Modelling*, 22(1):109–125.

Kanas, A. and Kouretas, G. P. (2007). Regime dependence between the official and parallel foreign currency markets for US dollars in Greece. *Journal of Macroeconomics*, 29(2):431–449.

Khalifa, A. A., Hammoudeh, S., and Otranto, E. (2014). Patterns of volatility transmissions within regime switching across GCC and global markets. *International Review of Economics & Finance*, 29:512–524.

Kim, B.-H., Kim, H., and Lee, B.-S. (2015). Spillover effects of the US financial crisis on financial markets in emerging Asian countries. *International Review of Economics & Finance*, 39:192–210.

Kim, C.-J. (1994). Dynamic linear models with Markov-switching. *Journal of Econometrics*, 60(1-2):1–22.

Kleimeier, S., Lehnert, T., and Verschoor, W. F. (2008). Measuring financial contagion using time-aligned data: The importance of the speed of transmission of shocks. *Oxford Bulletin of Economics and Statistics*, 70(4):493–508.

Koopman, S. J., Jungbacker, B., and Hol, E. (2005). Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements. *Journal of Empirical Finance*, 12(3):445–475.

Krugman, P. (1979). A model of balance-of-payments crises. *Journal of Money, Credit and Banking*, 11(3):311–325.

Kubelec, C. and Sá, F. (2012). The geographical composition of national external balance sheets: 1980 − 2005. *International Journal of Central Banking*, Vol. 8(2):143–189.

Lanne, M., Lütkepohl, H., and Maciejowska, K. (2010). Structural vector autoregressions with Markov switching. *Journal of Economic Dynamics and Control*, 34(2):121–131.

Lee, L.-F. (2002). Consistency and efficiency of least squares estimation for mixed regressive, spatial autoregressive models. *Econometric Theory*, 18(2):252–277.

Lee, L.-f. (2007). GMM and 2SLS estimation of mixed regressive, spatial autoregressive models. *Journal of Econometrics*, 137(2):489–514.

LeSage, J. and Pace, R. K. (2009). *Introduction to spatial econometrics*. London: Chapman and Hall/CRC.

Leung, H., Schiereck, D., and Schroeder, F. (2017). Volatility spillovers and determinants of contagion: Exchange rate and equity markets during crises. *Economic Modelling*, 61:169–180.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, pages 13–37.

Liow, K. H. and Ye, Q. (2017). Switching regime beta analysis of global financial crisis: Evidence from international public real estate markets. *Journal of Real Estate Research*, 39(1):127–164.

Liu, L. (2014). Extreme downside risk spillover from the United States and Japan to Asia-Pacific stock markets. *International Review of Financial Analysis*, 33:39–48.

Liu, Z., Quiet, S., and Roth, B. (2015). Banking sector interconnectedness: What is it, how can we measure it and why does it matter? *Bank of England Quarterly Bulletin*, page Q2.

Lopes, J. M. and Nunes, L. C. (2012). A Markov regime switching model of crises and contagion: The case of the Iberian countries in the EMS. *Journal of Macroeconomics*, 34(4):1141–1153.

Lucking, B., Bloom, N., and Van Reenen, J. (2018). Have R&D spillovers changed? NBER Working Paper No. 24622.

Luo, J. and Ji, Q. (2018). High-frequency volatility connectedness between the US crude oil market and China's agricultural commodity markets. *Energy Economics*, 76:424–438.

Ma, Y.-R., Zhang, D., Ji, Q., and Pan, J. (2019). Spillovers between oil and stock returns in the a bivariate causality between stock prices and exchange rates: Evidence from recent US energy sector: Does idiosyncratic information matter? *Energy Economics*, 81:536–544.

Magkonis, G. and Tsopanakis, A. (2018). The financial connectedness between Eurozone core and periphery: A disaggregated view. *Macroeconomic Dynamics*, pages 1–26.

Mandilaras, A. and Bird, G. (2010). A Markov switching analysis of contagion in the EMS. *Journal of International Money and Finance*, 29(6):1062–1075.

Markose, S., Giansante, S., and Shaghaghi, A. R. (2012). 'Too interconnected to fail' financial network of US CDS market: Topological fragility and systemic risk. *Journal of Economic Behavior & Organization*, 83(3):627–646.

