Three Essays on Financial Markets in Developed and Emerging Countries

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Intellectual Property Statement

The candidate confirms that the work submitted is her own and that appropriate credit has been given where reference has been made to the work of others.

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Abstract

The first chapter investigates whether macroeconomic factors play a role in explaining how long stock bubbles survive. To do this, it employs duration models, controls for endogeneity, and accounts for heterogeneity in stock markets. It documents that contemporaneous inflation and portfolio inflows might lead to longer duration of bubbles while the lags of inflation, portfolio inflows, yield spreads, and the volatility in gold prices appear to shorten the duration of bubbles. The results also show that the duration of bubbly stock episodes in high-income countries and countries with highly developed financial systems are less influenced by macroeconomic factors. Conversely, middle-income countries and countries with relatively less developed financial markets have a weaker ability to cope with macroeconomic shocks. Finally, the study finds that the effect of countries' real economic activity on the duration of stock bubbles is likely transmitted through the channel of growth in consumption expenditure.

The second chapter introduces the assumption of distinct breaks for testing of contagion. The empirical relevance of this assumption for the analysis of contagion is highlighted. In the first part of the chapter, it examines the existence of contagion through significant increases and breaks in conditional correlation of returns. It uses a sequential procedure to decompose the covariance matrix, test for changes and breaks in conditional correlation of returns, and estimates break dates. It documents that the test procedure detects breaks in conditional correlation of returns, in particular, during the recent global financial crisis, strongly supporting the occurrence of contagion across markets. The second part of the chapter examines the existence of contagion through volatility spillovers, and the importance of distinct breaks in the mean, variance, and correlations for the modelling of spillovers. It compares spillover indices obtained with distinct breaks against those obtained without distinct breaks. The study finds that distinct breaks characterize the evolution of volatility spillovers over time remarkably well. The main insight is that allowing for distinct breaks leads to time-variation in spillovers of volatilities.

The third chapter investigates whether the approach used in determining the start date of a financial crisis period matters for the magnitude of the estimates when measuring contagion through coskewness. The importance of choosing the right start date for modelling contagion is discussed. The estimation issues that could arise from inaccurately determining the correct start date are thoroughly discussed. The discussion shows that determining the start date endogenously leads to better result, which informed the choice of our empirical approach. The chapter then determines endogenously the start date of the recent global financial crisis for three different regions (developed Europe, Pacific and emerging Asia, and emerging Latin America) using two alternative test procedures – Quandt-Andrews and a variety of Bai and Perron test procedures. Based on the endogenously determined start date it tests for contagion through correlation and coskewness. It documents changes in correlations and coskewness during the global financial crisis, supporting the occurrence of contagion.

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List of Abbreviations

2SLS	two-stage least squares
ADF	Augmented Dickey-Fuller
ARA	absolute risk aversion
ARG	Argentina
BF	log of the Bayes factor
BEL	Belgium
BP	Bai and Perron
BRA	Brazil
CHL	Chile
CHN	China
clog-log	complementary log-log
COL	Columbia
CPI	consumer price index
DE	developed Europe
DEEs	developed and emerging economies
Dbs	duration of bubbles
ECB	European Central Bank
ELA	emerging Latin America
FGLS	feasible generalized least squares
FRA	France
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GDP	Gross Domestic Product
Gdpc	growth in GDP per capita
Gdpcvol	volatility in GDP per capita
GER	Germany
GFC	global financial crisis
GFEVDs	generalized forecast error variance decompositions
GSADF	Generalized supremum Augmented Dickey-Fuller test
HKG	Hong Kong
IMF	International Monetary Fund
IND	Indonesia
Infdf	GDP deflator
Infdfvol	Inflation volatility, GDP deflator
Infl	Inflation
Infvol	Inflation volatility
IRL	Ireland
ITL	Italy
JPN	Japan
KOR	Korea
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
MAL	Malaysia

MEX	Mexico
MCMC	Markov Chain Monte Carlo
Mpol	Interest rate gap
MSCI	Morgan Stanley Capital International
NET	The Netherlands
OECD	Organization for Economic Co-operation and Development
OLG	overlapping generations
PEA	Pacific and emerging Asia
PER	Peru
PHI	Philippines
POR	Portugal
Portf	Portfolio inflows
P	probability
PP	Phillips-Perron
QA	Quandt-Andrews
Rcons	Growth in consumption
Rgi	Growth in investment
Rgp	Real gold prices
Rgpvol	Volatility in gold prices
Rop	Real oil prices
Ropvol	Volatility in oil prices
SGN	Singapore
SP	sequential procedure
SPA	Spain
SSR	sum of squared residuals
TAI	Taiwan
THL	Thailand
US	The United States
UK	United Kingdom
VAR	Vector Autoregression
Yiespd	Yield spreads

Chapter 1: Introduction

1.1. Motivation

Bubbles and contagion are two important phenomena of international finance and are both of crucial concern for stock markets in developed and emerging economies (DEEs). This is because they can affect the pricing dynamics of stock markets. There are several motivations for interest in stock markets behaviour. Generally, the aim of stock markets is to provide efficient allocation of capital, which increases overall efficiency of the economy. Besides the important role of improving capital allocation, stock markets also boost savings and investment, which contributes to economic development. The markets allow for asset diversification thereby reducing the risk borne by investors. However, even if the stock market provides substantial benefits during tranquil times, during a financial crisis these can wane. This is because a crisis profoundly affects price formation and the dynamics of stocks behaviour. As will be discussed in this thesis, the transmission of external shocks from a notable crisis event, the global financial crisis (GFC) which originated from the US had significant repercussions for the dynamics of stock markets in DEEs. Shocks triggered by this crisis spilled over across borders, with serious disturbing trends in stock markets of DEEs.

Prior to the GFC, between 2000 and 2007, world real interest rates were generally lower than their level in the previous decade. This resulted in rapid growth of credit and rising stock prices. Moreover, stock price volatility was less than 15% between 2004 and 2007. During the GFC, however, stock markets were characterized by a sharp decline in prices. In addition, following a period of low volatility, unprecedented high levels of volatility with sharp increases of over 40%, were experienced across the stock markets of DEEs. Coupled with this, the correlation patterns between market returns suddenly increased during this crisis.

Typically, the above contrasting paths of stock returns have resulted in two well-established subjects of interest. On the one hand, prior to a crisis episode, the dynamics of stock returns can move above and beyond what is implied by their fundamentals, resulting in what is commonly referred to as *bubbles*. Financial liberalization, which results in expansion of credit for investment, is often accompanied by an increase in stock prices above its fundamental value

(Allen and Gale, 1999). Bubbles, which often are an important part of stock prices (Diba and Grossman, 1988a; Evans, 1991), can affect economic growth through various channels. First, bubbles can have crowding out effect because they absorb savings and do not allow capital to be channelled to the productive sectors for investment. This can have a dampening effect on long-run growth. Second, its collapse may result in severe recessions with huge economic costs and slow pace of recovery. Third, if the run-up in prices are financed by credit, amplification mechanism and spillover effects will set in (Brunnermeier and Oehmke, 2013). Moreover, if they burst, particularly those financed via leverage, an increase in default on repayments by borrowers is inevitable.

On the other hand, during a crisis episode, stock returns can co-move extremely across markets and lead to a phenomenon often referred to as *contagion*. Contagion between stock markets following a crisis is a crucial issue for DEEs. This is important because contagion between stock markets is not only a significant rise in cross-market dependence, but — as will be discussed in greater detail this thesis, — it causes breaks or unexpected changes in the international transmission mechanisms between markets (Pericoli and Sbracia, 2003; Corsetti et al., 2005; Khan and Park, 2009; Jung and Maderitsch, 2014). As such, contagion could cause a sudden change in the behaviour of stock returns, and this could disrupt the smooth functioning of markets. Understanding contagion from the viewpoint of breaks is, therefore, of importance because not only does it helps to uncover whether there is a sudden change in the behaviour of stock returns and the time when the change occurs, but because it would indicate how severely pricing dynamics has been affected.

Contagion is also associated with the transmission of shocks that spill over from one country to another during a crisis. These shocks when transmitted across stock markets, however, can have significant implications for international portfolio diversification benefits, which become significantly reduced due to extreme and correlated fall in stock returns and extreme volatility prompted by a global crisis event. In the last two decades, the nature and extent of DEEs' financial integration has changed. Stock markets in DEEs have experienced higher integration into international financial markets and this has strengthened cross-regional dependence between them. With a reinforced cross-market dependence, markets in DEEs are affected from the transmission of shocks that arise from a crisis event in a serious way. The design of optimal stock market policy requires knowledge of the changing dynamics of stocks prior to or during a financial crisis.

This thesis addresses some of these issues above. First, it attempts to determine the macroeconomic factors that affect the duration of bubbles in stock markets of DEEs. Two types of dimensions through which bubbles can be examined include bubble *dynamics* or bubble *durations*. In determining the role of macroeconomic factors on bubbles, the most frequently used dimension is the dynamics of bubbles. In addition, the driving forces are mostly accounted for by *domestic* factors, rather than *exogenous* factors. This thesis examines driving forces behind bubbles using their durations and it considers the role of both domestic and exogenous factors. It also examines these driving forces for countries with different degrees of financial development and income levels.

Second, it attempts to explore two aspects of contagion with the primary goal of drawing some policy implications for contagion in stock markets of DEEs: the type of break and the determination of the crisis start date for the analysis of contagion during the GFC. Empirical studies face several challenges in testing for the existence of contagion if the assumption made about breaks are not reasonable. With respect to the type of break, it can be either *common* or *distinct*. Most often, investigations of contagion are conducted by assuming that breaks in the covariance matrix are common, which implies that variances and correlations share the *same* break points. Contrary to the typical assumption made, this thesis relies on the assumption of distinct breaks and allows variances and correlations to have separate break points in order to investigate contagion. There is a possibility that variances and correlations have different break points. From this view, testing for breaks using the assumption of distinct breaks is important because it could reduce the bias of contagion tests and improve the measurement of contagion.

On the determination of the crisis start date for the analysis of contagion, the date can be set either *exogenously* or *endogenously*. The date, which is used for demarcating non-crisis period from crisis period prior to modelling of contagion, must be accurately determined or else, sample selection and estimation biases could arise if the date is not correctly determined. This thesis examines whether the approach used to determine the start date of a crisis matters for the magnitude of estimates of contagion using higher-order comoment like coskewness. It does so by assessing the magnitude of changes in coskewness of returns using both approaches. In order to succeed with tests for the existence of contagion and present convincing evidence, the type of break and how the crisis start date is *determined* is, thus, crucial.

The remainder of the chapter is structured into three sections. Section 1.2 lays out the contributions of this thesis and relates it to the academic and empirical debate and existing literature. Section 1.3 outlines the main empirical methodology for the quantitative inquiry. Finally, Section 1.4 presents the thesis' structure and a brief discussion of each chapter.

1.2. Contributions of the Thesis

This thesis aims to contribute to the existing literature on bubbles and contagion both empirically and methodologically.

It makes three empirical contributions to the existing literature in the context of DEEs. First, empirically, this thesis argues that the duration of bubbles is dependent on macroeconomic factors, which are domestic and exogenous. It has previously been found that domestic factors, such as interest rates can influence the duration of bubbles (He et al., 2019). Theoretically, it has been shown that even exogenous factors, such as fundamental total factor productivity shock could influence bubbles (Dong et al., 2020). The focus has shifted from *domestic* to *exogenous* factors. However, to what extent are these factors important in duration of bubbles across stock markets? This thesis explores the extent to which domestic or exogenous macroeconomic factors influence the duration of bubbles in the stock markets of DEEs. Moreover, does heterogeneity among markets affect the duration of stock bubbles? This thesis addresses possible measurement issues that arise from estimation, such as heterogeneity. Given that, there are manifestations of the duration of stock bubbles affected by macroeconomic factors; do these empirical manifestations differ depending on a country's degree of financial development and level of income? This thesis also explores the extent to which factors could influence duration of bubbles in the stock markets of countries at high and intermediate levels of financial development and countries with high and middle levels of income.

Second, this thesis also highlights an important occurrence of international finance: the significantly increased cross-market dependence of returns across stock markets during a crisis, that is, the occurrence of contagion. In the wake of the GFC, financial shocks from the US rapidly transmitted to DEEs stock markets with repercussions for the dynamics of stock returns (Samarakoon, 2011; Dimitriou et al., 2013; Dungey and Gajurel, 2014; Dungey et al., 2015). The global comovement of stock returns during this financial crisis has significantly increased in quantifiable terms (Bekaert et al., 2014). Beyond doubt, besides the rising extreme comovement, several structural changes and breaks that characterize the dynamics of stock markets has occurred. Accurate measurement of contagion has posed as a challenge. This thesis highlights specific measurement issues to address in order to overcome this challenge. Contagion, which is due to the transmitted shocks during financial crisis, could manifest itself in two ways; through significant increases and breaks in cross-market returns, and through spillovers of return volatilities (Pericoli and Sbracias, 2003). This thesis argued that the transmission of shocks has significantly increased the comovement of stock returns in DEEs and caused breaks in the process that generates the returns. However, did shocks transmitted from the recent GFC affect cross-market dependence, cause breaks in the conditional correlation of returns, and lead to contagion between markets in DEEs? These manifestations of breaks in returns can be examined under different assumptions. The focus in the literature has turned from assumption of *common breaks* in the covariance matrix of stock returns to *distinct breaks* in variances and correlations. Due to reliance on the assumption of common breaks, tests for breaks in variances and correlations are carried out simultaneously. This thesis, instead, relies on the assumption of distinct breaks and sequentially tests for contagion. It sequentially implements tests for contagion and treats all shocks in variances and correlations distinctly. It does so because several authors have argued that, during crisis, breaks in variances usually precede breaks in correlations. Still concerning the manifestation of contagion through spillovers of return volatilities, estimations of forecast error variance decompositions used for the computation of spillover indices, have still relied on the assumption of common breaks. Indeed, in this thesis, for this estimation, breaks are distinct, but does the assumption of distinct breaks matter for the evaluation of volatility spillovers of stock returns in DEEs? This thesis assesses the importance of distinct breaks for spillovers. It carries out this assessment by comparing the evolution of spillovers obtained under this assumption against those that did not rely on it.

Third, it is argued that the approach used to determine the crisis start date could be crucial for the analysis of contagion. Most often contagion is measured using correlation in stock return changes, rather than coskewness, which is a higher-order comoment of stock return distributions. This thesis examines whether the approach used to determine the start date matters for the analysis of contagion through coskewness. It examines this because it is likely that inference drawn may be unreliable due to the choice of date. Few authors have previously argued that the date chosen could have a direct impact on estimates of contagion models and affect inferences (Dungey, 2005; Baur, 2012). This thesis uses *endogenous* approaches for the determination of the date. However, does it matter whether the crisis start date is exogenously or endogenously determined for the analysis of contagion through coskewness? It addresses this research question and explores the magnitude to which estimates of contagion across stock markets is being affected by the choice of the crisis start date and highlights empirical implications of the choice of crisis start dates for contagion estimation and inference.

Methodologically, this thesis attempts to explore the determining roles on bubbles' duration and the empirical existence of contagion within the scope of DEEs using refined empirical methods. It uses quantitative methods to address potential issues of econometrics and to uncover required effects of time variation, and the extent to which underlying variables change. On the empirical investigation related to duration of bubbles, it is explored using advanced random-effects duration model, which controls for heterogeneity, that is, the multivariate complementary log-log (clog-log) model. The use of such model, which is suited for analysing data on durations, is still quite scanty in empirical studies. In this thesis, the use of duration models is required to determine the time-varying effects and its sizes. On the empirical research related to contagion, it is explored using a powerful and sophisticated econometric test — the sequential procedure (SP). Such a test is still very infrequently used in empirical studies. The use of this test is essential in order to determine the existence of breaks in the process that generates returns due to reliance on the assumption of distinct breaks in this thesis.

1.3. Research Methodology

In line with the contagion and stock bubble framework adopted in this thesis, research questions were evaluated using a range of econometric models and tests. With respect to duration of bubbles, an advanced time-series test — generalized sup augmented Dickey-Fuller test is used to generate the duration of bubbles. Then, to estimate the effect of macroeconomic factors on the duration of bubbles a multivariate clog-log model is used. In the context of contagion, in particular for the investigation of changes and breaks in the process that generates returns, a multivariate vector autoregression (VAR) based on dynamic simultaneous system of equations is used to estimate changes while a SP is used to determine whether there are breaks. Still within the context of contagion, for the determination of the crisis start date, Quandt-Andrews (QA) and Bai and Perron (BP) test procedures for structural breaks are used, while a regime switching model is adopted to uncover contagion through coskewness. This model is used in conjunction with individual and joint econometric tests. These investigations are done using stock markets situated in DEEs as a case study. In particular, the analysis was based on markets in developed Europe (DE), Pacific and emerging Asia (PEA), and emerging Latin America (ELA).

The sample period runs from 1995 to 2015 spanning over two decades. The data used come from secondary sources provided by the Morgan Stanley Capital International (MSCI), Thomson Reuters DataStream and Eikon, World Bank, International Monetary Fund (IMF) International Financial Statistics, World Bank's Global Financial Development database, and the Organization for Economic Co-operation and Development (OECD) data. The richness of these databases makes them appropriate for examining bubbles and contagion across stock markets.

The use of the different classes of empirical models and econometric tests in this thesis has lend itself to two methods: cross-section - time series and multivariate time series. The cross-section - time series method measures whether the relationships between the duration of bubbles and its driving factors holds and to what degree it holds. The multivariate time series method evaluates whether the comovement between markets changes and determines the magnitude of such changes if they indeed changed. It also determines whether there are breaks in the process that generates returns and the dates of such breaks if they existed.

1.4. Structure of the Thesis

This introduction aside, the thesis is divided into five chapters.

Chapter 2 is an econometric inquiry into the determining roles of macroeconomic factors on stock bubble duration. It econometrically examines the roles of growth in gross domestic product (GDP) per capita, inflation, real oil prices, real gold prices, volatility in GDP per capita, inflation volatility, volatility in oil prices, volatility in gold prices, the interest rate gap, yield spreads, and portfolio inflows on the duration of stock bubbles. It presents separate analyses on the role of these factors for stock bubble duration across groups of countries with different levels of income and financial development. While the existing literature has examined the factors using the dynamics of bubbles, this chapter argues that duration of bubbles is also an important characteristic of bubbles. The existing literature has also examined only domestic factors; this chapter argues that exogenous factors are also crucial. The chapter accounts for three important sources of bias that can affect estimates: firstly, it recognises heterogeneity among markets and the problem of unobserved random effects; secondly, the presence of endogeneity due to correlations of macroeconomic variables with the error terms; and thirdly, omitted variable bias that arises from the omission of other relevant explanatory variables in the estimation model. It discusses and applies two empirical methodologies. It discusses the generalized supremum Augmented Dickey-Fuller (GSADF) test, which it uses to test for the existence of bubbles and to date-stamp the periods of bubbles in stock markets of DEEs. It then discusses the multivariate clog-log model with random effects, which it uses to address the issue of heterogeneity among markets and to examine the roles of macroeconomic factors on stock bubble duration. The chapter goes on to show the main driving forces behind the duration of bubbles in stock markets of DEEs and for countries at high and intermediate levels of financial development, and at high and middle levels of income. It concludes with some potential implications derived from the results.

Chapter 3 aims to explore the importance of distinct breaks in the analysis of contagion across stock markets in DEEs. To analyse the occurrence of the phenomenon, the chapter considers two dominant manifestations of contagion: significant increases in the correlations of stock returns across markets, which cause breaks in the international transmission of shocks, and spillovers of volatilities. While the existing literature has treated the shocks in variances and correlations transmitted during crisis simultaneously, this chapter argues that treating shocks in variances and correlations sequentially is necessary for the accurate quantitative analysis of contagion. The chapter provides a detailed discussion of the econometric methodologies adopted for the accurate analysis of contagion between stock markets and describes the data. It adopts a multivariate VAR framework, which is the model used to econometrically estimate changes in return correlations between stock markets and other components — the conditional mean and conditional variances. It uses an algorithm for sequential testing, a novel testing procedure that is superior to the standard simultaneous procedure, to test for breaks in the conditional correlation of returns and breaks in the other components. It uses generalized forecast error variance decompositions (GFEVDs) to construct indices of volatility spillovers. The chapter presents the results from the analytical methods applied and offers empirical support for the occurrence of contagion across stock markets of DEEs. It draws some implications from the results of the empirical analysis for the existence of contagion among markets in DEEs.

Chapter 4 continues to investigate the phenomenon of contagion covered in chapter 3 but looks at contagion through coskewness and examines a different key issue about its appropriate estimation, that is, the choice of a correct start date of a crisis period. While the existing literature has determined the date exogenously and endogenously for the analysis of contagion through coskewness, this chapter argues that choosing endogenously is much better. It further argues that the choice of the crisis start date could affect estimation accuracy. The chapter presents the empirical methodology, which is divided, into two parts. The first part of the chapter applies a linear regression model, which is consistently estimated using least squares estimators. It then employs two separate tests: QA and a variety of BP test procedures for structural breaks, which are tests that allow break points to occur at unknown break dates or tests that endogenously detect break points from data. It applies these tests to the return generating processes, estimate breaks, and dates them. The second part of this chapter individually and jointly tests for the existence of contagion between stock markets in DEEs. It relies on an extension of regime switching model and adopts an advanced Bayesian approach, which is based on the Markov Chain Monte Carlo (MCMC) Gibbs sampling technique, for the estimation the model's parameters. Most importantly, the chapter provides an assessment of how the choice of the crisis start date affects the magnitude of changes in coskewness. It presents results that show decisive evidence for the existence of contagion through coskewness across stock markets of DEEs and highlights the importance of endogenously determining the start date of a crisis particularly for higher-order comoment like coskewness. The chapter discusses some important empirical implications of this analysis at the end.

Chapter 5 concludes with a discussion on the consequences of the determining factors of bubbles for policy in DEEs and a discussion of some of the implications the occurrence of contagion could have for portfolio diversification and identifies some areas for future research.

Chapter 2: Duration of Stock Bubbles and Macroeconomic Effects

2.1. Introduction

This chapter examines the role of macroeconomic factors in bubbles' duration for stock markets in DEEs. Existing studies on bubble duration only account for a factor related to the domestic economy while the role of exogenous factors have been largely ignored. This chapter fills this gap in the existing literature.

While there is an extensive and growing literature that examines the existence of bubbles in markets of DEEs, the literature that analyses the role of macroeconomic factors in determining duration of stock bubbles is still small (Lunde and Timmermann, 2004; He et al., 2019). The literature on the duration of stock bubbles focuses only on the role of monetary policy via changes in domestic interest rates. No study has considered whether the role of other domestic macroeconomic factors affect the duration of stock bubbles. There is evidence of a causal link between interest rates and duration of stock bubbles. Interest rates matter for bubbles duration because when it is raised it reduces the price of a stock that contains a bubble and dampens the bubble. It does so by crowding out resources that would otherwise be expended on a bubble (Barlevy et al., 2017), thereby decreasing the duration of the bubble (He et al., 2019). The chapter argues that one could anticipate a link between domestic factors that influence interest rates and duration of stock bubbles, because the former is an endogenous variable (Galí, 2014) that is determined by other factors. The most realistic choice of other domestic factors to use for our analysis are those that affect investor's preferences over time and changes the expected returns on stocks, as well as those that influence interest rates. The role of other domestic factors such as growth in GDP per capita, inflation, volatility in GDP per capita, inflation volatility, yield spreads, and portfolio inflows are considered. Moreover, one could argue that the exclusion of other important explanatory variables which can be relevant for analysis of stock bubbles duration might result in an omitted variable bias. For this study not to suffer from such a bias, this chapter includes other determining domestic factors. This chapter adds to the literature by examining the role of other domestic macroeconomic factors for the duration of stock bubbles.

Theoretically, it has been shown that exogenous shocks could influence bubbles (Dong et al., 2020). This chapter argues that exogenous macroeconomic factors will be important to gain additional insight into the crucial drivers of stock bubble duration in DEEs. Whether the dynamics of exogenous macroeconomic factors affect the duration of stock bubbles has not been considered by previous studies. The important role of exogenous factors such as real oil prices, real gold prices, volatility in oil prices, and volatility in gold prices on duration of stock bubbles has not been studied for stock markets in DEEs. This chapter contributes to the literature by investigating the role of exogenous macroeconomic factors for the duration of stock bubbles.

The estimates of the effects for the macroeconomic factors can be weakened due to the presence of endogeneity or spurious effects. In general, endogeneity can arise because of the correlations of the macroeconomic variables with the model error terms. This chapter argues that it is likely that a factor is determined by other macroeconomic factors in the model and vice-versa. This reverse causation between variables might bring about correlated errors or endogeneity, which clearly violates the assumption of independence and strict exogeneity. It, thus, controls for likely endogeneity by allowing macroeconomic variables to be endogenous. Specifically, it includes the lagged levels of macroeconomic variables in the model in order to mitigate endogeneity to some extent and to obtain consistent parameter estimates.

So far, the analysis conducted using the duration of stock bubbles has only focused on a country and not on DEEs. This chapter adds to this emerging literature by giving attention to the duration of bubbles in its analysis of macroeconomic factors in bubbles for stock markets in DEE. This chapter focuses on a set of stock markets across DEE; however, it does not assume that all markets across DEE are homogenous. It instead assumes that heterogeneity exists among markets. Typically, heterogeneity can arise as a result of investors' differential expectations (Boswijk, et al, 2007; Hommes, 2017), different local environments, or as a result of managers' different quality (Gormley and Matsa, 2014). These differences, which are not directly observable, could affect the duration of bubbles. In this context, the bias arising from heterogeneity might be caused by the correlation of unobserved country and market characteristics with the duration of bubbles. This chapter argues that it is crucial to account for this bias in order to obtain accurate parameter estimates. The degree to which it can affect the duration of stock bubbles has not been previously studied.

To examine the effects of macroeconomic factors on stock bubbles duration; the chapter employs the multivariate clog-log model, which is a duration model that allows us to account for the heterogeneity bias as earlier discussed. So far, no such model has been used for analysis on stock bubbles duration. It is advantageous to use this model because it is the most appropriate for analysing time-varying effects related to durations. This model estimates the effects via maximum likelihood estimation method. An attractive feature of this method is that it is an asymptotically efficient and consistent estimator.

The remainder of this chapter proceeds as follows. Section 2 presents the underlying theories on asset bubbles. Section 3 reviews the empirical literature. Section 4 briefly presents the data and empirical methodologies. Section 5 presents the simulation results for the existence of stock bubbles and its duration, reports the baseline results and the robustness checks. Section 6 concludes with some potential implications derived from the results.

2.2. Theories of Asset Bubbles: Beyond Equivalence of Asset Price with Fundamental Value

This section presents a critical review of the standard theory of asset prices and alternative considerations with the intention of providing the theoretical basis for the investigation in this chapter. Several economic theorists have attempted to understand or explain the economic phenomenon of asset bubbles. The economic theory on asset bubbles has evolved along different lines with the considerable changing global financial environment resulting in several competing theories on its existence. The view on asset bubble, however, as the non-equivalence of prices with its fundamental value defined as present value of future cash flow, has remained unchanged.

Historical episodes where asset prices rose rapidly and then collapsed have brought asset bubbles to the forefront of academic discussion. The view of bubbles as an important component of asset prices and explanations to rationalise its existence in markets led to a proliferation of theories of asset price bubbles. Three alternative theoretical considerations to asset price bubbles are the overlapping generations (OLG) model, “sunspot” model and behavioural explanations. Theories have even begun to recognize the important role of monetary policy and exogenous shocks as contributory factors in asset bubbles.

This section is divided into three sub-sections. Sub-section 2.2.1 discusses traditional neoclassical approach to asset price determination, which envision the asset price as always being equivalent to its fundamental value. The discussion focuses on assumptions made concerning economic agents' expectations, particularly rationally formed expectations, and the rationality of behaviour in asset markets. Based on a critique of this view of the asset price, sub-section 2.2.2 presents discussion on the existence of bubbles. Sub-section 2.2.3 presents asset price theories that recognise the important role of monetary policy and exogenous factors to explain the existence of bubbles.

2.2.1. The Asset Price Equivalence to Fundamental Value

There has been a long-standing theoretical debate on the existence or not of bubbles in asset prices. One view is that asset prices reflect economic fundamentals; that is, these prices equals the present discounted value of its dividends. This traditional approach usually finds it necessary to assume that all agent are rational; agents believe the price of an asset only depends on information about current and future returns about the asset. The price of an asset is thus determined by the expectation agents make about future prices and dividends, so that the price the asset is traded for reflects market fundamentals. This claims that asset markets work efficiently at allocating resources because no rational agent who has private information and information revealed publicly, can raise his expected utility by changing his portfolio (Blanchard and Watson, 1982). This view claims that bubbles cannot emerge when agents are infinitely lived and have homogenous expectations.

The standard present value model to asset pricing rests on a no arbitrage condition; the equivalence of an assets' price with a constant stream of dividend payoff, is given as:

$$r_{t+1} = \frac{p_{t+1} - p_t + d_{t+1}}{p_t} = \frac{p_{t+1} + d_{t+1}}{p_t} - 1 \qquad (2.1)$$

where r_{t+1} is the required rate of return from one period, t to another, $t+1$ while p_t denotes the asset price at time t, and d_{t+1} denotes the bounded dividend payoffs in period $t+1$. The subscript $t+1$ denotes that the return only becomes known in period $t+1$. Rearranging Eq. (2.1) and expressing it using conditional expectation operator, gives:

$$p_t = E_t\left[\frac{d_{t+1} + p_{t+1}}{1+r_t}\right] \qquad (2.2)$$

where $E_t[\cdot]$ is the expectations operator and it is conditional on information available at time t. More precisely, Eq. (2.2) states that the price of an asset at time t comprises of the future price, p_{t+1}, the one-period dividend payoff, d_{t+1} and the discount factor, $1+r_t$.

Solving Eq. (2.2) in a forward manner, one obtains its recursive solution given as

$$p_t = E_t\left[\sum_{i=1}^{k}\left(\frac{1}{1+r_{t+i}}\right)^{i} d_{t+1}\right] + E_t\left[\left(\frac{1}{1+r_{t+k}}\right)^{k} p_{t+k}\right] \qquad (2.3)$$

Eq. (2.3) shows that the value of an asset is determined by two terms. The first term on the right-hand side is the expected discounted streams of future dividend payoffs whereas the second term is the expected discounted future movement in asset prices. There exists a *unique* solution to Eq. (2.3) which is derived based on the underlying idea that in the future there will be convergence of the expected discounted value of the asset to zero. Thus, in the limit $k \to \infty$, the expected discounted dividend payoff is ultimately zero and is given by

$$\lim_{k\to\infty} E_t\left[\sum_{i=1}^{k}\left(\frac{1}{1+r_{t+k}}\right)^{k} p_{t+k}\right] = 0 \qquad (2.4)$$

Following through from the convergence assumption, the intrinsic value of an asset can be defined in terms of the expected discounted sum of payoffs and is specified by:

$$p_t^f = E_t\left[\sum_{i=1}^{\infty}\left(\frac{1}{1+r_{t+i}}\right)^i d_{t+i}\right] \qquad (2.5)$$

and suppose that

$$\lim_{k\to\infty}\frac{p_{t+k}}{r_k} = 0 \quad \forall\, t, \quad (2.6).$$

Eq. (2.6) represents the transversality condition, which is necessary for optimality. In this limit case, when the behaviour of agents is optimized, all arbitrage opportunities are exploited. With this condition, the present value model must have a unique solution where equilibrium is established between an asset's price and fundamentals, that is, $p_t = p_t^f$. The condition therefore guarantees that the present value of an asset is zero and there is no bubble component. More than one solution can be obtained if the assumption of convergence in Eq. (2.4) does not hold. One of such solution is given as:

$$p_t = p_t^f + p_t^b \qquad (2.7)$$

Specifically, p_t^b is defined as

$$p_t^b = E_t\left[\frac{p_{t+1}^b}{1+r_t}\right].$$

From Eq. (2.7) it is readily seen that asset prices, p_t has two components; the observed market fundamentals component which is that part of asset price that is determined by the expected discounted sum of payoffs, p_t^f and the unobserved bubble component, p_t^b which are primarily associated with price dynamics that are abnormal. The first insight given by Eq. (2.7) is that the fundamental value of an asset appertains to the discounted sum of future dividend payoffs while current bubbles are subject to the expected discounted value of future bubbles. A bubble occurs when $p_t^b > 0$ and the plim of p_t^b is given by;

$$p_t^b = \lim_{k\to\infty} \frac{p_{t+k}^b}{r_k}.$$

In asset price theory, the notion of bubbles exists when the price of an asset is higher than would be warranted by its fundamental value (Blanchard, 1979; Bernanke and Gertler, 2000; Scherbina and Schlusche, 2014). The movements in the price of the asset is unexplained by information available at the time, often resulting in a rapid price increase and this is soon followed by a burst or at best a dramatic fall (Blanchard and Watson, 1982). The occurrence of this notion is thus attributed to the fact that an investor agrees to pay a price that exceeds the present value of future payoffs for an asset (Frömmel and Kruse, 2012).

In a key seminal contribution, Tirole (1982) makes an important argument that rules out bubbles; an argument that relies on backward induction. Assume, for instance, that at time T an asset is identified to have a final payoff PT. Then at time $T-1$ the asset must be worth the discounted present value of PT, otherwise it would create an arbitrage opportunity. Since no rational agent would buy an asset at a price above the discounted present value; because they would incur a loss, bubbles cannot exist at $T-1$ or at any point in time. Moreover, there is a clear sense in which a bubble cannot occur because the rate of growth in bubbles must exceed that of the economy (Tirole, 1985). In a similar vein, Blanchard and Fischer (1989) have argued that the growth of bubbles is supposed to be equal to that of fundamentals e.g., interest rates, but that after a while the price of bubbles will become overwhelmingly larger than the economy's growth, which invalidates the existence of bubbles.

Since Tirole's contribution, the work by Santos and Woodford (1997) has concerned itself with conditions for the nonexistence of asset bubbles. Their work relied on an intertemporal general equilibrium model that involves economies that allow bubbles as an equilibrium phenomenon. They demonstrated that pricing bubbles in asset markets could never occur in an intertemporal equilibrium especially if the aggregate endowment of the economy has a finite value. Theoretically, bubbles are ruled out if the underlying asset pays an infinite stream of dividends (Hellwig and Lorenzoni, 2009). Therefore, even though investors expect asset prices to continue to rise and they may be willing to pay more for the assets with the expectation of earning capital gains, the present value of dividend payoffs will remain constant. Thus, investor's rational expectations that asset prices will continue to rise is self-fulling belief.

As discussed above, the existence of asset bubbles are ruled out in asset markets. With all the interesting and numerous arguments on its non-existence, it seems unlikely that explanations on its absence will not be refuted by any other theory, but this long-run standing theory has been rejected and criticized on several grounds. One of such criticism is its failure to allow other solutions for equilibrium. An economy characterised by a unique steady-state equilibrium, which is globally stable, is consistent with the traditional paradigm. It thus rejects the possible occurrence of other equilibria in asset price models and does not consider that multiple equilibria can arise in asset price models. Second, beside this criticism, a well-known critique is the assumption that information is symmetric. Third, it almost exclusively assumes that markets are efficient; that is, there are no opportunities for arbitrage. This assumption of strong efficiency in asset markets has been questioned. Blanchard and Watson (1982) have shown that arbitrage does not by itself preclude bubbles. Fourth, the use of simplified assumptions and their failure to agree that expectations are heterogeneous. Fifth, reliance on the assumption of the behaviour and expectations of agents as being rational is not only unrealistic but is at odds with the behaviour of agents. Sixth, it relies on an infinitely lived agent paradigm, that is, every agent that holds or buys an asset willingly does so even if they were to be forced to keep their holdings of the asset forever. With this paradigm, bubbles are generally ruled out; this is because the owner's personal use value cannot be less than the current price of the asset. With all these criticisms it is inevitable that very different views to the traditional approach will be postulated.

2.2.2. The Asset Price Non-equivalence to Fundamental Value

The asset price model has gone beyond the traditional view that the price of an asset is tantamount to its fundamental value. Considering this, several theoretical models with well-substantiated explanations for the existence of bubbles have been postulated. In the first class of models, the introduction of OLG into asset price framework provides an environment in which bubbles can emerge (Samuelson, 1958; Tirole 1985; Grossman and Yanagawa, 1993; Farhi and Tirole, 2011; Martin and Ventura, 2012). The framework assumes households are heterogeneous and markets are incomplete, which can allow bubbles to occur. Still in this framework, the economy is characterized by two steady states: bubbly and bubble less. Bubbles can exist, but a necessary condition for its existence is that the economy be "dynamically inefficient"; that is, there will be an over-accumulation of capital in the bubble less equilibrium because interest rate is sufficiently low.

There are specific instances in which agents are inclined towards paying more for an asset than they otherwise would if the agents were to be forced to hold the asset endlessly. In an OLG model, every agent will be inclined to pay a price for the asset equal to the discounted sum of the returns (that is, the returns the agent receives while alive) in addition to the sale price of the asset (in present value terms) in the period in which the agent intends to sell it. With the introduction of OLG into the asset market theory, it means the current price of the asset will go above the owner's personal use value (Allen et al., 1993).

The second class of theoretical model developed to support the existence of asset bubbles was models with "sunspot" equilibria (Cass and Shell, 1983; Shell and Wright; 1993). In these models, bubbles are the result of fluctuations in the prices of assets that are driven by shocks that are extraneous (sunspots) to fundamentals. The notion of bubbles is not understood exclusively by the model of sunspot equilibria but is closely related to the model of multiple equilibria, where exogenous variables that act to coordinate expectations elicit shifts between high and low steady states: that is, a multiplicity of equilibria occurs but these equilibria are *indeterminate*. The indeterminacy arises because several other equilibria are close to the initial equilibrium. In this view, the expectations, which are self-fulfilling, result in a continuum of possible equilibria none of which are globally stable steady-state equilibria, but locally stable.

In the final class of models, the behaviour of agents provides a plausible channel that generates the bubble phenomenon. Bubbles can emerge because of; agents' herding and non-rational behaviour (Shiller, 2015), heterogeneous beliefs among agents (Harrison and Kreps, 1978; Scheinkman and Xiong, 2003; Hong et al., 2006; Miller and Stiglitz, 2010; Xiong, 2013), investors' sentiment (Temin and Voth, 2004; Martin and Ventura, 2012), and asymmetric information and short sales restrictions (Allen et al., 1993; Scheinkman and Xiong, 2003; Conlon, 2004; Haruvy and Noussair, 2006). A prominent theory, the notion of 'riding the bubble', that also supports the existence of bubbles in asset markets was proposed by Abreu and Brunnermeier (2003). The expectation of earning excess return motivates arbitrageurs to invest in highly overvalued assets and this optimistic belief gives rise to bubbles that continue to survive for longer periods. In which case, bubbles can still exist regardless of there being so many rational investors with highly capitalized portfolios in the market.

2.2.3. The Role of Monetary Policy and Exogenous Shocks in Asset Bubbles

Along with the theoretical proposition of bubbles in asset markets, came the importance of knowing its contributing factors. As such, the theory on the pricing of assets has been extended to introduce monetary policy, which is conducted through interest rate, as an important determinant of bubbles. In a recent theory proposed by Galí (2014) he acknowledged the determining role of the central bank in supplying liquidity to financial markets for trading and demonstrated that there exists a relationship between bubbles and the interest rate. An increase in the current or anticipated interest rate is assumed to lower the fundamental value of the asset but raises the expected return on bubbles or the expected growth of the bubble component. In this view, changes in interest rate can affect bubbles via two important channels, both of which are important for this chapter. Firstly, through the "risk-taking" behaviour of investors, where the risk preferences of the investors have an influence on bubbles. For this channel to operate it must rest on the assumption of risk neutrality, which simply implies that an investor is indifferent to risk. Under this assumed risk, the expected return on bubbles is equal to the interest rate and there are no expected excess returns. In this vein, a monetary policy rule that implies a positive response of the interest rate to a bubble leads to an amplification in the movement of the latter. Secondly, through the eventual comovement between the innovations component of bubbles with the innovations in interest rate. Indeed, here, the innovations in bubbles are taken to be *indeterminate*. Galí (2014) has shown that both persistent and transitory increases in the interest rate have a positive effect on subsequent growth rate of bubble dynamics.

Dong et al., (2020) extend the theoretical analysis of the impact of monetary shocks on asset bubbles and stresses particularly the role of exogenous shocks on asset bubbles, i.e., the unexpected events that happen outside a country but could affect the performance of markets in that country. As a result, the focus of bubbles in assets markets shifted to the role of exogenous shocks. A link is proposed between interest rates, exogenous shocks and asset bubbles in a new Keynesian framework with infinitely-lived agents. In this view, the response of monetary policy on asset bubbles does not only depends on the type of interest rate rule which is important in specifying the interest rate to be set by the central bank but also on the type of exogenous shocks that hits the economy. They show how interest rate rule affects the dynamics of asset bubble in response to exogenous shocks. They also show how a higher interest rate response to asset bubbles could reduce bubble volatility but raise inflation volatility.

In sum, this discussion shows theoretical consideration for the determining roles of changes in interest rate and exogenous shocks on bubbles in asset markets.

2.3. Empirical Literature

This section reviews existing studies of stock market related to two strands of literature: the identification and the determinants of bubbles. It then contrasts the existing literature to the research conducted in this chapter.