Mensi, W., Boubaker, F. Z., Al-Yahyaee, K. H., and Kang, S. H. (2018). Dynamic volatility spillovers and connectedness between global, regional and GIPSI stock markets. *Finance Research Letters*, 25:230–238.

Merton, R. C., Billio, M., Getmansky, M., Gray, D., Lo, A. W., and Pelizzon, L. (2013). On a new approach for analysing and managing macrofinancial risks (corrected). *Financial Analysts Journal*, 69(2):22–33.

Mink, M. (2015). Measuring stock market contagion: Local or common currency returns? *Emerging Markets Review*, 22:18–24.

Mink, M. and De Haan, J. (2013). Contagion during the Greek sovereign debt crisis. *Journal of International Money and Finance*, 34:102–113.

Minoiu, C., Kang, C., Subrahmanian, V., and Berea, A. (2015). Does financial connectedness predict crises? *Quantitative Finance*, 15(4):607–624.

Minoiu, C. and Reyes, J. A. (2013). A network analysis of global banking: $1978-2010$. *Journal of Financial Stability*, 9(2):168–184.

Minoiu, C. and Sharma, S. (2014). Financial networks key to understanding systemic risk. *IMF Research Review*, 28.

Miyakoshi, T. (2003). Spillovers of stock return volatility to Asian equity markets from Japan and the US. *Journal of International Financial Markets, Institutions and Money*, 13(4):383–399.

Mobarek, A., Muradoglu, G., Mollah, S., and Hou, A. J. (2016). Determinants of time varying co-movements among international stock markets during crisis and non-crisis periods. *Journal of Financial Stability*, 24:1–11.

Morck, R. and Yeung, B. (2016). China in Asia. *China Economic Review*, 40:297–308.

Narayan, P. K., Narayan, S., and Prabheesh, K. (2014). Stock returns, mutual fund flows and spillover shocks. *Pacific-Basin Finance Journal*, 29:146–162.

Nomikos, N. and Salvador, E. (2014). The role of volatility regimes on volatility transmission patterns. *Quantitative Finance*, 14(1):1–13.

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *Journal of business*, pages 61–65.

Peltonen, T. A., Rancan, M., and Sarlin, P. (2019). Interconnectedness of the banking sector as a vulnerability to crises. *International Journal of Finance & Economics*, 24(2):963–990.

Pesaran, M. H. and Yang, C. F. (2016). Econometric analysis of production networks with dominant units. Cambridge Working Papers in Economics 1678.

Poledna, S., Molina-Borboa, J. L., Martínez-Jaramillo, S., Van Der Leij, M., and Thurner, S. (2015). The multi-layer network nature of systemic risk and its implications for the costs of financial crises. *Journal of Financial Stability*, 20:70–81.

Pradhan, R. P., Arvin, M. B., and Ghoshray, A. (2015). The dynamics of economic growth, oil prices, stock market depth and other macroeconomic variables: Evidence from the G-20 countries. *International Review of Financial Analysis*, 39:84–95.

Psaradakis, Z., Ravn, M. O., and Sola, M. (2005). Markov switching causality and the money-output relationship. *Journal of Applied Econometrics*, 20(5):665–683.

Raddant, M. and Kenett, D. Y. (2016). Interconnectedness in the global financial market. OFR WP 16-09.

Rigobon, R. (2002). The curse of non-investment grade countries. *Journal of Development Economics*, 69(2):423–449.

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

Roy, R. P. and Roy, S. S. (2017). Financial contagion and volatility spillover: An exploration into Indian commodity derivative market. *Economic Modelling*, 67:368–380.

Salant, S. W. and Henderson, D. W. (1978). Market anticipations of government policies and the price of gold. *Journal of Political Economy*, 86(4):627–648.

Sander, H. and Kleimeier, S. (2003). Contagion and causality: An empirical investigation of four Asian crisis episodes. *Journal of International Financial Markets, Institutions and Money*, 13(2):171–186.

Schiavo, S., Reyes, J., and Fagiolo, G. (2010). International trade and financial integration: A weighted network analysis. *Quantitative Finance*, 10(4):389–399.

Semmler, W. and Chen, P. (2014). Financial stress, regime switching and macrodynamics: Theory and empirics for the US, the EU and non-EU countries. *Economics: The Open-Access, Open-Assessment E-Journal*, 8(2014-20):1–42.