2.3.1. Identification of Stock Market Bubbles in the Empirical Literature

The empirical investigation of asset bubbles in the context of stocks can be traced to the pioneering studies by West (1987), Diba and Grossman (1988a), and Diba and Grossman (1988b). The existing literature has used two different ways to identify bubbles. First, the existence or not of bubbles may be determined by testing the validity of the standard present value model; in fact, it tests whether stock prices deviated from their fundamental values (See, e.g., Shiller, 1980; LeRoy and Porter, 1981; West, 1987, among others). Second, bubbles can be identified by empirically testing (i) whether the price-dividend ratio follows a non-stationary process (bubble dynamics exist) or mean-reverting process (no bubbles) (see, e.g., Campbell and Shiller, 1988; Cochrane, 1992; Craine, 1993; Cuñado et al., 2005; Koustas and Serletis, 2005; Cuñado et al., 2007; McMillan, 2007, among others) and (ii) whether the dynamic behaviour of the underlying asset returns has explosive processes (see, e.g., Diba and Grossman, 1988a; Shi and Song, 2014; Escobari et al., 2017, among others). Due to the difficulty of estimation a fundamental value, the second approach is more commonly used in recent empirical research to detect bubbles.

However, these studies have done so using different empirical methods. Some studies relied on the fractional integration method to examine whether stock prices and dividends are fractionally cointegrated, i.e., a long run relationship exists between stock prices and dividends but deviations from equilibrium exhibit hyperbolic decay rate or extreme persistence (Caporale and Gil-Alana, 2004; Cuñado et al., 2005; Koustas and Serletis, 2005; Frömmel and Kruse, 2012). Evidence of fractional cointegration between stock prices and dividends indicate the absence of bubbles. This approach to detecting stock bubbles has been criticised by McMillan (2007) who argues that the approach is incapable of capturing the non-linear linkages between rapidly rising prices and fundamentals in the stock market.

In addition, numerous studies applied log-periodic power law models, which can capture faster-than-exponential growth in the stock prices to detect bubbles. In other words, certain log-periodic accelerating oscillatory trends appear to emerge prior to the sudden significant decline in the stock prices (Johansen et al., 2000; Sornette and Johansen, 2001). In a pioneering contribution by Sornette et al. (1996), the authors present evidence of the power law in the US stock index. They find log-periodic accelerating trend in the stock index prior to the abrupt global stock market crash of 1987. Meanwhile, they caution that the sample for estimation needs to contain data up to the 'critical point' or else the findings may differ. In more recent work, Johansen and Sornette (2010) find persistent declines in stock prices of the US and Japan. They present evidence of log-periodic bubbles connected to market crashes of exogenous origins. In addition, Jiang et al. (2010) find log-periodic oscillatory trends in the Chinese market. Similarly, Zhang et al. (2016) using extensive dataset detected stock bubbles that captured actual crashes in the US.

Many studies which rely on regime switching models consider Markov chain processes and how they affect price-setting behaviour. These studies assume that policy changes, which affect fundamentals, can cause prices to exhibit excessive volatility and this may incite the formation of bubbles. In an earlier study by Driffill and Sola (1998) the authors present weak evidence of bubbles in stock prices for the US. They find that bubbles are caused by the non-linearities in the data on fundamentals. Van Norden and Schaller (1999) demonstrated that stock bubbles switch between two distinct regimes. Psaradakis et al. (2004) find that a time-varying discount factor explains why stock price diverges from their fundamental value. Brooks and Katsaris (2005), who use a three-regime Markov model, document that in the third regime where stock bubbles are growing there is a higher probability of switching next to an explosive regime. Moreover, they show that stock bubbles may collapse when the volume of trading increases abnormally. Gürkaynak (2008) point out that the behaviour of stock prices can be influenced by switching fundamentals. However, despite the usefulness of switching models in detecting bubbles, they have been criticized because the number of unobserved regimes to be included in the model is user-specified making it susceptible to estimation errors.

Some studies test for the presence of stock bubbles by applying nonparametric Bayesian methods and capture market uncertainties by allowing for non-finite regimes, which grows as the sample size increases. Based on this method, a stock bubble occurs when the degree of uncertainty about fundamentals in a certain regime is high. For example, Li and Xue (2009) who consider two switching regimes conclude that uncertainties about the future economic performance of the US had a significant impact on the stock market. In a more recent study, using the Bayesian method Shi and Song (2014) detected a notable stock bubble episode in the US. Although, the Bayesian method generates robust results, Geweke (2007) argues that its theoretical construct is still at the nascent stage. Moreover, when the prior probability is wrongly specified, the approximate Bayes factors may be adversely affected. Similarly, Li and Yu (2012) argue that Bayesian analysis are computationally challenging and complex to apply.

The final group of studies concentrates on checking for possible (non)stationary of stock prices using methods based on the autoregressive process. Previous studies in this strand have relied on left-tailed test to detect the existence or not of bubbles. The test examines whether the stochastic process of stock prices is stationary or not. Evans (1991) cautions against the use of this test because it cannot differentiate between stationary and strictly stationary processes. Another empirical issue with the test is its weak statistical power which is well-documented in the existing literature (see, e.g., Diebold and Rudebusch, 1991; Ng and Perron, 1995; Schwert, 2002). A new empirical technique provided by Phillips and Yu (2011) and Phillips et al. (2011) is the right-tailed test which helps to overcome the near observational equivalence problem of the left-tailed test because it correctly differentiates between the two stationary processes. Its asymptotic efficiency property enables it to locate multiple bubbles consistently. Moreover, the technique can date the start and collapse of bubbles. The investigation of bubbles is only plausible for asset prices that are commonly characterized by persistent run-ups and subsequent collapse, i.e., periodically collapsing. An attractive feature of this test is that it can capture these types of bubbles. This chapter relies on this empirical strategy to test if stock bubbles exist and to date the bubbles and obtain its duration.

2.3.2. Determinants of Stock Market Bubbles in the Empirical Literature

Most of the existing studies on stock markets have concentrated mostly on identifying the existence or not of bubbles rather than the determinants of bubbles. This has changed recently, and growing strand of literature investigated the determining factors that influence bubble dynamics (see, e.g., Narayan et al., 2013; Wang and Chen, 2019) and bubble durations across markets.

The first strand of literature examined only the effect of monetary policy shocks on stock bubbles. Empirical studies in this strand have used interest rates to capture the effect of monetary policy. Galí and Gambetti (2015) investigated the impact of monetary policy shocks on bubbles in the US market. They estimated a VAR model with time-varying coefficients and obtained the associated impulse responses using data from 1960Q1 to 2011Q4. The authors find evidence linking prolonged episodes of stock price run-ups in response to a tightening of monetary policy. On the other hand, Caraiani and Călin (2018) revisited the results in Galí and Gambetti (2015) and re-estimated their model but included the shadow rate, which is constructed from a model conditioned with a large information set. Using the shadow rate, they confirmed the finding of the earlier study, but found a much lower positive impact of shocks from monetary policy on bubbles. In general, this strand of literature has concluded that shocks from monetary policy through the interest rate is an important determining factor of bubbles in stock markets.

A second strand of literature goes beyond examining the important role of a single factor, the interest rates. This strand of literature examined the role of other determining factors that could be crucial for the analysis of bubbles. For example, Narayan et al. (2013) used a cross-sectional model to examine the determinants of bubbles in the US market. The authors find trading volume had a positive effect on bubbles while price volatility had the reverse effect. In a more recent work by Wang and Chen (2019), the authors explored the factors, which contributed, to bubbles in 22 stock markets. They utilized a panel Logit model and dataset on trading volume, price volatility, interest rate, growth rate of monetary aggregates, growth rate of personal consumption, growth rate of foreign exchange reserve and credit as a ratio to GDP growth rate covering the period 2000Q1 to 2018Q3. The authors empirically confirmed that monetary policy played a significant role in stock bubbles. Apart from this, they also find that the trading volume, the volatility of prices and the growth of credit (both current and lagged) are positive drivers of bubbles. This strand of literature has generally concluded that the trading volume, price volatility and growth of credit are important driving forces behind stock bubbles.

Another strand of literature investigating the underlying macroeconomic factors concentrated on the duration of bubbles (Lunde and Timmermann, 2004; He et al., 2019). Lunde and Timmermann (2004) were the first to empirically investigate whether duration of stocks for bull and bear markets depend on an underlying macroeconomic factor, the interest rates. They relied on duration models and estimated via state-space technique using sample data covering the period 1885 to 1997 for the US. They find that changes in real interest rates have a weak effect on the probability that a bull or bear market survives for a certain duration. In this strand, the paper most closely related to ours is a recent study by He et al. (2019). The author modelled the effect of risk-free interest rate and its changes on stock bubbles' duration for China during the period 1992 to 2013. Using duration models based on logistic regression, they find that an increase in the interest rate leads to a decrease in the duration of bubbles. Their finding suggests that monetary policy plays a role in suppressing bubbles' duration, which is inconsistent with the finding of Lunde and Timmermann (2004). Thus far, this growing strand of literature have explicitly focused on the stock market in only one country. Moreover, all the evidences in this strand, which have been based on the interest rate effect alone, have yielded mixed results. Given that much of the literature is on the determining role of interest rates on the duration of bubbles, this chapter argues that the propagation of monetary policy shocks via interest rates alone cannot fully explain the duration of bubbles. Alternative factors that could possibly influence the duration of bubbles in the context of DEEs might have to be considered. It is not yet clear to what extent alternative macroeconomic factors will influence the duration of bubbles across stock markets. Accordingly, these alternative factors motivated by the existing studies, which have examined the influence of macroeconomic variables on stock pricing are elaborated upon below.

Stock market studies indicate that measures of real economic activity often has an impact on the pricing behaviour of stocks because it affects the cash flows of firms (see, e.g., Chen et al., 1986; Fama, 1990; Chen, 1991; Ritter, 2005, among others). In a recent study by Österholm (2016), the author presents evidence of the existence of a long-run relationship between stock prices and real economic activity. Empirical evidence in support for the components of economic activity such as consumption also exists. For instance, some studies find a link between stock returns and consumption (Lettau and Ludvigson, 2001; Parker and Julliard, 2005; Da, 2009; Bansal et al., 2014; Lioui et al., 2014). The coherent explanation for this relationship is based on the theory on consumption asset pricing. During the phase of a business cycle trough, consumption normally falls and so does the price of risky assets but expected returns rises. It rises because risk-averse investors will have to be compensated with higher risk premium for holding risky assets (Campbell and Cochrane, 1999). Thus, based on this theory, consumption is relevant for explaining the changes in stock returns.

Several empirical studies examine the role of inflation in stock pricing and present evidence that inflation accounts for stock returns (Fama, 1981; Flannery and Protopapadakis, 2002). An increase in inflation has a positive impact on the discount rate, which subsequently reduces the real cash flows of firms and changes the expected return on stocks. In addition, there is evidence that stock returns react to exogenous shocks such as commodity price shocks. Global real commodity prices have been shown to be linked to stock price activity (Kilian and Park, 2009; Sadorsky, 1999). Several studies provide evidence of stock returns interaction with oil prices (Jones and Kaul, 1996; Miller and Ratti, 2009). Sadorsky (1999) present evidence that shows that this linkage became stronger post-1986 and that real oil prices now primarily explain a higher percentage of changes in stock returns than interest rates. Regarding oil price volatility, Park and Ratti (2008) find that stock returns respond positively to increases in real oil prices while it reacts negatively to increases in its volatility. In a recent contribution by Diaz et al. (2016), they find a negative effect of oil price volatility on stock returns. Overall, most of the findings suggest that real oil prices and its volatility may lead to changes in expected returns. It has also been documented in the existing literature that stocks returns are correlated with gold prices (Smith, 2001).

In the existing literature, empirical evidence in support of macroeconomic volatility as a source of economic shock for determining stock returns have been documented (Beeler and Campbell, 2009; Bansal et al., 2014). This literature suggests that macroeconomic volatility is a priced source of risk in stock markets. A different strand of literature finds that stock returns and its predictability are influenced by yield spreads (Asprem, 1989; Rapach et al., 2005; Humpe and Macmillian, 2009). For instance, Fernandez-Perez et al. (2014) find that the slopes of yield curves can provide a better forecast of the probability of bear markets. Finally, several studies suggest that portfolio flow shocks are a source of excess returns in stock markets (Bohn and Tesar, 1996; Froot et al., 2001; Hau and Rey, 2004; Fratzscher, 2012).

This chapter extends this strand of literature in four ways. Firstly, the existing studies used a univariate model, which controls for just one underlying macroeconomic variable. This chapter instead considers an alternative specification, specifically a multivariate model that controls for other factors that might affect bubbles' duration. Monetary policy shocks via interest rates cannot be the only factor that can potentially affect duration of bubbles in stock markets. This chapter thus incorporates more underlying factors which are absent from the existing works to have a deeper understanding of bubbles' duration.

The omission of other possible explanatory variables in the duration model, which can be relevant for the analysis of bubbles' duration, can result in an omitted variable bias. The earlier studies suffer from a serious shortcoming arising from this bias. It is unclear whether a statistically insignificant time varying interest rate result of the existing paper remains tenable when alternative models consisting of more variables are considered. To avoid this bias, this chapter instead incorporates other time varying macroeconomic factors, which can affect investor's preferences over time, influence the dynamics of stock returns and even predict the future behaviour of stocks.

The second way this chapter extends the existing literature is to provide a cross-country analysis. The prior empirical analyses were based on country-level sample for the US and China stock markets. Unlike the prior works, our sample covers a broad set of stock markets in different regions. Studying more stock markets allows us to generalize about the empirical results. The set of countries in our sample differ by levels of income and financial development.

It thus seems beneficial to investigate whether macroeconomic variables have different impact on the duration of bubbles across group of countries with different levels of income and financial development. Using data grouped in these categories will allow us: (i) to estimate the effects on the duration of bubbles within each subgroup especially when the effects obtained using the entire sample fails to provide significant estimates, and (ii) to improve the precision of estimates because there will be less variability in the distribution of the data.

The third way this chapter extends the existing literature is by assuming that markets are heterogeneous. Since our study covers a set of stock markets, it cannot be assumed that markets are homogeneous. If homogeneity across markets is assumed, then it means that all markets have similar characteristics, and such an assumption could be misleading. Moreover, when duration models with heterogeneous groups is specified, but controls for heterogeneity is omitted it might result in the misspecification of the functional form and this can cast doubt on the validity of the model. Based on these, this chapter recognises that there will be some inherent differences in the characteristic of markets, which could affect bubbles' duration. Thus, a novel contribution of this chapter is that it controls for these important sources of differences across markets by allowing for heterogeneity effect arising from random unobserved factors. These factors, which are peculiar to each market, may be partly responsible for lower (higher) duration of bubbles. In this chapter, bias due to heterogeneity is caused by the correlation of unobserved market characteristics with the duration of bubbles. By specifying duration models that accounts for the presence of this bias this chapter can address this concern. This chapter thus correct for this bias because ignoring the unobserved effects may lead to underestimation of the coefficient of the macroeconomic variables and lead to misleading inference about the macroeconomic effects. By controlling for heterogeneity, this chapter can elude the problem of biased coefficient estimates.

The fourth way this chapter extends the literature is by controlling for endogeneity or spurious effects. The macroeconomic effects can be weakened because of the presence of endogeneity caused by the correlations of the macroeconomic variables with the model error terms. In this case, endogeneity causes the assumption of independent errors to be violated. In many empirical studies where macroeconomic variables are considered, they are treated as endogenous because of the potential for reverse causality. The model in this chapter assumes there is an endogenous association among the macroeconomic variables. Thus, it controls for the possible problem of endogeneity by including the lagged levels of macroeconomic variables. This enables us to eliminate the spurious effects and to determine the lagged effect of the variables on the duration of bubbles. This chapter does not include first order lags because including more lags can result in considerable loss in initial time periods. This chapter, therefore, separates between two channels through which the macroeconomic factors can exert influence on stock bubbles' duration: (i) the contemporaneous effects, and (ii) lagged effects.

2.4. Data and Empirical Methodology

The empirical implementation of the causal effects of macroeconomic variables on the duration of stock bubbles is not direct but involves two steps. The first step involves testing for the existence of stock bubbles, dating the bubbles, and obtaining its durations using the generalized supremum Augmented Dickey Fuller test. In the second step, clog-log models are estimated via maximum likelihood method to obtain the macroeconomic effects.

2.4.1. The Generalized Supremum Augmented Dickey-Fuller Test

The basic equation for the Augmented Dickey-Fuller (ADF) regression required for testing the stationarity of data in an AR(1) process is given as:

$$x_t = \gamma T^{-\tau} + \partial x_{t-1} + u_t \qquad u_t \sim i.i.d.(0, \Omega) \ \forall t \qquad \text{where } \partial = 1 \qquad (2.8)$$

where x_t is the asset return, γ is the intercept coefficient, T is a fraction of the population size and τ represents the coefficient that localizes and influences the extent of drift and the intercept as T tends to infinity, ∂ is the slope coefficient, u_t is a martingale difference sequence since the expectations of $u_t$with its historical series are zero. The stochastic autoregressive process is typically assumed to have a root of 1.

By reformulating Eq. (2.8) into a reduced form version, a new equation, Eq. (2.9), with linear stochastic k^{th} order autoregressive process is obtained as:

$$x_t = \varphi + \sum_{i=1}^{k} \omega_i \, \Delta x_{t-1} \; + \varepsilon_t \quad (2.9)$$

where $x_0$is fixed, φ is the intercept, k is the maximum lag length, $\omega_i = 1 \ldots k$ are the lagged differences of coefficient x_t, the change operator is denoted as Δ and the uncorrelated error term is ε_t with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t) = \sigma^2$.

Detecting of bubbles in an underlying asset involves testing of hypothesis. Thus, to test for bubbles using the conventional ADF test, the null hypothesis of unit root process is tested against an alternative of stationarity and this is given by:

$$\mathrm{H}_0\colon |\psi| = 1 \text{ against } \mathrm{H}_A\colon |\psi| < 1$$

However, to test for multiple bubbles that collapse periodically the recursive GSADF test which is a rolling window right-tailed test developed by Phillips et al. (2014) and which has high power against the conventional ADF test is used. Thus, it is apposite to test the null of unit root against the alternative that multiple bubbles collapse periodically, and this is given by:

$$\mathrm{H}_0\colon |\psi| = 1 \text{ against } \mathrm{H}_A\colon |\psi| > 1$$

The null of unit root states that the observations on an underlying variable follow a random walk whereas the alternative premise states that the probability distribution of the error is heavy tailed towards the right.

The GSADF test statistic is expressed as:

$$\mathrm{GSADF}(r_0) = \sup_{r_1 \in [0, r_2 - r_0], r_2 \in [r_0, 1]} ADF_{r_1}^{r_2} \qquad (2.10)$$

where r_0 is a fraction of the full sample or minimum window size. r_1 and r_2 denote the first and last data points of the sample, respectively.

Before the test is conducted, recursive estimation of Eq. (2.9) is first carried out using the sequential PWY[1] estimator. The recursive estimation is performed by allowing, r_1 and r_2 to change but only if the data points are inside the defined limits $r_1 \in [0, r_2 - r_0]$ and $r_2 \in [r_0, 1]$, respectively.

The right-tailed critical values of the non-standard distributions for the finite samples do not rely on the theory of asymptotic distribution but the distributions are evaluated by a feasible alternative, which involves simulation via MCMC technique. When the $\mathrm{GSADF}(r_0)$ statistic exceeds the simulated critical value, the null hypothesis of unit root is rejected in favour of the alternative that multiple bubbles collapse periodically. Hence, rejection of the null hypothesis indicates the existence or presence of multiple bubbles in an underlying asset.

The recursive GSADF test is useful in detecting bubbles because the window of the sample is not fixed throughout the estimation, therefore it allows for more flexibility in estimating the stability of the coefficients. Moreover, the test allows for switching of regimes from a unit root to periodically collapsing bubbles and vice versa. Further, the test has a non-linear structure, which enables it to detect multiple episodes of periodically collapsing bubbles. The sequential PWY estimator applied in estimating the episodes of bubbles and dating their start and end periods is asymptotically efficient and consistent.

2.4.2. Duration Models

This sub-section presents the clog-log duration models for investigating the influence of macroeconomic variables on the duration of bubbles. To estimate these effects, this chapter considers two types of models: (i) baseline model without controls for country-specific characteristics, and (ii) model with random effects.

[1] See Phillips et al. (2015) for an in-depth discussion about the estimator.

2.4.2.1. Baseline Model

The hazard function is a principal part of duration analysis. It is the instantaneous hazard rate of an event, where the hazard rate is the conditional probability that an event happens in a time interval given that the event has not yet happened by time t. In this chapter, the hazard rate is the conditional probability of a stock bubble completing its survival after time t. An advantage of using the hazard function is that it can be used to predict the conditional probability of an event which involves maximizing the conditional log-likelihood function instead of the unconditional density function which can result in loss of efficiency. Thus, it is plausible to use this function because it can accurately predict the hazard rates of the factors that could potentially influence the probability of stock bubble.

In studies based on duration analysis, the response variable is a point event (failure) which occurs after a duration (survival or failure time). In this chapter, the point event is an episode of periodically collapsing stock bubble while the survival or failure time is the duration of the bubbly episode. Accordingly, the survival function, $S(t)$ which is the probability of a stock remaining in a bubbly state prior to t is defined as:

$$\mathrm{S}(t) = \Pr(T > t) = \int_0^\infty f(t)\mathrm{dt} \qquad (2.11)$$

where t denotes the time period, T is the survival time, $f(t)$ is the probability density function of T.

The hazard function is expressed as:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(bust\ at\ t + \Delta t | boom\ at\ t)}{\Delta t} \qquad (2.12)$$

or

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t < T < t + \Delta t | T > t)}{\Delta t} \qquad (2.13)$$

Applying the conditional probability rules, we have

$$= \lim_{\Delta t \to 0} \frac{\Pr\{t < T < t + \Delta t | T > t\} / \Pr\{T > t\}}{\Delta t}$$

$$= \lim_{\Delta t \to 0} \frac{[F(t + \Delta t) - F(t)] / \Delta t}{S(t)}$$

$$= \frac{\partial F(t) / \partial t}{S(t)}$$

$$= \frac{f(t)}{S(t)}$$

The derivative of the standard cumulative distribution function, $1 - S(t)$. Since

$$\frac{\partial logS(t)}{\partial t} = \frac{\partial S(t) / \partial t}{S(t)} = -\frac{f(t)}{S(t)}$$

Similarly, $h(t)$ can be expressed as the derivate of the survival function (in logarithm) given by

$$h(t) = -\frac{\partial logS(t)}{S(t)}$$

Since stock bubbles is not an event that occurs continuously in time but it can only occur at a discrete-time, for instance, the length of time in a bubbly state; a change can only occur at the end of the bubble. Based on this, we treat the length of time in bubbles as discrete-time variable because we count the number of periodically collapsing bubbles.

In discrete-time, Eq. (2.13) is given by;

$$\mathrm{S}(t | x_{i1}, \dots, x_{in}) = \mathrm{S}_0(t)^{\exp\,(\beta_0 + \beta_1 x_{i1} + \,\dots + \beta_n x_{in})}, \qquad (2.14)$$

where $\mathrm{S}(t | x_{i1}, \dots, x_{in})$ states the probability for each country$i$with the time-varying covariates $x_{i1}, \dots, x_{in}$ to survive until time t, and $\mathrm{S}_0(t)$ is the survival function at the starting point when the corresponding set of covariates all equal zero. Since we have now established the link between the survival and hazard functions, we next consider one of the popular discrete-time duration models, the clog-log model given as

$$h(t|x_{i1}, \ldots, x_{in}) = 1 - [1 - h_0(t)]^{\exp(\beta_0 + \beta_1 x_{i1} + \ldots + \beta_n x_{in})}. \qquad h_0(t) > 0 \qquad (2.15)$$

The transformation for the model's probabilities is estimated with maximum likelihood estimators. The motivation for the use of this estimator is because it is an asymptotically efficient and consistent estimator, and it has the ability to look for the best estimate for the parameters.

To model the effect that macroeconomic factors have on bubbles' duration, this chapter adopts the clog-log model, which is an extension of the multivariate generalized linear model. This model has several attractive features: First, it allows time-varying covariates to be combined with flexible duration specifications (Jenkins, 1995). Second, the estimated coefficients of factors are simpler to interpret (McCullagh, 1980). Third, maximum likelihood techniques, which have the asymptotic property of consistency and efficiency, are used for estimation of its parameters and for inference. Fourth, it allows for asymmetric power transformations in the probabilities or the fitting of asymmetrically transformed probabilities to data. It thus provides the best fit for the parameters because it allows the error distributions to be asymmetric. Fifth, it is flexible enough to accommodate heterogeneity across markets from the different countries.

The probability that bubbles will survive is fitted in a clog-log model. Accordingly, this chapter specifies a hazard function as follows:

$$h(t) = \Pr\big(T = t \,|T \geq t;\ \Phi(\beta_0 + x'_{it}\beta)\big) \qquad (2.16)$$

where $h(t)$ denotes the probability of a stock market bubble surviving at time t given that the stock bubble had not yet occurred at t. If the probability of bubbles' duration fails, then $h(t)$ is the probability that it fails after period t, or the probability that it survives at least until period t. T is the duration of bubbles, which represents the expiration time. $\Phi(\cdot)$ is the standard cumulative distribution function. β_0 is the intercept. x_{it} is a vector of time-varying observed country-level covariates for country i with $i = 1, \dots, N$ at year t with $t = 1, \dots, T$. β is the linear vector of parameters corresponding to the time-varying covariates in x.

The hazard function of the multivariate regression model of interest is then given by

$$h(t) = 1 - exp[-exp(h_0(t) + \gamma' DF + \delta' EF + \varphi'(L) DF^* + \tau'(L) EF^*)] \qquad (2.17)$$

where $h_0(t)$ is the underlying baseline hazard rate at time t when the corresponding set of covariates all equal zero. DF and EF represents the vectors of domestic and exogenous factors, respectively. $DF^*$and $EF^*$are the vector of the lagged macroeconomic variables. L is the lag operator. γ, δ, φ and τ are the vectors of unknown slope coefficients.

This chapter takes into consideration each country's period at risk to bubbles and the period of non-occurrence of bubbles during the given time interval. This allows us to model the probability of bubbles' duration using binary responses associated within each time interval. The regression that this chapter wants to fit using a model for binary response data, or the more popular logit binary link cumulative distribution function is given by

$$\Pr(y_{it} = 1) = \Phi(\beta_0 + \gamma' DF + \delta' EF + \varphi'(L) DF^* + \tau'(L) EF^*) \qquad (2.18)$$

where y_{it} is binary response variable, which represents the probability of bubbles surviving or that the market in country i exits the bubbly state at duration, t. The left-hand side of Eq. (2.18) takes on a value of 1 when the market exhibit bubbles in period t or a value of 0 if it does not. The binary response variable is represented by:

$$y_{it} = \begin{cases} 1, & \text{stock market exhibit bubbles ,} \\ 0, & \text{otherwise.} \end{cases} \qquad (2.19)$$

The associated conditional log-likelihood function of the hazard function where it assumes that the errors are normally distributed with zero mean and orthogonal to observable country data is then given by

$$\log L_i = \sum_{i=1}^{N} c_i \log\left(\frac{h_{it}}{1-h_{it}}\right) + \sum_{i=1}^{N}\sum_{t=1}^{T} \log(1-h_{it}) \qquad (2.20)$$

where c_i denotes the completed stock bubble episode.

The log-likelihood function for the model can be re-written in form of a binary response variable as:

$$\log L_i = y_{it} \log h_{it} + (1-y_{it}) \log(1-h_{it}) \qquad (2.21)$$

2.4.2.2. Model with Random Effects

The baseline model assumes that the duration of bubbles in the hazard function is influenced only by country-specific factors that are directly observable, i.e., the macroeconomic factors. However, some unobserved country-specific factors that can explain duration of bubbles across markets, as earlier explained, have not been captured by the model. Omitting these unobserved effects could cause downward bias in the coefficient estimates, resulting in the underestimation of the covariate effects. It is important to control for heterogeneity bias in the model for the reasons previously discussed. To overcome this empirical issue, the chapter extends the baseline specification by incorporating the random effects. The linear hazard function, which captures these unobserved country differences as random disturbances, is given by

$$h(t|x_{i1}, \ldots, x_{in}, \eta_i) = \Pr\big(T = t \mid T \geq t;\ \Phi(\beta_0 + x_{it}'\beta, \eta_i)\big),$$

$$= F\big(1 - exp - (exp[h_0(t) + \gamma' DF + \delta' EF + \varphi'(L) DF^* + \tau'(L) EF^* + \eta_i])\big). \qquad (2.22)$$

where all the terms remain as earlier described in Eq. (2.17) and (2.18). η_i is vector of random effects, which accounts for the unobserved country-specific effects. It is a sub-component of the normally distributed random disturbance, and it is independent of the $x_{it}'s$.

To estimate the hazard function in Eq. (2.22), one can rely on proportional hazards or random effects distributional assumptions. If the function is estimated by imposing the proportional hazards assumption on its conditional distribution, then there should be equal correlation between the vectors of covariates, $x_{it}'s$ (Allison, 2010). Hence, the hazard rates will rise or fall by a proportionate amount for each country i at time t. If one chooses to adopt this assumption, then the entire time units will have similar intervals. Although this assumption has been commonly applied in duration analysis, this chapter does not rely on it because there are a few concerns: First, many empirical applications that impose this assumption employ the partial log-likelihood estimator that is not an efficient estimator for robust inference. Second, the usage of a similar interval for all observations has been criticised because it can lead to biased estimates and even lead to misleading inference.

To obtain consistent estimates and prevent spurious inference, it is more reasonable and appealing to base our estimation of the hazard function on the random effects assumption, i.e., that the observed explanatory variables are uncorrelated with unobserved heterogeneity, (x_i, η_i). In other words, the errors of the random variable η_i are distributed independently of the explanatory variables, x_i. The chapter thus relies on this assumption and estimate the function by including the Gaussian distributions of random variables to correct the bias arising from heterogeneity. The maximization of the marginal distribution of random errors is estimated using the maximum likelihood estimator via the likelihood function, which is a more consistent estimator of η_i than the partial log-likelihood one. To obtain the approximate marginal distribution of the random errors, the chapter employs a Gaussian quadrature type of approximation. More explicitly, it uses the mean-variance adaptive Gauss-Hermite quadrature approximation technique to integrate out the value of random effects. It employs this technique because it ensures asymptotic convergence to the true parameter value, it can reliably fit the random effects model, and it provides accurate approximations.

2.4.3. Data

To, empirically, investigate the determinants of bubbles' duration; the chapter next describes the data set. The investigation will be executed in two stages. In the first stage, which involves the simulation of multiple episodes of bubbles and the dating of these episodes, it employs data that consists mainly of the weekly closing prices of country's stock prices. The entire sample for this data covers the period, 03 January 1995 until 03 November 2016. It thus contains 1,140 observations, which is presumably large enough to enable us to detect multiple episodes of bubbles in the data.

Prior to testing whether the martingale component of stock prices has an explosive path, the chapters first model it as a stochastic process. To proceed, it transforms all the prices using the standard natural logarithm in order to derive their logged return series, formulated as: $r_{it} \equiv ln(p_{it}/p_{it-1})$, $t = 1, 2, \ldots, T$ with r_{it} denoting the return on stocks for country i at time t, whereas p_{it} and p_{it-1} denote the prices at periods t and $t-1$, respectively. Next, it obtains the episodes of bubbles and date them using recursive GSADF test via Monte Carlo simulation. Finally, it constructs the duration of bubbles (Dbs) from the date-stamped periods.

In the second stage, where the chapter will empirically examine the effect of macroeconomic factors on duration of bubbles using clog-log models, it uses a series of underlying domestic and exogenous variables for a panel of 21 countries[2]. The main country-level explanatory variables the chapter uses to examine the key sources of bubbles' duration are: countries' real economic activity measured in terms of the growth in GDP per capita $(Gdpc)$, inflation $(Infl)$, real oil prices (Rop), real gold prices (Rgp), volatility in GDP per capita $(Gdpcvol)$, inflation volatility $(Inflvol)$, volatility in oil prices $(Ropvol)$, volatility in gold prices $(Rgpvol)$, portfolio inflows $(Portf)$, interest rate gap[3] $(Mpol)$ which captures the contribution of monetary policy and yield spreads[4] $(Yiespd)$ which captures the expectations about countries' future economic growth performances.

Next, to check the robustness of our baseline results, the chapter includes alternative variables. Real GDP per capita is removed and is replaced with growth in consumption $(Rcons)$ and growth in investment (Rgi), which are both components of economic activity. Also, for the robustness analysis, it removed inflation and replaced it with the GDP deflator $(Infdf)$, which

[2] A more detailed description of the list of countries grouped by income and financial development levels is presented in Appendix 1.
[3] This is computed by taking the difference of the short-term real interest rates from the Wicksell's natural rate of interest, which is obtained and extracted using the Hodrick-Prescott filter.
[4] Yield spreads which measures the slope of the real term structure is calculated as the difference between the 10-year sovereign bond yields and the treasury bills rates.

is an alternative measure of inflation. It excludes inflation volatility derived from inflation and replaced it with inflation volatility derived from GDP deflator[5] ($Infdfvol$). All the data are arranged in a panel because they are cross-sectional time-series.

The data for the explanatory variables described above spans the period 1995 to 2015. It covers a sample of countries drawn from DEE namely: Australia, Belgium, Brazil, China, Colombia, Germany, Hong Kong, Indonesia, Ireland, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, New Zealand, Portugal, Singapore, Spain, Thailand and the U.S[6]. The data are obtained from different sources. Data on stock prices come from the MSCI database on *Bloomberg*. The data on the macroeconomic factors originate primarily from a variety of sources namely: *DataStream and Eikon, the International Monetary Fund, the Global Financial Development database,* and *the World Bank*.

Prior to the empirical estimations, the chapter conducted some preliminary data checks. Two separate checks are conducted because as stated earlier our investigation will be in two stages. The first check is carried out using only data on stock returns, while the second one is implemented using data on the macroeconomic factors and the duration of bubbles. Table 2.1 reports the summary statistics. Panel A presents the summary statistics for the log of average stock returns. Some interesting insights emerge. The lowest and highest returns are in China and Mexico, respectively. The standard deviation of the log of average stock returns is highest for Colombia, which implies that it has a higher variability while Japan has the lowest variability. There is, of course, considerable heterogeneity across countries as revealed by the different standard deviation results. In addition, the skewness are less than zero for most returns (excluding Brazil, Indonesia and Italy). This indicates that stock returns have flatter left-tails unlike the normal distribution. The kurtosis are all non-zero indicating peaked and fat-tailed distributions. The normality test is rejected as shown by the Jarque-Bera statistics. The negative skew, excess kurtosis and Jarque-Bera statistics all indicate that the distributions of stock returns are non-normal.

[5] A more detailed description of the variables, its description and sources are presented in Appendix 2.
[6] Unfortunately, the sample size is restricted to these countries because we were unable to find evidence of bubbles in some countries and because of the constraint in obtaining consistent macroeconomic data.

Panel B presents the summary statistics for the duration of bubbles and the macroeconomic factors. It can be seen that the average duration of bubbles for all countries in the sample is 13.37 weeks. Panel C presents the contemporaneous correlations. It shows quite many negative associations between macroeconomic factors and duration of bubbles with just a few positive associations. It also shows that the macroeconomic factors that has highest and lowest correlations with Dbs are $Inflvol$ and Rgp, respectively.

Table 2.1: Summary Statistics

Panel A: Stock Returns Data

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Australia	6.3697	6.4450	7.1250	5.6539	0.4449	-0.0331	1.3411	130.91***
Belgium	4.2269	4.2776	4.7935	3.3565	0.3213	-0.3348	2.1183	58.22***
Brazil	7.1714	7.1004	8.4478	5.6550	0.6977	0.0226	1.7066	79.55***
China	1.7083	1.9437	2.6103	0.5229	0.5071	-0.7073	2.2841	119.38***
Colombia	5.6175	5.9450	7.2395	3.7199	1.1168	-0.1419	1.5227	107.49***
Germany	4.5358	4.5969	5.1053	3.7346	0.3129	-0.6083	2.6238	77.01***
Hong Kong	6.9252	6.9124	7.5331	6.1298	0.3279	-0.1000	1.9872	50.62***
Indonesia	7.4208	7.3508	8.8021	5.6607	0.9360	0.0490	1.4277	117.46***
Ireland	4.0079	4.1020	4.8377	2.9291	0.5293	-0.3814	1.8474	90.73***
Italy	4.2637	4.2071	4.8671	3.6514	0.3395	0.0913	1.7309	78.09***
Japan	1.9354	1.9451	2.3013	1.3605	0.1988	-0.3884	2.5776	37.14***
Korea	5.6717	5.7577	6.4443	4.1403	0.5996	-0.4518	2.0487	81.77***
Malaysia	4.7166	4.8575	5.3571	3.1844	0.4472	-0.5089	2.4414	64.03***
Mexico	7.9717	8.0752	8.9469	6.4097	0.7147	-0.2122	1.5213	112.41***
Netherlands	4.4238	4.4511	4.8963	3.6556	0.2884	-0.5330	2.7000	58.25***
New Zealand	4.2232	4.2978	4.7454	3.5069	0.2795	-0.6256	2.4154	90.60***
Portugal	4.1861	4.2191	4.8315	3.5222	0.3463	-0.0416	1.9622	51.48***
Singapore	6.7553	6.7458	7.3220	5.6775	0.3728	-0.3583	2.1022	62.68***
Spain	4.5476	4.6261	5.1895	3.3200	0.3880	-1.3803	4.7839	513.12***
Thailand	2.0899	2.1394	3.1819	0.5684	0.6564	-0.3400	1.9894	70.48***
US	7.0392	7.0623	7.6405	6.0707	0.3307	-0.4716	3.2798	45.98***

All series are in natural logarithm. ***denotes 1% significance level. Min. and Max. denote minimum and maximum.

Panel B: Duration of Bubbles and Macroeconomic Factors

Variable	Mean	Std. Dev.	Min.	Max.
Dbs	13.251	16.454	0.000	53.000
Gdpc	4.506	3.928	-13.422	33.527
Infl	3.558	5.621	-4.480	66.010
Portf	35.833	59.913	0.330	294.680
Yiespd	1.227	2.725	-14.766	12.002
Mpol	0.000	2.256	-21.973	13.893
Rop	69.665	380.635	0.0009	3206.052
Rgp	927.422	5003.331	0.0148	40592.321
Gdpcvol	6.920	1.015	3.087	10.827
Inflvol	0.727	0.494	0.016	3.492
Ropvol	0.366	1.191	0.0001	7.100
Rgpvol	1.0534	1.587	0.001	9.903
Infdf	3.756	7.003	-6.007	89.497
Infdfvol	0.802	0.573	0.035	3.816
Rcons	3.432	4.105	-12.658	30.733
Rgi	3.622	13.259	-49.210	138.439

Panel C: Contemporaneous Pairwise Correlations Matrix

	Sbs	*Gdpc*	*Infl*	*Portf*	*Yiespd*	*Mpol*	*Rop*	*Rgp*	*Gdpcvol*	*Inflvol*	*Ropvol*	*Rgpvol*	*Infdf*	*Infdfvol*	*Rcons*	*Rgi*
Dbs	1															
Gdpc	0.0403	1														
Infl	-0.0026	-0.1415	1													
Portf	0.0705	0.1318	-0.1273	1												
Yiespd	-0.0097	-0.0956	-0.1367	0.0471	1											
Mpol	0.0464	0.0004	-0.4971	0.0050	-0.0871	1										
Rop	-0.0350	-0.0174	-0.0655	-0.0537	-0.0148	0.0009	1									
Rgp	-0.0460	-0.0279	-0.0700	-0.0541	-0.0083	-0.0006	0.9697	1								
Gdpcvol	-0.0067	0.0235	-0.3385	0.3539	0.0361	0.0014	0.0762	0.0978	1							
Inflvol	0.1076	-0.1135	0.6037	-0.0209	-0.1002	-0.1469	-0.1045	-0.1135	-0.3143	1						
Ropvol	-0.0058	-0.0483	-0.0943	-0.0681	-0.0041	0.0090	0.8783	0.8837	0.0984	-0.1403	1					
Rgpvol	-0.0203	-0.0681	-0.0817	-0.0795	-0.0170	0.0043	0.8100	0.8225	0.1718	-0.1238	0.9600	1				
Infdf	0.0391	-0.0554	0.9246	-0.1236	-0.1534	-0.4731	-0.0652	-0.0654	-0.3154	0.5470	-0.0909	-0.0781	1			
Infdfvol	0.0472	0.0264	0.4992	0.0814	-0.0167	-0.1180	-0.1239	-0.1232	-0.1814	0.6818	-0.1532	-0.1490	0.5530	1		
Rcons	-0.0128	0.6222	0.1995	-0.0282	-0.1736	-0.1669	-0.118	-0.1140	-0.1234	0.1342	-0.1470	-0.1526	0.3556	0.3165	1	
Rgi	0.0015	0.6081	-0.1111	0.0521	-0.0627	0.0717	-0.033	-0.0365	0.0044	-0.1098	-0.0563	-0.0666	0.0539	0.0432	0.5400	1

Another preliminary check that the chapter conducted are unit root tests for stationarity. It is crucially important that it carries out this check in order to examine whether stock returns exhibit nonstationary behaviour. Evidence that returns follow a nonstationary path or random walk process might indicate that it has explosive characteristics and that it is unpredictable. These characteristics could also indicate the presence of bubbles. The unit root tests were conducted by relying on several standard approaches; the Augmented Dickey-Fuller, Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). Table 2.2 presents the unit root test results for logged stock returns.