Sewraj, D., Gebka, B., and Anderson, R. D. (2018). Identifying contagion: A unifying approach. *Journal of International Financial Markets, Institutions and Money*, 55:224–240.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3):425–442.

Silva, T. C., de Souza, S. R. S., and Tabak, B. M. (2016). Network structure analysis of the Brazilian interbank market. *Emerging Markets Review*, 26:130–152.

Sok-Gee, C., Karim, M. A., and Karim, M. (2010). Volatility spillovers of the major stock markets in ASEAN-5 with the US and Japanese stock markets. *International Research Journal of Finance and Economics*, 44:161–72.

Sun, A. J. and Chan-Lau, J. A. (2017). Financial networks and interconnectedness in an advanced emerging market economy. *Quantitative Finance*, 17(12):1833–1858.

Tonzer, L. (2015). Cross-border interbank networks, banking risk and contagion. *Journal of Financial Stability*, 18:19–32.

Turner, C. M., Startz, R., and Nelson, C. R. (1989). A Markov model of heteroskedasticity, risk and learning in the stock market. *Journal of Financial Economics*, 25(1):3–22.

van de Leur, M. C., Lucas, A., and Seeger, N. J. (2017). Network, market and book-based systemic risk rankings. *Journal of Banking & Finance*, 78:84–90.

van Lelyveld, I. and Veld, D. i. (2014). Finding the core: Network structure in interbank markets. *Journal of Banking & Finance*, 49:27–40.

Van Rijckeghem, C. and Weder, B. (2001). Sources of contagion: Is it finance or trade? *Journal of International Economics*, 54(2):293–308.

Vitali, S., Battiston, S., and Gallegati, M. (2016). Financial fragility and distress propagation in a network of regions. *Journal of Economic Dynamics and Control*, 62:56–75.

Walid, C., Chaker, A., Masood, O., and Fry, J. (2011). Stock market volatility and exchange rates in emerging countries: A Markov-state switching approach. *Emerging Markets Review*, 12(3):272–292.

Wang, G.-J., Xie, C., Jiang, Z.-Q., and Stanley, H. E. (2016). Who are the net senders and recipients of volatility spillovers in China's financial markets? *Finance Research Letters*, 18:255–262.

Wang, G.-J., Xie, C., and Stanley, H. E. (2018). Correlation structure and evolution of world stock markets: Evidence from Pearson and partial correlation-based networks. *Computational Economics*, 51(3):607–635.

Yarovaya, L., Brzeszczyński, J., and Lau, C. K. M. (2016a). Intra and inter-regional return and volatility spillovers across emerging and developed markets: Evidence from stock indices and stock index futures. *International Review of Financial Analysis*, 43:96–114.

Yarovaya, L., Brzeszczyński, J., and Lau, C. K. M. (2016b). Volatility spillovers across stock index futures in Asian markets: Evidence from range volatility estimators. *Finance Research Letters*, 17:158–166.

Ye, W., Zhu, Y., Wu, Y., and Miao, B. (2016). Markov regime-switching quantile regression models and financial contagion detection. *Insurance: Mathematics and Economics*, 67:21–26.

Yellen, J. (2013). Interconnectedness and systemic risk: Lessons from the financial crisis and policy implications: A speech at the American economic association/American finance association joint luncheon, San Diego, California. *American Finance Association*.

Yilmaz, K. (2010). Return and volatility spillovers among the East Asian equity markets. *Journal of Asian Economics*, 21(3):304–313.

Yu, H., Fang, L., Sun, B., and Du, D. (2017). Risk contribution of the Chinese stock market to developed markets in the post-crisis period. *Emerging Markets Review*.

Zhang, D. (2017). Oil shocks and stock markets revisited: Measuring connectedness from a global perspective. *Energy Economics*, 62:323–333.

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

Zhang, D. and Fan, G.-Z. (2019). Regional spillover and rising connectedness in China's urban housing prices. *Regional Studies*, 53(6):861–873.

Zhang, D., Lei, L., Ji, Q., and Kutan, A. M. (2019). Economic policy uncertainty in the US and China and their impact on the global markets. *Economic Modelling*, 79:47–56.

Zheng, T. and Zuo, H. (2013). Reexamining the time-varying volatility spillover effects: A Markov switching causality approach. *The North American Journal of Economics and Finance*, 26:643–662.