Table 2.2: Unit Root Tests at Levels for Logged Stock Returns

	ADF				PP				KPSS	
Series	ψ_γ	p-value	ψ_t	p-value	ψ_γ	p-value	ψ_t	p-value	ψ_γ	ψ_t
Australia	-1.5590	0.5033	-2.2042	0.4862	-1.5297	0.5183	-2.1698	0.5055	3.6278	0.3536
Belgium	-1.8935	0.3356	-1.8420	0.6836	-2.0242	0.2765	-1.9830	0.6095	0.3115	0.2667
Brazil	-1.4222	0.5726	-1.6685	0.7647	-1.4712	0.5481	-1.7712	0.7182	2.7749	0.4272
China	-1.5407	0.5127	-1.9572	0.6234	-1.6939	0.4341	-2.0843	0.5535	1.2116	0.6325
Colombia	-0.6865	0.8480	-1.5098	0.8261	-0.6833	0.8488	-1.4888	0.8332	3.4453	0.4642
Germany	-2.3463	0.1577	-2.4029	0.3777	-2.3579	0.1542	-2.4305	0.3633	1.4089	0.2073
Hong Kong	-1.6792	0.4416	-2.6721	0.2485	-1.8510	0.3559	-3.0021	0.1320	3.0893	0.3354
Indonesia	-1.2707	0.6450	-2.1137	0.5371	-1.2535	0.6529	-2.1649	0.5083	2.1871	0.5488
Ireland	-1.0428	0.7396	-1.7840	0.7121	-1.1371	0.7029	-1.8276	0.6908	1.8912	0.4056
Italy	-1.6577	0.4526	-2.0550	0.5698	-1.6877	0.4373	-2.0754	0.5585	0.9096	0.5960
Japan	-2.3771	0.1485	-2.3136	0.4256	-2.4644	0.1246	-2.4051	0.3766	0.2543	0.2327
Korea	-0.9347	0.7774	-2.5785	0.2904	-1.0851	0.7236	-2.9651	0.1426	3.8309	0.2649
Malaysia	-1.3814	0.5927	-2.0227	0.5877	-1.6982	0.4319	-2.3558	0.4028	1.9900	0.4625
Mexico	-1.4177	0.5749	-2.2666	0.4515	-1.4181	0.5747	-2.3234	0.4203	3.9663	0.3826
Netherlands	-2.4467	0.1292	-2.3592	0.4010	-2.4339	0.1326	-2.3434	0.4095	0.5487	0.2810
New Zealand	-1.6673	0.4477	-1.9161	0.6454	-1.7306	0.4155	-1.9798	0.6112	0.8269	0.2610
Portugal	-1.2857	0.6382	-2.0521	0.5715	-1.4407	0.5634	-2.1250	0.5307	1.0057	0.5342
Singapore	-1.4539	0.5568	-2.2460	0.4629	-1.6582	0.4524	-2.5102	0.3231	2.5488	0.3719
Spain	-3.0155	0.0338	-2.4575	0.3495	-3.0171	0.0336	-2.4503	0.3531	1.6617	0.5505
Thailand	-1.5907	0.4870	-2.3921	0.3834	-1.6694	0.4467	-2.5097	0.3233	1.4428	0.5783
US	-2.4099	0.1392	-2.6421	0.2615	-2.4106	0.1390	-2.5898	0.2851	2.4046	0.3109

Notes: All series are in natural logarithm. ψ_γ constant whereas $\psi_t$denotes constant and trend. The ADF and PP tests $H_0: \rho = 0$ against $H_1: \rho \neq 0$. The null for the KPSS test is stationarity.

The tests were carried out at levels and using the maximum lag available. All the tests employed failed to find evidence of stationarity. This implies that there is relatively high persistence in stock returns. More precisely, it implies that stock returns diverge from its mean values and follows a random walk.

2.5. Estimation Results

With the econometric methodologies set aside in the previous section, this section will present the results from the recursive GSADF test and the clog-log model for markets in DEE.

2.5.1. Recursive GSADF Test for Stock Market Bubbles

Prior to performing the recursive GSADF test[7] for each country, the chapter will first determine the parameters for simulation. Phillips et al. (2015) has suggested that the formula, $r_0 = 0.01 + 1.8/\sqrt{\mathrm{T}}$ (where T refers to the total number of observations) be used for the calculation of the minimum window size. It adopted this formula and obtained the minimum window size to be used for our recursive regression. The lag order, k to be used for the recursive regression is set to a maximum of 1, ($k = 1$)[8]. Once it has determined the parameters for the simulation, the 95% exact finite critical values sequence for the test will be obtained using a Monte Carlo algorithm. Iteration of the algorithm is done up to 1000 times in order to generate the critical values. Following this iteration, the test statistics will then be computed. Apart from this computation, the 90%, 95% and 99% distributional quantiles, which are the right-tailed critical values, are computed. These quantiles are used for deciding whether stock returns exhibit explosive behaviour.

The number of trading days in stock markets usually ranges between 252 to 260 days in a year. It is expected that markets are informationally efficient and that current information about

[7] The Phillips method is a stop-start method, where when the bubble bursts one must restart the process. So, it is backward looking and can only detect bubbles ex-post and cannot model the entire process ex-ante or the persistence of the process. This weakness can be overcome using the random coefficient model proposed by Banerjee et al. (2020).
[8] The reason for adopting this setting is that Phillips et al. (2014) have demonstrated that the selection of k using an alternative approach, the top-down approach of Campbell and Perron (1991) results in extreme size distortions and this can reduce the statistical power of the test.

fundamentals are rapidly reflected in prices. Hence, if there were any deviation of prices from their fundamental value up to a minimum duration[9], d_m of 6 periods this would be considered a bubble.

Table 2.3: Recursive GSADF Results for Explosive Stock Behaviour

Country	GSADF test statistics	
Australia	2.2152*	
Belgium	3.4357***	
Brazil	2.5462**	
China	2.8114**	
Colombia	3.0532***	
Germany	3.3368*	
Hong Kong	2.9578***	
Indonesia	5.6884***	
Ireland	4.0490*	
Italy	3.5617*	
Japan	2.9481***	
Korea	2.3608*	
Malaysia	3.4452***	
Mexico	3.8813***	
Netherlands	3.0308*	
New Zealand	2.3567***	
Portugal	2.7517**	
Singapore	3.7580***	
Spain	2.7594**	
Thailand	2.7065**	
US	2.3036*	
Finite sample critical values		
99%	95%	90%
2.8999	2.4644	2.2222

Note: The finite critical values of the GADF tests are estimated from Monte Carlo simulations based on 1000 replications. The total number of observations, T= 1140 and the lag, k=1. ***, **, * indicates 1%, 5% and 10% significance level, respectively.

Table 2.3 presents the result of the recursive GSADF test. The test detects multiple explosive paths in logged stock returns at the conventional significance levels for the countries

[9] Phillips et al. (2011) have suggested that the minimum duration be constrained to $Log(n)$, where n is the number of trading day in stock markets.

examined[10]. For instance, the result shows that the test statistic of 4.04 for Ireland exceeds its critical value at 99%. This resulted in the rejection of the null hypothesis, $\mathrm{H}_0\colon |\psi| = 1$ of unit root (random walk) and implies that there were multiple episodes of bubbles. Similarly, in Belgium the test statistic of 3.43 is above its corresponding 99% critical value of 2.89. The null hypothesis, $\mathrm{H}_0\colon |\psi| = 1$ of unit root is thus rejected against the alternative, $\mathrm{H}_A\colon |\psi| > 1$ of multiple bubbles at the 1% level of significance.

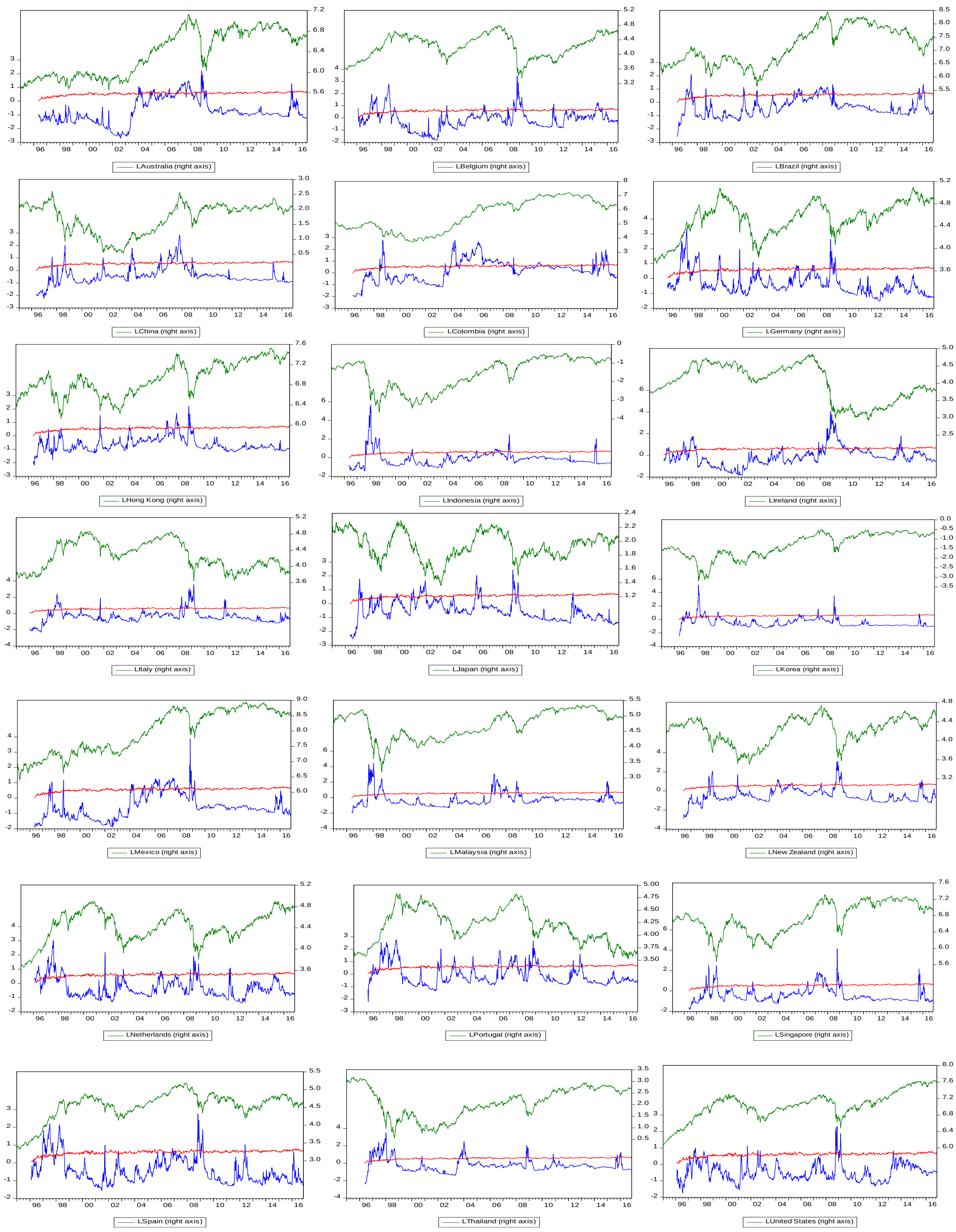
Figure 2.1 displays the test results for bubbles in the respective countries. It shows the observed log of stock returns and the simulated test statistics alongside its corresponding 95% critical value sequence. The green line traces out the log of stock returns. The blue line is the test statistic sequence while the red line is its corresponding asymptotically distributed critical value at 95% confidence level. It can be seen from the figure that at times the test statistics lies above their critical values. This is clear indication of the presence of bubbles. It can also be seen that some markets have more pronounced explosive behaviour than others have. For instance, episodes of bubbles appear to be more prominent in Germany, Japan, and Portugal. There are, however, fewer episodes of bubbles in Indonesia, Korea, and the US.

Figure 2.2 plots the duration of bubbles across stock markets. The figure displays the duration of bubbles prior to the GFC, during the crisis and post-crisis. The figure allows us to gain a deeper insight into the duration of bubbles. Our goal here is to compare the length of time that bubbles survived during these different periods. Some interesting findings across markets are revealed. It can be clearly observed that there were bubbles across markets particularly prior to the GFC. This is because the log of stock returns exceeded the minimum duration in most of the markets during this period. In terms of the type of economy, it is obvious that more emerging economies experienced bubbles and had durations that were longer than those of their developed counterparts, particularly in 2005 and 2006. A more interesting picture emerges during the GFC period. More stock markets seem to have had dramatic episodes of bubbles that lasted for an extended time. These dramatic episodes are witnessed in markets of both DEEs. As shown in the plot, during the post-crisis period particularly in 2015, there is an

[10] The data for Chile, France, Philippines, and the United Kingdom (UK) were also tested for bubbles. However, the test failed to show evidence of bubbles in their stock markets during the period examined. Due to the lack of evidence of bubbly episodes, these countries were excluded from our study. Although we found evidence of bubbles for Taiwan, Argentina, and Peru, we had to exclude them in the second stage due to paucity of macroeconomic data.

emergence of bubbles with long durations. This is surprising and so, there is need for us to better understand what factors are affecting bubbles' duration in stock markets across countries.

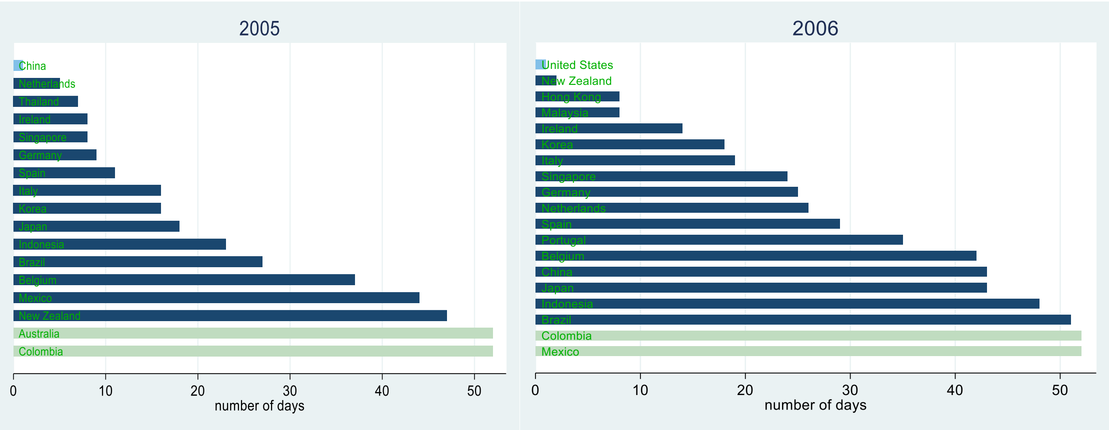
Figure 2.1: Recursive GSADF Test Results Based on Backward Regression for Stock Returns



Notes: the *blue* lines indicate the recursively estimated GSADF sequence while the *red* line is the 95% standard sequential critical value computed via Monte Carlo simulation technique.

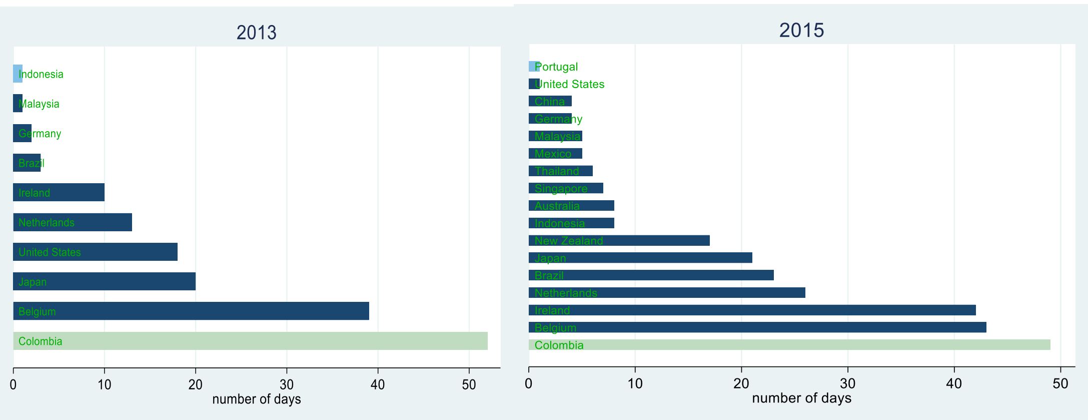
Figure 2.2: The Duration of Stock Bubbles Pre-Crisis, Crisis and Post-Crisis

Pre-crisis



crisis

Post-crisis



Source: GSADF estimates based on Bloomberg data

Notes: The light blue histogram is the country with lowest number of bubble episodes each year. The green histogram is the country with highest number of bubble episodes each year. Pre-crisis is not including Hong Kong, Malaysia, Portugal and the US in 2005 and Thailand in 2006. During the crisis, Japan is omitted in 2007. Post-crisis is not including Australia, China, Hong Kong, Italy, Korea, Mexico, New Zealand, Portugal, Singapore, Spain and Thailand in 2013 and Hong Kong, Italy, Korea and Spain in 2015. These countries were omitted because there is no statistical evidence from the recursive GSADF estimates to support stock bubble episodes during these periods.

2.5.2. Results of Contagion Models

The results of the baseline model with and without random effects and the model using splitted sample of countries are presented in this sub-section.

2.5.2.1. Baseline Model Results

This section analyses the quantitative results for the covariate effects of macroeconomic factors on duration of bubbles. Columns (1) and (2) of Table 2.4 reports the baseline results using the model without controls for unobserved differences across countries. The model controls for endogeneity. It also controls for within-country correlation in the residuals in order to obtain robust standard errors and for the statistical improvement of the covariate's coefficients. The results are interpreted in terms of the size of covariate effects and as the probability of a bubble ending.

The result of the baseline model shows that contemporaneous inflation is important for understanding how long a bubble survives as it yields a significant positive effect. An increase of 10% in the general price level increases the duration of bubbles by 0.72%. This suggests that an increase in the general price of goods and services lowers the probability that the bubble will end. The result also shows that the coefficient of portfolio inflows is positive and statistically significant at the 5% level. A rise in portfolio inflows increases the duration of bubbles. Specifically, a 10% increase in portfolio inflows is associated with a 0.10% increase in the duration of bubbles. This implies that surge of portfolio inflows triggered by higher returns in the home country reduces the probability that a bubble will end.

The chapter next considers the conditioning set of macroeconomic variables for addressing possible endogeneity[11]. It is interesting to find evidence of the effect of lagged variables in determining the duration of bubbles. The size of the effect of these lagged covariates appears larger than their contemporaneous effects. One possible explanation for this is that the overall effect is affected by the presence of endogeneity. In all, there are four statistically significant

[11] Potential endogeneity could arise because of the correlation of regressors with error terms.

lagged explanatory variables, which are inflation, portfolio inflows, yield spread and volatility in gold prices.

Table 2.4: Results of the Baseline Model

	Model without Random Effects		Model with Random Effects	
Variables	Coefficients (1)	*p*- values (2)	Coefficients (3)	*p*-values (4)
<u>Domestic factors</u>				
Gdpc	-0.025	(0.025)	-0.022	(0.024)
Infl	0.072^{**}	(0.035)	0.063	(0.053)
Portf	0.010^{**}	(0.005)	0.011	(0.008)
Yiespd	0.029	(0.031)	0.010	(0.052)
Mpol	0.067	(0.064)	0.063	(0.064)
<u>Exogenous factors</u>				
Rop	0.009	(0.006)	0.009	(0.009)
Rgp	-0.000	(0.000)	-0.000	(0.001)
<u>Volatility of factors</u>				
Gdpcvol	0.007	(0.107)	0.035	(0.112)
Inflvol	0.155	(0.228)	0.204	(0.219)
Ropvol	0.518	(1.629)	0.637	(1.476)
Rgpvol	0.276	(0.236)	0.199	(0.283)
<u>Lag of factors</u>				
Gdpc_L1	0.034	(0.021)	0.043^{*}	(0.024)
Infl_L1	-0.099^{***}	(0.029)	-0.104^{**}	(0.044)
Portf_L1	-0.009^{*}	(0.005)	-0.010	(0.008)
Yiespd_L1	-0.080^{**}	(0.035)	-0.084^{*}	(0.046)
Mpol_L1	-0.063	(0.049)	-0.068	(0.056)
Rop_L1	0.006	(0.007)	0.006	(0.012)
Rgp_L1	-0.001	(0.001)	-0.001	(0.002)
Gdpcvol_L1	-0.164	(0.112)	-0.180	(0.156)
Inflvol_L1	0.290	(0.234)	0.411^{*}	(0.247)
Ropvol_L1	1.486	(1.481)	1.582	(1.639)
Rgpvol_L1	-0.784^{***}	(0.251)	-0.805^{***}	(0.310)
_cons	1.088	(0.739)	0.974	(1.017)
Controls –unobserved effects		No		Yes
Wald test statistic		1.20E+06		35.75
		(0.000)		(0.032)
$ln\sigma_u^2$				-2.819^{***}
				(0.923)
Likelihood ratio test (χ^2)				3.70
				(0.027)

Notes: Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, respectively. The estimates reported are the standardized and not the exponentiated coefficients. The standard errors for the clog-log model using clustered by country residuals and the model with heteroskedastic standard errors that controls for unobserved heterogeneity are given in the parenthesis. The Wald test statistic with asymptotic χ^2 distributions for coefficient restrictions and likelihood ratio tests for the absence of unobserved heterogeneity are reported.

Inflation exerts a strong negative influence on the duration of bubbles. Precisely, a 10% increase in lagged inflation results in a 0.99% decrease in the duration of bubbles. Since the past errors of inflation reflect inflation persistence (inflation rates do not change immediately because its past levels influence future prediction of inflation), the result indicates that high level of inflation persistence increases the probability that the bubble ends.

Portfolio inflows exerts a strong negative influence on the duration of bubbles. The result show that portfolio inflows has the weakest lagged effect on the duration of bubble and the relationship is negative. Indeed, a 10% increase in lagged portfolio inflows leads to 0.09% decrease in the duration of bubbles. This implies that large portfolio inflows in the previous period increases the probability that a bubble will end.

Yield spreads has a negative coefficient estimate of -0.080. A 10% increase in yield spreads in the previous period is associated with a 0.8% decrease in the duration of bubbles.

The volatility in gold prices is negatively related to the duration of bubbles and has an effect of 7.84%. This suggests that past effects of shocks from gold and uncertainty are associated with a decrease in the duration of bubbles. Higher volatility in gold prices (lagged) may dampen speculative trading in stock markets and increases the probability that a bubble will end.

It striking to find that the coefficients of growth in real GDP per capita and yield spreads are not statistically different from zero. This indicates that these factors have no significant effect on the duration of bubbles. Similarly, the view that sustained accommodative policy stance (which translates to cheaper cost of borrowing or credit) is a determinant of bubbles is not evidenced in this chapter. Our result is thus inconsistent with the findings of He et al. (2019) but somewhat consistent with that of Lunde and Timmermann, (2004).

To evaluate whether the baseline model yielded consistent estimates, the chapter conducted a model diagnostic check using the conventional Wald test for joint effects which tests the null hypothesis of all the coefficients being zero. The test is strongly statistically significant at the 1% level with $p = 0.000$ leading to a rejection of the null hypothesis that all the coefficients are jointly equal to zero. Thus, the chapter concludes that the set of coefficients used for regressions are valid for the estimations. Overall, there is evidence that the duration of bubbles is dependent on both domestic and exogenous factors.

In column (3) and (4) of Table 2.4 the chapter report the fitted estimates of the regression based on the model with random effects. There are clear differences between this result and previously obtained baseline result. Even though the baseline model controlled for within-country correlations it still suffers from bias arising from the lack of control for unobserved country heterogeneity. This is because it does not pick up any variations arising from random effects. The inclusion of random effect lowers the degree of bias in the estimates of parameters and provides greater precision by improving the models fit. The Table also reports the likelihood ratio test for the unobserved heterogeneity, which shows that the variability arising from country-specific heterogeneity exists as indicated by the Chi-square, χ^2 statistic, which is statistically significant at 5% level ($p = 0.027$). Moreover, the error due to each country from the aggregate error term measured as the sigma squared ($ln\sigma_u^2$) is strongly significant at the 1% level further indicating the presence of heterogeneity across country.

The result shows that the coefficient estimates of the contemporaneous factors are not statistically different from zero; only the lagged covariates are significant. An obvious explanation for the absence of contemporaneous relationship is that it could be caused by the influence of measurement errors arising from unobserved heterogeneity. The chapter finds that the relationship between the duration of bubbles and the lagged growth in GDP per capita is positive and statistically significant at the 10% level. With an estimated coefficient of 0.043, it implies that a 10% growth in lagged income increases the duration of bubbles by approximately 0.4%, keeping other factors constant. This positive link suggests that improvement in country's overall economic situation via household's previous level of real personal income leads to a lower probability that the bubble will end.

Holding other factors constant, inflation in the previous period is negatively significant, and this is consistent with the baseline result. The only difference is that the coefficient estimate is slightly larger in magnitude. Another significant variable, which has coefficient estimates that are similar in sign and magnitude with the baseline result, is the lagged yield spreads. The lagged yield spreads with an estimated coefficient of -0.084 is statistically significant at the

10% level. This suggests that expectation about countries' economic outlook and previous shape of the yield curve are both important for explaining the duration of bubbles across countries.

The random effects regression also presents evidence of lagged volatility effects. The important role of consumer prices in explaining duration of bubbles is manifested by the effect of its previous volatility levels. Its effect is nearly four times larger than the effect of previous changes in its level, i.e., lagged inflation. The result shows that it is statistically significant with a positive coefficient estimate of 0.411. A 10% increase in inflation volatility in the previous period leads to an increase of 4.1% in the duration of a bubble. This suggests that volatility in the inflation rate in a previous period might raise the current price of stocks (as a consequence of investor's decision to hedge against inflation risk), cause bubbles to exist, and reduce the probability that bubbles will end.

With respect to the coefficient estimate of volatility in gold prices in the previous period, the chapter finds that it is strongly significant at the 1% level and yields a large negative effect of 8.05% on the duration of bubbles. This suggests that greater volatility of gold prices in the previous period might destabilize stock prices and cause overvaluation of stocks. This result shows the importance of the effect of exogenous shocks arising from the global commodity market and confirms the strong linkage between this market and the stock market. Overall, there is considerable evidence that the lagged effects of growth in GDP per capita and inflation volatility lengthen the duration of bubbles, whereas the lagged effects of inflation, yield spreads, and volatility in gold prices shorten the duration of bubbles.

2.5.2.2. Results of the Model using Splitted Sample of Countries

Tables 2.5 shows the results for the model with random effects, which controls for unobserved heterogeneity and is based on the splitted sample of countries. The chapter conducts a comparative analysis of covariates effects. It first compares the effects of high-income countries to those of middle-income countries (columns (1) and (2)). It then compares the effects of countries with high level of financial development to those at the intermediate level (columns (3) and (4)).

Table 2.5: Results of the Model using Splitted Sample of Countries

Variables	(1) High-Income level		(2) Middle-income level		(3) High level of financial development		(4) Intermediate level of financial development	
	Coefficients	*p*-values	Coefficients	*p*-values	Coefficients	*p*-values	Coefficients	*p*-values
Gdpc	0.016	(0.034)	0.040**	(0.016)	-0.021	(0.029)	0.123***	(0.043)
Infl	0.061	(0.124)	0.132	(0.081)	0.031	(0.083)	0.148	(0.137)
Portf	0.008	(0.009)	0.094**	(0.044)	0.009	(0.008)	0.342	(0.223)
Yiespd	0.067	(0.106)	0.015	(0.083)	0.013	(0.063)	0.338	(0.304)
Mpol	0.070	(0.132)	0.117	(0.099)	0.062	(0.093)	0.093	(0.149)
Rop	0.018	(0.014)	2.379	(1.714)	0.013	(0.011)	5.196	(3.778)
Rgp	0.000	(0.001)	-0.358***	(0.136)	0.000	(0.001)	-1.104***	(0.381)
Gdpcvol	-0.099	(0.142)	0.888**	(0.401)	-0.097	(0.137)	2.792***	(1.077)
Inflvol	0.544	(0.382)	-0.105	(0.461)	0.405	(0.316)	-0.462	(0.891)
Ropvol	2.566	(1.991)	-8.720*	(4.882)	1.956	(1.786)	-26.542**	(11.182)
Rgpvol	0.471	(0.377)	-0.556	(0.776)	0.368	(0.340)	-0.539	(1.713)
Gdpc_L1	0.025	(0.032)	0.048	(0.031)	0.044	(0.028)	0.258**	(0.126)
Infl_L1	-0.027	(0.122)	-0.123*	(0.067)	-0.103	(0.066)	-0.109	(0.130)
Portf_L1	-0.007	(0.009)	-0.083*	(0.047)	-0.008	(0.008)	-0.062	(0.211)
Yiespd_L1	-0.153	(0.098)	-0.117	(0.084)	-0.091*	(0.054)	-0.181	(0.284)
Mpol_L1	0.022	(0.130)	-0.096	(0.087)	-0.073	(0.084)	0.131	(0.150)
Rop_L1	0.018	(0.018)	0.978	(1.927)	0.012	(0.014)	8.583*	(4.834)
Rgp_L1	-0.003	(0.003)	0.087	(0.115)	-0.002	(0.002)	-0.055	(0.248)
Gdpcvol_L1	-0.308	(0.211)	-0.322	(0.371)	-0.192	(0.191)	-0.330	(0.692)
Inflvol_L1	-0.102	(0.356)	0.962**	(0.470)	0.188	(0.313)	2.526**	(1.091)
Ropvol_L1	-0.477	(2.234)	8.719**	(3.693)	-0.031	(1.997)	26.174**	(10.643)
Rgpvol_L1	-0.735*	(0.435)	-0.780	(0.680)	-0.716*	(0.384)	-2.756*	(1.669)
_cons	2.514*	(1.400)	-3.546	(2.159)	1.925	(1.221)	-18.201***	(6.197)
Likelihood ratio test (χ^2)	3.17	(0.038)	0.00	(1.000)	1.81	(0.089)	0.00	(1.000)
Wald test statistic	25.26	(0.2848)	31.60	(0.0845)	26.95	(0.2129)	19.54	(0.6115)
$ln\sigma_u^2$	-2.342***	(0.871)	-15.781	(69.847)	-2.776***	(1.035)	-15.229	(82.887)

Notes: Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01, respectively. The estimates reported are the standardized and not the exponentiated coefficients. The robust standard errors are shown in the parenthesis. The Wald test statistic with asymptotic χ^2 distributions for coefficient restrictions and likelihood ratio tests for the absence of unobserved heterogeneity are reported.

In middle-income countries, growth in GDP per capita is positive and marginally significant. When it increases by 10%, it may lead to increases in the duration of bubbles by 0.40%. This suggests that real income effects matter for bubbles' duration in middle-income countries. The result shows that portfolio inflows is significantly positive and this positive effect has an estimated coefficient of 0.094. A 10% increase in portfolio inflows is strongly associated with a 0.94% increase in the duration of bubbles in middle-income countries. This suggests that portfolio inflows from other countries to these countries may probably results in higher demand for equity securities by foreign investors, which will subsequently lead to higher prices and overvaluation and possibly cause bubbles to survive longer. The result also shows that the real price of gold is strongly statistically significant and has a negative explanatory effect, yielding a modest coefficient estimate of -0.358. This implies that a 10% increase in real price of gold lowers the duration of bubbles by 3.6%.

For the coefficient estimates of the volatility of macroeconomic factors, the chapter finds that both variability in GDP per capita and the real price of oil are significant for middle-income countries. Volatility in oil prices yields the largest effect on the duration of bubbles. A 10% rise in the volatility in oil prices lead to increases of 87.13% in the duration of bubbles. This result is shows that uncertainties about the future real price of oil appear to be more closely linked to the future price changes in stocks.

Turning next to the lagged influences of macroeconomic factors, the chapter reports statistically significant results at the 10% level for the lagged inflation effect on bubbles' duration. It has a coefficient estimate of -0.123, which implies that it explains 1.23% of the 10% decrease in the duration of bubbles. Previous changes in the price level may increase the probability that bubbles will end. In addition, the result shows that lagged portfolio inflows is negatively associated with the duration of bubbles. As lagged portfolio inflows increases by 10%, duration of bubbles increases by 0.83%.

In terms of the lagged effect of volatility of the macroeconomic factors, the lagged values of inflation volatility and real price of oil are both important determinants of the duration of bubbles in middle-income countries at the emerging phase of growth. Both factors, which are statistically significant at 5%, affect the duration of bubbles positively although the volatility in the real price of oil exerts the largest positive influence. The result shows that 10% increases in inflation volatility and the real price of oil leads to increases of 9.62% and 87.19%, respectively in the duration of bubbles. It suggests that greater volatility in previous inflation may likely elongate the duration of bubbles. Likewise, for the linkage between volatility in oil prices and the duration of bubbles, the chapter finds that the lagged effect of a rise in oil price fluctuations triggered by exogenous shocks of oil volatility seem to impact on the duration of bubbles. For high-income countries, the result shows that the volatility in gold prices in the previous period has a strong effect in explaining bubbles' duration. The lagged volatility effect is statistically significant at 10%. For a 10% rise in the volatility in gold prices there may be a negative effect of 7.35% on the duration of bubbles.

The chapter now turns to the results based on the level of financial development (columns (3) and (4)). It finds that countries with a high level of financial development have less significant predictors of the duration of bubbles. A quick glance at the results show that the factors are yield spreads and volatility in gold prices both of which have a significant negative lagged effect. However, the magnitude of the effect of yield spreads appears to differ from that of the volatility in gold prices, which exhibits a much larger effect. Turning next to countries at the intermediate level of financial development, the result shows that the crucial factors that might be responsible for explaining the duration of bubbles include the contemporaneous variables; growth in GDP per capita, real gold prices, volatility in GDP per capita and volatility in oil prices. For the lagged variables it finds significant results for: growth in GDP per capita, real oil prices, inflation volatility, volatility in oil prices, and volatility in gold prices. The comparative analysis shows that the influence of income and price effects, economic uncertainties, and exogenous shocks are crucially important in understanding the duration of bubbles across stock markets.

Taken together, this chapter finds few differences between the results for countries with high-income and those with highly developed financial systems. The findings show that the duration of bubbles for countries in these sub-groups appear to be explained only by lagged macroeconomic factors – yield spreads and real gold prices. The results generally revealed that the duration of bubbles, for countries in these sub-groups, is less influenced by macroeconomic factors. This implies that stock markets in these sub-groups have a better ability to deal with macroeconomic shocks. Similarly, it finds that there is not much difference between the results for countries with middle-income and those at the intermediate level of financial development. The results largely showed that countries in these sub-groups tend to be influenced by both contemporaneous and lagged macroeconomic factors. This implies that markets in these sub-groups have a weaker ability to deal with macroeconomic shocks. It thus seems that the more developed a country's financial system and the higher the country's per capita income, the less likely it is for the duration of bubbles to be affected by macroeconomic factors.

To evaluate whether the inclusion of a random intercept in our model is reasonable, the chapter conducted a check using the conditional likelihood ratio test for unobserved heterogeneity. The test compares between two models, the model with random effects versus a similar model but without random effects. It tests for the null hypothesis that all random intercepts are the same and rejection of this hypothesis indicates that inclusion of the random intercept is reasonable. Table 2.5 shows that the asymptotically distributed χ^2 with a statistic of 3.17 has an associated *p*-value of 0.038, which is statistically significant at 5% for high-income countries. This results in the rejection of the null hypothesis that the random effects are zero. Further, it suggests that differences in income levels exists within and between countries in this sub-group, which can considerably affect the coefficient estimates. In the case of middle-income countries, the specification test yields a *p*-value of 1.000 resulting in the strong non-rejection of the null hypothesis that the random effects are zero. When the chapter now consider sub-groups based on countries' level of financial development, the highly financially developed countries have differences in random unobserved variations since it rejected the null hypothesis because the reported *p*-value of 0.089 is significant at 10%. However, it reached a different conclusion for countries at the intermediate level of financial development, which seem not to have any differences in random unobserved effects.

2.5.3. Robustness Checks

The previous section has shown that domestic and exogenous factors are important determinants of bubbles' duration in stock markets of DEE. This section checks for the robustness of our baseline results.

2.5.3.1. Price and Real Income Effects

To test the robustness of the baseline model the chapter first checked whether the components of real economic activity would have an impact on the duration of bubbles. Decomposing aggregate income into its key components is crucial for determining the channels of transmission. We, thus, excluded real GDP per capita from the model and included growth in consumption and investment. After conducting this robustness check, it went on to conduct another check where it excluded inflation based on the CPI and replaced it with an alternative measure of inflation, the GDP deflator.

Table 2.6 contains the results of the robustness checks. The chapter finds that the sizes of the coefficient estimates are overall trivially smaller than the baseline results, but the signs remain the same. The results are quite interesting as it finds a relationship between growth in household consumer spending and the duration of bubbles in countries' stock markets. Evidence of this relationship is confirmed with a marginal statistical significance at 5% albeit revealing a negative association with the duration of bubbles. A 10% increase in household consumption may be related with a 0.65% decrease in the duration of bubbles. This suggest that an increase in the allocation of household's incomes for the procurement of goods and services decreases the duration of bubbles and increases the probability that bubble ends. When households overspend on procuring consumption goods and services, it significantly reduces household savings and wealth. This will contract the amount of funds available for investments like stocks and this could presumably explain why it increases the probability of bubbles ending. The tendency for bubbles to end increases with growth in household's consumption.

In contrast, the coefficient of the contemporaneous growth in investment is positive but statistically insignificant. This suggests that the duration of bubbles is not related to growth in real investments. There is no significant evidence supporting the riding of bubbles hypothesis that stresses on continuous investment in highly overpriced stocks by arbitrageurs so as to exploit additional payoffs before the bubbles eventually crashes as plausible explanation. There is, however, evidence of a lagged positive effect of growth in investment on the duration of bubbles. As growth in investment increases by 10%, duration of bubbles increases by 0.32%. Since arbitrageurs decide to ride on bubbles because they are fairly optimistic that they can resell the overpriced stocks later for a much higher price this could influence bubbles' duration.

Table 2.6: Robustness Results

Variables	Coefficients	*p*-values
Domestic factors		
Rcons	-0.065**	(0.030)
Rgi	0.005	(0.008)
Infdf	0.035	(0.030)
Portf	0.005	(0.008)
Yiespd	0.020	(0.050)
Mpol	0.058	(0.052)
Exogenous factors		
Rop	0.009	(0.009)
Rgp	-0.000	(0.001)
Volatility of factors		
Infdfvol	0.170	(0.205)
Ropvol	0.339	(1.382)
Rgpvol	0.082	(0.223)
Lag of factors		
Infdf_L1	-0.043*	(0.024)
Portf_L1	-0.005	(0.008)
Yiespd_L1	-0.089**	(0.044)
Mpol_L1	-0.039	(0.047)
Rop_L1	0.006	(0.012)
Rgp_L1	-0.001	(0.002)
Rgp_L1	-0.001	(0.002)
Infdfvol_L1	0.337	(0.215)
Ropvol_L1	2.075	(1.548)
Rgpvol_L1	-0.751***	(0.267)
Rcons_L1	-0.049	(0.030)
Rgi_L1	0.032***	(0.010)
_cons	0.333	(0.235)
Wald test statistic	37.65	(0.020)
Likelihood ratio test (χ^2)	2.97	(0.042)
$ln\sigma_u^2$	-2.691***	(0.836)

Notes: Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01, respectively. The estimates reported are the standardized and not the exponentiated coefficients. The standard errors clustered by country are shown in the parenthesis. The Wald test statistic with asymptotic χ^2 distributions for coefficient restrictions are reported.

Overall, the results show that bubbles' duration is not primarily driven by the amount of available new stock of capital invested but rather by growth in consumption. The joint test for the coefficients yields Wald statistics of 37.65 with a *p*-value of 0.0201 resulting in the rejection of the null that all the coefficients are jointly zero. Whereas the likelihood ratio test yields Chi-square statistics of 2.97 with a *p*-value of 0.042, which indicates that it is statistically insignificant at the conventional level. It, further, implies that unobserved heterogeneity affects estimated coefficients. The chapter thus concludes that there is evidence of variations across countries in the sample.

In sum, the baseline model shows that these are some significant determinants of longer duration of bubbles. For instance, the chapter finds that an increase in contemporaneous inflation creates increased demand for stocks, which can result in the overvaluation of stock prices. The continuous overvaluation of stocks may lead to the formation of bubbles with long duration. Similarly, surges in portfolio inflows might trigger stock price increases and if prices continue to soar, then bubbles may occur. The continuous rise in prices may lengthen the duration of bubbles. At the same time, the model shows evidence of shorter duration of bubbles influenced by some factors. For instance, more persistence in inflation as captured by past inflation appears to shorten the duration of bubbles. As well, past portfolio inflows, which can influence future inflows and the yield spreads in the previous period, could also shorten this duration. Similarly, fluctuations in uncertainty about commodity prices in the previous period, in this case the volatility in gold prices in the previous period, may curtail speculative trading across stock markets and shorten the duration of bubbles. Finally, improvements in economic performance, i.e., growth in income measured using growth in GDP per capita, yield spreads and interest rate gap (cheaper cost of borrowing) are not important determining factors of the duration of bubbles.

With regards to the model that controls for random effects, there is evidence that growth in income in the previous period and inflation volatility in the previous period could lead to longer duration of bubbles. There is also evidence that inflation in the previous period, yield spreads in the previous period and volatility in gold prices in the previous period could bring about shorter duration of bubbles. Past inflation, i.e., expectations about the economic outlook, is important for explaining the duration of bubbles across countries. Increase in inflation in the previous period might cause the current price of stocks to rise. The rise in the current price of stocks occurs because investors prefer to hedge against the risk of future instability in general prices. Hence, they hedge against inflation risk. Hedging against inflation risk may cause bubbles to exist and to survive for a short duration. The previous shape of the yield curve is also important in understanding the duration of bubble. Also, previous variations in economic uncertainty as captured by volatility in gold prices in the previous period is an important determinant because it appears to lessen speculative trading in stock markets which results in the contraction of bubbles' duration. If investors had previously found it difficult to predict the likelihood of certain economic events, then it is likely that this uncertainty can inhibit speculative trading in stock markets and eventually reduce the duration of bubbles.

The chapter presents robust evidence that growth in household expenditure influences the duration of bubble across stock markets. The more households utilize their incomes for consumption, the shorter the duration of bubbles. Overconsumption by households reduces household savings and shrinks the amount of funds available for investment in stocks and this could be a plausible explanation for the shortened duration of bubbles. In addition, the duration of bubbles is driven by past inflation, past yield spreads, fluctuations in past gold prices, and growth in investment in the previous period.

2.6. Conclusion

This chapter focused on the impact of macroeconomic factors on the duration of bubbles in stock markets of DEE. More precisely, it examined the roles of domestic and exogenous factors on the duration of bubbles. The existing literature examining the role of macroeconomic factors on the duration of bubbles accounts for only the effect of monetary policy via real interest rates and ignores other possible important factors. This chapter circumvented this omitted variable bias by including other important macroeconomic variables as suggested by the existing theoretical and empirical literature.

Our estimations are executed in two stages. Firstly, the recursive GSADF test, which is implemented using Monte Carlo simulations, is applied to the log of stock returns. The test is used to examine the presence of bubbles and to date stamp bubble episodes. The result of this test showed that there are multiple explosive processes in stock returns, which is evidence of the bubble phenomenon. Secondly, the clog-log baseline model was used to analyse the impact of macroeconomic factors on the duration of bubbles. It is estimated on a panel of 21 countries with sample data spanning from 1995 to 2015. The parameters of the model are estimated using the maximum likelihood estimator. It then controlled for an important measurement error caused by endogeneity bias, which can invalidate the inference. This chapter circumvented this bias through the inclusion of lagged macroeconomic variables in the model.

The baseline model presented evidence of contemporaneous inflation and portfolio inflows leading to longer duration of bubbles. Conversely, the lags of inflation, portfolio inflows, yield spreads and the volatility in gold prices appear to shorten the duration of bubbles. It also showed that the effect of interest rate gap on the duration of bubbles is insignificant. This finding is inconsistent with the existing evidence. This chapter thus argued that accommodative monetary policy, which is supposed to lower the cost of borrowing, does not influence the duration of bubbles across stock markets.

After controlling for endogeneity, this chapter also controlled for heterogeneity bias arising from unobserved differences in country characteristics. This bias could have implications on the size and significance of the macroeconomic effects that affect the duration of bubbles. It estimated a clog-log model with random effects to control for this bias. It presented evidence that showed that unobserved random effects have an impact on bubbles' duration. This evidence showed that unobserved heterogeneity is important for understanding the role of macroeconomic factors in explaining bubbles' duration. Moreover, it presented evidence that the lags of growth in per capita income and inflation volatility are likely to lead to longer duration of bubbles. However, the lags of inflation, yield spreads and the volatility in gold prices decreases the duration of bubbles and these findings are broadly consistent with the baseline results. Moreover, the findings revealed that the duration of bubbles for countries with high-income and highly developed financial systems are less influenced by macroeconomic factors. On the contrary, the result showed that middle-income countries and those at the intermediate level of financial development have weaker ability to cope with macroeconomic shocks.

Finally, the robustness checks largely confirmed the results for the baseline case, as both the sign and explanatory power of the relationship remained robust to changes in the model. From the robustness checks, it documented that growth in consumption is important in explaining bubbles' duration. Overall, our analysis showed that countries' domestic and exogenous factors play important roles in understanding the duration of bubbles. In addition, our analysis of the duration of bubbles stressed the importance of controlling for endogeneity and heterogeneity. The findings in this chapter are important because our understanding of macro-financial interactions, particularly interactions between global stock markets and the broader economy, is enriched.

The analysed macroeconomic effects have crucial policy implications for the stock market and the economy. The lags of inflation and its volatility, which reflect uncertainty and rise in persistence, are particularly important because both factors affect the duration of bubbles. This chapter suggests that policymakers should endeavour to prescribe more effective policies to stabilize the rates of inflation.

A potentially interesting area that can be considered for future research is to extend the scope of this study to investigate how changes in the business cycles can affect the duration of bubbles in stock markets. Investigating the effect of the state of economies on bubbles' duration is important in understanding whether there are variations in bubbles' duration during economic recessions or booms.

The limitation of this chapter is that given the small number of countries in the sample for middle-income countries and those at the intermediate stage of financial development, it means that the evidence reveals only the likely effects from the interactions between factors and the duration of bubbles. In addition, it used total portfolio inflows to proxy for short-term capital inflows because of the absence of data on this type of flows. In which case, the usage of this proxy variable can likely impinge on the resultant effect.

Chapter 3: Assumptions about Breaks and its Implications for Analysis of Stock Market Contagion

3.1. Introduction

This chapter argues that there are distinct breaks in variances and correlations of returns and relies on the assumption of distinct breaks to examine contagion among stock markets in DEEs during the GFC. This crisis is of importance because it exerted considerable turmoil on markets in DEEs and markets experienced sharp decreases in returns. This chapter argues that the crisis induced cross-market comovement of returns and caused contagion between markets, but the extent of contagion seems to differ depending on the type of break: common breaks in covariance or distinct breaks in the components of covariance, that is the variances and correlations. Empirically, the transmission of common shocks could indicate the existence of common breaks. Studies on contagion have generally relied on the standard assumption of common breaks. Under this assumption, common breaks in the covariance matrix are modelled. As such, breaks in the variance and correlation matrices are treated simultaneously. Treating breaks simultaneously could be problematic because it could lead to biased estimates of breaks (Blatt et al., 2015) because each component has its own distinct break point. A convenient way of handling this problem is to adopt an alternative assumption. Simply, one could assume that common shocks to variances are distinct from common shocks to correlations, and treat breaks in each of them sequentially, one at a time. This could be achieved through decomposition of the covariance matrix into variances and correlations. The literature on stock market contagion mainly considers breaks that are common in the covariance matrix of stock returns but has not focused on distinct breaks when analysing contagion. This chapter attempts to fill this gap in the literature.

There is a broad literature that tests for contagion from the US market to markets in DEEs. This literature documents that common shocks are transmitted during crisis and tests for contagion across markets in DEEs (Chiang et al., 2007; Baur and Fry, 2009; Khan and Park, 2009; Kenourgios, et al., 2011; Celık, 2012; Kenourgios, et al., 2013; Dungey and Gajurel, 2014; Kenourgios and Dimitriou, 2015; Hemche et al., 2016). There is also a growing literature that examines contagion through changes and breaks in the return process. This literature has relied on the assumption of common breaks and has treated breaks in variances and correlations simultaneously (Billio and Caporin, 2010). Even though the existing literature has stressed on the distinctness of breaks and that evidence of contagion might be affected depending on how breaks are treated, there is still scarce analysis on distinct breaks and the possible existence of contagion in DEEs. Forbes and Rigobon (2002) have highlighted that changes in variance are distinct from changes in correlation. They have pointed out that testing for changes in the covariance matrix does not allow for the detection of contagion. This is because the source of the change in the covariance matrix would be unknown as it could arise from a rise in variance or from an increase in correlation. Similarly, Manner and Candelon (2010) have pointed out that breaks in variances differs from breaks in correlations. They have shown that breaks in variances always precede breaks in cross-market dependence and that tests of contagion can turn out to be biased when breaks in variances and correlations are simultaneously estimated. This is because their transmission times are unlikely to perfectly coincide. Yet, so far, no empirical analysis has been conducted using the alternative assumption of distinct breaks for the analysis of contagion between markets in DEEs. This chapter contributes to the literature by focusing on distinct breaks for the analysis of contagion.

To test for changes and breaks in returns, and the possible existence of contagion in DEEs, this chapter employs a multivariate VAR model, which is a system of equations that provides parsimonious correlation specifications for the analysis of contagion. The model can allow for multiple breaks in underlying time series, which affords us greater precision in the detection of structural breaks than using a univariate model (Bai and Perron, 1998; Qu and Perron, 2007; Li and Perron, 2017). For the estimation of the model's parameters, the chapter utilizes the feasible generalized least squares (FGLS) procedure, which yields asymptotically efficient estimators. Tests for breaks using this model have relied on the assumption of common breaks and typically been carried out simultaneously, this chapter extends this literature and test for breaks sequentially. The chapter treats the model as though there is only a single break point and then estimates the entire break points one at a time. To implement all these, the chapter applies a SP. It executes the test procedure using a dynamic programming algorithm that sequentially searches for the location of breaks in all parameters. The procedure is advantageous because it provides computational savings. Moreover, when the procedure is applied, the break point estimator remains consistent even if the number of breaks in the series are incorrectly specified (Bai, 1997).

It is indisputable that empirical tests provide a beneficial tool in analysing contagion whose occurrence can be examined in different settings. Nonetheless, this chapter agrees with Forbes and Rigobon (2001) that there is a need for a concrete working definition of the concept of contagion as this is important for empirical accuracy. The chapter adopts Forbes and Rigobons' (2002) definition, which refers to contagion as a significant increase in the correlation of returns. These increases must be large enough to cause breaks in the transmission of shocks between markets. However, this chapter also recognizes the different ways through which contagion can occur. It, thus, analyses the possible existence of contagion using an alternative definition. It follows Pericoli and Sbracias' (2003) who defines contagion as spillovers, which are interaction effects or the linkages between markets. Diebold and Yilmaz (2009, 2012) show the possibility of analysing the possible existence of spillover contagion through the estimation of GFEVDs and the computation of spillover indices. Although our analysis follows their method of analysis for spillovers in DEEs it, however, continues to assume that breaks are distinct.

The remainder of the chapter is structured as follows. Section 2 presents the theoretical literature. Section 3 presents the empirical literature. Section 4 presents the data and empirical methodologies. Section 5 presents the results on tests for contagion, spillovers analyses and robustness checks. Section 6 concludes.

3.2. Theoretical Literature

In this section, the so-called phenomenon of contagion will be defined, and its main channels of transmission will be set out. Emphasis will be placed particularly on contagion as the propagation of shocks, and contagion as spillovers of volatilities and breaks in correlations will also be discussed.

3.2.1. Contagion and the Propagation of Shocks

The definition of contagion in international finance has altered over the years. Scholars have come up with several definitions, probably one of the earliest definitions is that offered by King and Wadhwani (1990). To them contagion is considered a rise in the correlation between markets during a crisis. Changes in cross-market dependence therefore require a positive change in the correlation of returns across markets. While for Eichengreen and Rose ((1999), p. 33) “contagion variable reflects an unmeasured shock to fundamentals that strikes several countries simultaneously”. In this view, shocks play an important role in the propagation mechanisms between markets. Shocks to fundamentals are the main source of changes in cross-market dependence. Similarly, Edwards ((2000), p. 874) refers to contagion as “a situation where the effect of an external shock is larger than what was expected by experts and analysts”. The common element of these definitions is the acknowledgement that changes in cross-market dependence does not reflect contagion except such changes are driven by external shocks.

With the proliferation of definitions, scholars thought it important to come up with standard working definitions of what constitutes contagion. In line with this thinking, contagion has now been categorized into two different types: shift and pure contagion.

The former is the less restrictive definition, and it is sometimes referred to as fundamental-based contagion. This type of contagion occurs when cross-market dependence significantly increases following a shock[12] to a particular country or set of countries (Forbes and Rigobon, 2001). Dornbusch (2000) then elaborate on the sort of shock that could be transmitted. In his view, common or idiosyncratic shocks are often transmitted. Common shocks are shocks common to all markets, transmitted through disturbances to fundamentals. As to idiosyncratic shocks, these shocks are country specific. Shocks can also cause breaks in the international transmission mechanisms between markets. This chapter adopts the less restrictive definition of contagion.

The latter is a more restrictive definition of contagion. This type of contagion is usually transmitted through channels that are non-fundamental. Dornbusch et al. (2000) point out that such contagion will happen regardless of changes in fundamentals; it simply happens by virtue of investors’ behaviour[13]. Usually, when there is a change in the risk appetite of investors’, there is a tendency for them to re-evaluate their portfolio allocation strategies. Investors’ risk appetite will increase if they prefer to hold risky assets relative to non-risky ones. Because of their preference, the demand for and prices of risky assets will rise. Conversely, when their risk

[12] The shock could be transmitted through financial linkages, trade ties or other fundamentals. See Hernández and Valdés (2001) for a comprehensive discussion on the drivers of contagion.
[13] As a result, this type of contagion is often referred to as investor-behaviour contagion.

appetite falls, there will be a simultaneous fall in the demand for and prices of risky assets. In their famous paper, King and Wadhwani (1990) demonstrate that the occurrence of contagion is as a result of attempts by rational investors to deduce information from price changes in other markets. Similarly, Corsetti et al. (2005) document that market sentiments such as investors' irrational herding behaviour, changes of expectation equilibrium and unanticipated market panics can lead to contagion.

3.2.2. Contagion as Spillovers of Volatilities and Breaks in Correlations

As discussed in the sub-section above, external shocks are important for the occurrence of contagion. In this sub-section, contagion will be discussed as spillovers of volatilities and breaks in the correlation of returns.

The specification describing the behaviour of returns across markets is given as:

$$\begin{aligned} r_i &= \beta_i + \gamma_i f + \varepsilon_i \\ r_j &= \beta_j + \gamma_j f + \varepsilon_j \end{aligned} \tag{3.1}$$

where, r_i and r_j represent market returns in countries, i and j, respectively. β_i and β_j are the constants, γ_i and γ_i denote country-specific factors while f denotes the common factors (events) that affect the distribution of market returns, and ε_i and ε_j are zero-mean random variables with finite-variance which can be viewed as the country-specific/idiosyncratic risk of assets.

In a two-country model with asset markets, the standard framework used to model the data generating process which generates the market returns in countries, i and j is given in Eq. (3.1). This expression decomposes each country's market return into the expected mean of returns, the product of the country-specific and common factors, and the country-specific risks. In most markets, a change in the variance of an asset's return can either be determined by the common factor, country-specific risks, or jointly by both (Corsetti et al., 2005).

Eq. (3.1) is determined jointly by the set of assumptions about the variance and covariance given as follows:

$$\begin{gathered}
\mathrm{Var}(f|\mathrm{C}) = (1+\delta_1)\mathrm{Var}(f|\mathrm{T}) \\
\mathrm{Var}(\varepsilon_j|\mathrm{C}) = (1+\delta_2)\mathrm{Var}(\varepsilon_j|\mathrm{T}) \\
\mathrm{Var}(\varepsilon_i|\mathrm{C}) = \mathrm{Var}(\varepsilon_i|\mathrm{T}) = \mathrm{Var}(\varepsilon_i) \\
\mathrm{Cov}(\varepsilon_i,\varepsilon_j|\mathrm{C}) = \mathrm{Cov}(\varepsilon_i,\varepsilon_j|\mathrm{T}) = 0
\end{gathered} \tag{3.2}$$

where, δ_1 and δ_2 denote the proportional change in variance of the market return compared with the tranquil period. C and T represent crisis and tranquil periods, respectively. Assuming country j is the source country of a global crisis, an increase in the variance of r_j does not imply that both δ_1 and δ_2 will be positive.

Given the model in Eq. (3.1), and making use of the key assumptions of the model (3.2), the correlation coefficient between the market returns, r_i and r_j in the tranquil period T is given by:

$$\mathrm{Corr}(r_i,r_j|\mathrm{T}) = \frac{1}{[1+\frac{\mathrm{Var}(\varepsilon_i)}{\gamma_i^2\mathrm{Var}(f|\mathrm{T})}]^{1/2}[1+\frac{\mathrm{Var}(\varepsilon_j|\mathrm{T})}{\gamma_j^2\mathrm{Var}(f|\mathrm{T})}]^{1/2}},$$

Similarly, the correlation coefficient in the crisis period C, is

$$\mathrm{Corr}(r_i,r_j|\mathrm{C}) = \frac{1}{[1+\frac{\mathrm{Var}(\varepsilon_i)}{\gamma_i^2\mathrm{Var}(f|\mathrm{C})}]^{1/2}[1+\frac{\mathrm{Var}(\varepsilon_j|\mathrm{C})}{\gamma_j^2\mathrm{Var}(f|\mathrm{C})}]^{1/2}}.$$

When these two formulations are compared, there are two possible explanations for a rise in correlation. On the one hand, higher correlation during a crisis inevitably signifies an increase in the variance of the common factor f as opposed to the variance of the country-specific risk ε_j. Pericoli and Sbracia (2003) highlight that the increase in the variance, which reflects asset price volatility, could spill over from the crisis country to other countries and lead to the occurrence of contagion. On the other hand, higher correlation during a crisis may also be associated with an increase in the size of the country-specific factors, γ_i and γ_j. Thus, contagion occurs when the increase in correlation during a crisis ends up being significantly higher than the extent of dependence implied by the process in (3.1) and (3.2), i.e., the increase in correlation is too strong that it cannot be explained by the behaviour of the common and the country-specific factors. Put differently, contagion occurs when a crisis linked to country j, generates a higher correlation between market returns due to some structural change in the global economy, which affects the connections across markets. The higher correlation between market returns must be large enough to cause breaks. It, thus, implied that contagion has occurred, when higher correlation leads to breaks in the international transmission mechanisms between markets.

A contrasting view is that increases in cross-market dependence does not indicate contagion but interdependence. In this view, it is recognized that cross-market dependence could remain at high levels in all time periods. Forbes and Rigobon (2002) have attributed such sustained increases in cross-market dependence to prevailing strong relations among countries. When there is no change in correlation it is an indication that the decoupling of some markets has taken place. Decoupling suggest that the markets are insulated or unaffected by a crisis.

3.2.3. The Channels of Transmission for Contagion

A more in-depth way of understanding contagion is to uncover the various possible channels of its transmission[14]. There are three main channels identified in the theoretical literature: the correlated-information channel, the correlated-liquidity shock, and the cross-sectional portfolio rebalancing channel.

Assuming there are two countries, i and j with two stock markets[15] $SM[i]$ and $SM[j]$ and two real sectors $RS[i]$ and $RS[j]$. The correlated-information channel operates under three precise mechanisms (Figure 3.1). Firstly, if there is a negative shock in country i, which is diffused via

[14] See Forbes (2012) for discussion of the main channels of contagion.
[15] A contagion model for Bank Debt vs Sovereign Debt markets during the European sovereign debt crisis was also proposed by Acharya et al. (2014) and Banerjee et al. (2020).

real links, and if this shock is publicly perceived, then country $j's$ real market can be affected by the same shock. Since macroeconomic information has an effect on the dynamics of stock prices, eventually, markets in the two countries react to the diffused negative real shocks (Block A). Secondly, negative shocks in country i (publicly perceived) impact on pricing mechanism of the market in country j. However, country $j's$ real and stock markets are insulated from these negative shocks (Block B). Lastly, if information about the negative shock is private, then the informational effect of this private news causes stock prices to fall in country i. Nevertheless, with the fall in prices in country i, stock prices in country j also fall because of the relevancy of the private information in country i which is relevant to country j, but unknown to country j yet (as depicted in block C). It is only in the case explained in Block C that contagion occurs via the correlated-information channel (Pritsker, 2013). Moreover, it is mostly in markets with an efficient price discovery process that contagion can be diffused to other markets through this channel (Longstaff, 2010).

Figure 3.1: Correlated-information Channel

Block A

$$\begin{tikzcd} RS[i] \arrow[r] \arrow[d] & RS[j] \arrow[d] \\ SM[i] & SM[j] \end{tikzcd}$$

Block B

$$\begin{tikzcd} RS[i] \arrow[r, "/" marking] \arrow[d] & RS[j] \arrow[d, "/" marking] \\ SM[i] & SM[j] \end{tikzcd}$$

Block C

$$\begin{tikzcd} RS[i] \arrow[d] & RS[j] \\ SM[i] \arrow[r] & SM[j] \arrow[u] \end{tikzcd}$$

Source: (Pritsker, 2013)

In the correlated liquidity shock channel, investors may have need for liquid assets like cash. They can liquidate part of their portfolio in a market, or they can liquidate their stock holdings in other markets to meet their cash needs. The shocks that arise from the liquidation of their portfolio in one market are then diffused to other markets (Calvo, 1999; Pritsker, 2013). Because of the correlated liquidation, the aggregate level of liquidity will fall, and this can affect the pricing mechanism in markets (Longstaff, 2010).

The cross-market portfolio-rebalancing channel is firmly anchored on the rational expectations model posited by Kodres and Pritsker (2002). This channel holds that investors that are risk averse transmit shocks across markets by rebalancing their portfolios. Typically, the response of investors to changes in market risks, following a shock in a given market, is to rebalance their portfolio in other markets[16]. The readjustment of their portfolios elicits the transmission of shocks across markets, shocks with contagious effects. This cross-market rebalancing of portfolios, which is induced by shocks in one market that spreads to others, will influence the pricing mechanism. This is because the rebalancing of portfolios will cause increased synchronization of stock prices across all markets. Kodres and Pritsker (2002) corroborate this view and demonstrate that shocks, in particular idiosyncratic shocks, are transmitted across markets by investors with different information when they rebalance their portfolios.

3.3. Empirical Literature

This section reviews existing studies of contagion across stock markets and brings out the distinction between them and the empirical research carried out in this chapter.

3.3.1. Contagion - Breaks in the Returns Generating Process

Breaks in the Returns Generating Process – Beyond Significant Increases in Returns?

The empirical literature on contagion across stock markets is vast and growing. It usually focuses on unexpected significant increases in cross-market correlation of stock returns during periods of financial crisis; periods, which are characterized by a fall in global, market returns. In a seminal paper by King and Wadhwani (1990), they find contagion after the 1987 US market crash using correlations to approximate for contagion. Bekaert et al. (2003) present evidence of contagion during the South-East Asian crisis. Hon et al. (2007) present evidence of increased cross-market correlation of returns during the technology bubble. Fry-McKibbin et al. (2014) find that contagion occurred during the GFC. These studies have generally found higher correlation of returns across markets during crisis. They have interpreted this as evidence of contagion. However, it has been argued that significant increases in the correlation of returns among markets might not be sufficient evidence of contagion. As pointed out by Forbes and Rigobon (2002), higher correlations between markets could be due to

[16] This reaction by investors is mainly to minimize their exposure to the risks.

heteroscedasticity; that is increases in volatility. They argued that market volatility usually increases during crisis periods and that correlations across markets would also increase during such periods. In addition, they argued that higher correlations could be due to strong linkages between markets and not due to a crisis. Indeed, they concluded that the interpretations given by some previous works does not reflect contagion.

The previous studies, which have measured contagion via increases in correlation of returns, have assumed time variation in the correlations structure of returns. This indicates that the process that generates these returns follows a random walk and varies each period (Ramchand and Susmel, 1998; Syllignakis and Kouretas, 2011; Celık, 2012; Bekaert et al., 2014). Some others have assumed asymmetric dependence in the correlation of returns (Yiu et al., 2010; Samarakoon, 2011; Kenourgios, et al., 2011; Dimitriou et al., 2013), while some studies have assumed that correlations switches between regimes (Edwards and Susmel, 2001; Billio and Caporin, 2005). In all, they have largely focused on the behaviour of correlation distributions, while possible structural instability in the correlation of returns have been ignored.

Some studies have argued in favour of stable correlation of returns, that is the slopes of correlations are constant over time (Panton et al., 1976; Philippatos et al., 1983; Kaplanis, 1988; Ratner, 1992). However, these studies have been subject to criticism due to their failure to acknowledge trends, cycles and breaks in the correlation of returns (Baur, 2003). Their lack of acknowledgement could potentially result in misleading inferences. These criticisms have triggered a recent literature on testing the stability of the correlation of returns that have rejected the null hypothesis of constant correlations (see, e.g., Lee and Kim, 1993; Ramchand and Susmel, 1998; Baig and Goldfajn, 1999). Since their rejection indicates the possibility of breaks in the correlation of returns, it is crucially important to capture breaks in these time-variations.

Some support for time variation in the correlation matrix of returns has been presented by Longin and Solnik (1995). They suggested that the time variation in returns can originate from three different sources, specifically from: (i) a possible time trend, (ii) threshold and asymmetric correlation structures, and (iii) the effect of economic regressors. These sources of time variation in returns could affect the distribution of correlations. However, not only is the behaviour of the correlation of returns important for the analysis of cross-market linkages, its stability is also important. Changes in return correlations may thus be partly due to its behaviour itself, which varies continuously with time, and partly due to either economic or financial shocks. These structural shocks, which could be transmitted to markets, might cause breaks in the return generating process of the cross-market correlations. Failing to capture such breaks in the return generating process of the cross-market correlations could increase the likelihood of errors in statistical inference. If a portfolio of stocks is affected simultaneously by shocks from both transmitting and receiving countries, then the set of shocks that will influence returns across all markets will increase. Both sources of shocks will increase cross-market correlations, and this will eventually result in a "correlation breakdown". Structural breaks could potentially induce time variation in the correlation of returns. As a result, the literature has increasingly advocated for the investigation of breaks in the parameters of the correlations matrix of errors (Boyer et al., 1997; Forbes and Rigobon, 2002; Corsetti et al., 2005). The evidence of which would indicate changes in the transmission mechanisms between markets and contagion across markets. With the recognition that time variation in cross-market correlation of returns could be spurred by shocks, it is important to investigate breaks in these returns.

A growing body of literature measures contagion by examining changes in correlation of returns, while at the same time examining the existence of breaks in the return dependence structures (see, e.g., Chiang et al., 2007; Celık, 2012). Most of these studies have favoured the use of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) type models and its generalizations for their analysis. In this sort of models, possible heteroscedasticity is taken into account and the correlation behaviour among several markets can be examined without including a large number of parameters. Its usefulness notwithstanding, the literature has highlighted three shortcomings regarding it reliability, particularly in the presence of breaks. Firstly, they are sensitive to the presence of breaks and the persistence in variance could lead to an over-estimation of the parameters (Lamoureux and Lastrapes, 1990). Secondly, GARCH models cannot handle breaks because they are models with path dependence; future conditional variances are influenced by changes in the parameter of conditional variance at time t. They are unable to handle breaks because the path dependence causes the size of the state space to grow over time. As He and Maheu (2010) point out, state space with a large size is computationally challenging to evaluate. Thirdly, the short-term matrix of correlations rather than the long-term matrix is modelled as evidence for contagion.

Recent empirical research on changes and breaks in the correlation of returns for the analysis of contagion has been modelled using general linear multivariate models such as models in a VAR framework. Billio and Caporin (2010) investigated the presence of contagion by testing for breaks in the correlation of returns for Asian and American stock markets from 1995 to 2005. In their work, they used the unconditional correlation of returns rather than the conditional correlation of returns as a measure of cross-market linkage. They relied on two different approaches to estimate changes in correlation of returns and for the detection of breaks in the unconditional correlation of returns. Firstly, they employed multivariate statistical analyses, the concordance and strength indicators. Secondly, they relied on a multivariate VAR model with GARCH errors. The authors find that unconditional correlation of returns are characterized by breaks. They showed that some of these breaks coincided with notable crisis events and interpreted this as evidence of contagion.

This chapter differs from the related work in several respects. Firstly, in existing work the structure of the model used to detect breaks is based on the unconditional correlations' matrix, which relies on the implicit assumption of constant correlation. It is thus assumed that the residuals of correlations are independent of past information at time $t-1$. This assumption is restrictive, but it guarantees the positive definiteness of the covariance matrices, i.e., it allows the conditional variance to be non-zero and the correlation matrix to be linearly independent/full rank (Engle and Sheppard, 2001). However, when inference is conducted using this assumption and the unconditional distributions of correlations, the resultant parameter estimates may lack precision. This could be a possible source of measurement error in the underlying model.

In contrast, our study abandons this assumption and does not use the matrix of unconditional correlations for several reasons. Estimates based on this matrix tend to be biased downward and this could affect inference (Boyer et al., 1997). The hypothesis of constant correlations in returns has been rejected empirically (Tsui and Yu, 1999) and returns have been found to vary over time. Stock returns are also characterized by fat-tailed distributions and heteroscedastic variance, such assumption is inappropriate for data with such characteristics. Under the assumption of constant correlations, parameter estimates are imprecisely estimated. This is because a small parameter space is used to search for the matrix of correlation vectors. In fact, the chosen estimator utilizes only the sub-spaces of this small parameter space to perform the search and to generate the vectors rather than using real observations. Policy prescription could be affected because changes caused by the transmission of shocks are not reflected in unconditional correlations. Indeed, Kim et al. (2015) rightly point out that unconditional correlations are not useful for policy purposes. In order to avoid measurement errors and improve the precision of parameter estimates, abandonment of the assumption of constant correlations and elimination of the matrix of unconditional correlations is necessary. Thus, in contrast to this assumption and the matrix of unconditional correlations discussed here, our study relies on the conditional distribution of correlations and allow correlations to be conditional on its past realizations or return processes. At the moment, no empirical research exists that relies on the conditional correlations in VAR models for the analysis of contagion in DEE.

Secondly, in the previous works, break points in the correlation matrix are detected, but they are determined at *known* points in time, i.e., their locations are exogenously determined or chosen with prior reference to data. This requires the author to impose breaks to the return generating processes. However, this sort of procedure has a few shortcomings, which are well documented in the literature. Prior knowledge of the location of break points contradict conventional theory of distribution (Diebold and Chen, 1996). It is likely to detect a break wrongly when none exists, and this could be misleading. The break date might be falsely detected because it is endogenous: correlated with the data (Hansen, 2001). It could conceal some trends, which may be crucial for detecting contagion (Tabak et al., 2016). In contrast to Billio and Caporin (2010), the focus of our study is placed on endogenously determined break points. Thus, the chapter allows changes in the parameters of the model to occur at *unknown* points in the sample; the location of breaks in the data is not known. The matrix of correlations will not be governed by a known break-point process, but by an unknown process.

Thirdly, previous works assumed that breaks in correlations occur at common dates in the system of equations. Because they relied on this assumption, they applied a procedure that estimates break points simultaneously. If common break dates are assumed, all equations can only be estimated simultaneously (Bai and Carrion-I-Silvestre, 2009). This study, in contrast, relies on the assumption of distinct breaks and tests for the presence of breaks by applying a SP. This procedure is used for several reasons. It is used to decompose the covariance matrix of residuals into variances and correlations prior to testing for breaks. It, thus, allows one to separate breaks in the parameters of the conditional correlations from those in the mean and variance matrices. It is used to test for breaks, but it does so sequentially, i.e., even if there are multiple break points, it will estimate a single break point at a time (Bai, 1997). To estimate the break points multi-dimensional data is used. This, in turn, improves the power of the sequential test and the detection of breaks in finite samples becomes more precise. There are some appealing features about this procedure. It is more flexible in estimating changes in coefficients and break dates. It remains efficient even with samples of moderate sizes and it provides savings in computational time.

Fourthly, the confidence intervals of the estimated break dates are missing in the previous works. This is supposed to be a natural offshoot of estimations, but it is omitted. Because it is omitted, the statistical reliability and robustness of their estimated break dates can be questioned. It is even difficult to justify that the dates were consistently estimated due to their failure to provide confidence intervals. In contrast, this chapter constructs confidence intervals and ensures that the break dates are consistently estimated. Confidence intervals and the tests for their significance are performed using block bootstrap method (Efron, 1987; Künsch, 1989; Efron and Tibshirani, 1994; Horowitz, 2019). This method generates intervals with small lengths, and it is asymptotically valid because as the sample size increases, the number of breaks does not reduce. When this method is used in a VAR model, even in a model with conditional heteroscedasticity[17], inference remains statistically valid (Brüggemann et al., 2016).

Fifthly, the two-stage least squares (2SLS) estimator is applied to estimate the parameters of the VAR model in the previous works. This estimator, which is analogous to a generalized instrumental variable estimator, cannot consistently estimate the parameters because of the problem of weak instrument identification (Chao and Swanson, 2005). In contrast, this chapter utilizes a feasible alternative estimator based on the FGLS for the estimation of the parameters. This estimator corrects for two econometric biases that can arise when one is estimating relations across different units, in this case stock markets. The first bias it can correct is the bias due to heteroscedasticity. This bias arises because the error variances for all markets are different. If one does not control for the presence of heteroscedasticity across units, estimates

[17] Innovations with distributions that are unknown and not Gaussian independent.

may be subject to substantial bias. The second bias is serial correlation, which arises because of omitted variables, and the correlation of errors with regressors. Unlike the 2SLS, which suffers from endogeneity bias particularly in the absence of valid instruments, the FGLS can be used even when errors are serially correlated. It is, thus, fully robust to bias from heteroscedasticity and serial correlation. In addition, the 2SLS has a lower efficiency relative to the FGLS, particularly when it is assumed that the mean and variance parameters are independent. In contrast, the FGLS is asymptotically efficient for estimating all parameters of the model.

Besides these contributions, our study complements the existing literature on spillovers. As already mentioned before, contagion can also occur when volatility spills over. In most of the existing literature, spillovers among markets have been measured by assuming that breaks are common (Beirne, et al., 2013; Jung and Maderitsch, 2014). This indicates that shocks were treated simultaneously. In contrast, this chapter assumes that breaks are distinct and treats shocks separately. It estimates GFEVDs and then uses them to compute spillover indices. In general, it attempts to explore the importance of distinct breaks for the measurement of spillovers, with a view to improving measurement. So far, no empirical research exists that relies on this assumption for the measurement of spillovers across markets in DEE.

3.4. Data and Empirical Methodology

In this section, a detailed discussion of the econometric methodologies applied in the estimation of stock market contagion and the data used is provided. Because this chapter relies on three different methodologies for analysis, this section on methodology is divided into three. The first of these sub-sections provides the multivariate VAR framework, which is the main model used to estimate changes in the correlation of returns between markets and changes in the parameters of other components, i.e., changes in the conditional means and variances. The second sub-section presents an algorithm for the sequential procedure, which is used to test for breaks in the conditional means, variances, and correlations. The third sub-section presents the methodology on the generalized forecast error variance decompositions, which is required for the computation of spillover indices.

3.4.1. Multivariate VAR Model

To study contagion among stock markets, the model in this chapter is based on the VAR, which is a system of multivariate equations, and which belongs to the family of linear multivariate regression models. Modelling in this multivariate framework provides parsimonious correlation specifications for the analysis of contagion. Moreover, it allows for multiple breaks of a set of series and enables one to identify shifts in the parameters of interest with higher probability than in a univariate model (Bai and Perron, 1998; Qu and Perron, 2007). Usually, breaks can be estimated with a higher precision when the system contains auxiliary equations. Even if the parameters of auxiliary equations are restricted to be invariant across regimes, the break can still be estimated with a higher precision. The inclusion of auxiliary equations, thus, allows one to locate the break better. This is because these equations bring additional influences on the system of equations (Perron, 2006). However, a poorly estimated break in an equation could affect the likelihood function via the error variance of that equation and through correlation with the remaining auxiliary equations. This framework, thus, can improve the efficiency of estimation, but one needs to ensure that there is no correlation between the errors. Potential endogeneity problems, which could bias estimates, may arise when regressors are a function of the response variable and errors are correlated. This model addresses such problems by allowing endogenized variables to depend on their past lags. The model is used to analyse the set of relationships across markets and for evaluating the effects of random innovations (unforeseeable changes). When estimations are carried out in this model, the variance of errors is substantially lower, and the efficiency of the model is improved.

The standard specification of the reduced form multivariate *p*th-order VAR for estimating joint dynamics is given by:

$$\mathbf{y}_t = \boldsymbol{B}_{0,t} + \sum_{i=1}^{p} \boldsymbol{B}_{i,t}\mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t \qquad t = 1, \dots, \mathrm{T} \qquad (3.3)$$

where $\mathbf{y}_t = [y_{1,t}, \dots, y_{n,t}]'$ is the n x 1 dimensional vector of stock returns in weeks t, $\boldsymbol{B}_{0,t}$ is the n x 1 vector of intercepts. $\boldsymbol{\varepsilon}_t = [\varepsilon_{1,t}, \dots, \varepsilon_{n,t}]'$ is the n x 1 vector of random innovations.

$\boldsymbol{B}_{i,t}$ is the coefficient matrices or the parameter vector of the *p*th-order autoregressive component of past lagged endogenous variables.

The model given by Eq. (3.3) allows for time-variation, i.e., it allows the effects of the random innovations to change over time[18]. It also subjects the parameters to structural breaks with *unknown* change points. It relies on standard assumptions but allows for conditional heteroscedasticity and serial correlation in the innovations. It allows for these because financial returns usually have these characteristics.

It has earlier been mentioned that contagion can be identified when there is an increase in the correlation of returns across markets following a crisis event. The extent of change in the correlation of returns is measured using the covariance matrix $\boldsymbol{\Sigma}_t$ of the innovations $\boldsymbol{\varepsilon}_t$. A change in $\boldsymbol{\Sigma}_t$ can either be caused by an increase in the variance or correlation of returns.

The n x n covariance matrix, $\boldsymbol{\Sigma}_t = \mathbf{S}_t\mathbf{R}_t\mathbf{S}_t$ is decomposed as below:

$$\sum_t = \begin{bmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \cdots & \sigma_n \end{bmatrix} \begin{bmatrix} 1 & \rho_{12} & \dots & \rho_{1n} \\ \rho_{21} & 1 & \cdots & \rho_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n1} & \cdots & \cdots & 1 \end{bmatrix} \begin{bmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \cdots & \sigma_n \end{bmatrix}$$

The covariance matrix between two stock markets (i, j) is the product of the sample correlation coefficient, $\mathbf{R}_t$ with off-diagonal elements ρ_{ij} and the variance matrix, $\mathbf{S}_t$ with diagonal standard deviations σ_i, σ_j. The elements of the correlation matrix ρ_{ij} measures the strength of contemporaneous dependence between the two markets.

Often, during crisis, which is marked by increased market uncertainty, it is possible for some of the elements of the variance matrix $\mathbf{S}_t$ to strengthen. It is also possible that the transmission

[18] The parameters of eqn (3.3) changes randomly and the analysis is based on time-varying parameters (See Bataa et al. 2013, Blatt et al. 2015). The VAR methodology is used for examining dynamic interactions between stock returns across countries.

of such crisis will not occur synchronously across countries but sequentially; it is conceivable that the transmission of crisis occurs some periods after the eruption of the crisis. If one decides to impose an assumption of synchronous/simultaneous breaks in the variance and correlations, it could bias the estimates of structural break dates.

This chapter relaxes this assumption and allows breaks to occur sequentially. To identify contagion, therefore, this chapter tests the correlation matrix $\mathbf{R}_t$ for structural breaks at *unknown* points in time conditional on breaks in the variance. Prior to testing and estimating breaks in the correlations and the variances, the intercept $\boldsymbol{\beta}_{0,t}$ and coefficient matrices $\boldsymbol{\beta}_{i,t}$ are combined into the coefficient matrix $\boldsymbol{\beta}_t$ which corresponds to conditional mean. It is important that they be combined because it is also likely that $\boldsymbol{\beta}_t$ has structural breaks (see, e.g., Wang and Thi, 2007; Dungey and Gajurel, 2014).

3.4.2. The Sequential Procedure

This chapter adopts a SP to determine the existence of breaks in the parameters of our model. The idea of using this procedure is to estimate break points one at a time or separately (Baltagi et al., 2016). This procedure was first developed by Bai and Perron (1998, 2003a) but extended by Qu and Perron (2007) to the case of general linear multivariate models that includes the VAR. They provided an efficient estimation algorithm based on iterations to compute estimates and to search for *common* breaks in the mean and covariance matrix. This chapter adopts this algorithm but modifies it to allow for *distinct* breaks in the decomposed covariance matrix. To separate the breaks in the conditional means, the variances and the correlations, this chapter utilizes the iterative procedure proposed in Bataa et al. (2013). It follows the modified algorithm which is outlined in six steps as follows:

Step 1. To estimate the break dates in the mean, first set the number of breaks in the mean or VAR coefficients m_B, and then estimate the break dates $\hat{T}_1^{(\mathrm{B})}, \dots, \hat{T}_{m\mathrm{B}}^{(\mathrm{B})}$. In addition, estimate the coefficient matrix $\widehat{\boldsymbol{B}}_t$ for each of the corresponding regimes.

Step 2. Compute the residuals $\hat{\boldsymbol{\varepsilon}}_t$, from each iteration of the FGLS. Set the number of breaks mS in the standard deviations $\boldsymbol{S}_t$ and the associated break dates $\hat{T}_1^{(\mathrm{S})}, \ldots, \hat{T}_{m\mathrm{S}}^{(\mathrm{S})}$ conditional on breaks in the mean from Step 1. Use the computed residuals to estimate the standard deviations $\hat{\sigma}_{it}$ for each of the corresponding regimes.

Step 3. Compute the standardized residuals $\tilde{\varepsilon}_t = \hat{\varepsilon}_t / \hat{\sigma}_{it}$. Set the number of breaks mR in the correlation matrix $\boldsymbol{R}_t$ and the associated break dates $\hat{T}_1^{(\mathrm{R})}, \ldots, \hat{T}_{m\mathrm{R}}^{(\mathrm{R})}$ conditional on breaks in the mean and standard deviations from Steps 1 and 2, respectively.

Step 4. Return to Step 2 and repeat but conditional on the breaks previously found in $\boldsymbol{R}_t$.

Step 5. Return to Step 1 and repeat but conditional on both the breaks in standard deviations[19] S_t and the correlation matrix $\boldsymbol{R}_t$.

Step 6. Continue to perform each of the previous iteration between Steps 1-5 until there is no change in the number of break points and the estimated break dates.

Using the modified algorithm outlined above all the coefficients of the model are tested for multiple structural changes, using the pseudo-likelihood ratio test, under the null hypothesis of no change in the coefficients against the alternative hypothesis with a set number of breaks, m. The test relies on multivariate normal distributions; however, this does not imply normality i.e., that the observations in the sample are independent and identically distributed. The asymptotic distributions of the resultant test statistics allow for any deviations from normality to be corrected. The test does not depend on the finite-sample distribution but on the asymptotic one, so the exact finite-sample critical value cannot be obtained. To compute the corresponding critical values therefore, this chapter uses Monte Carlo simulations. This is because critical values obtained through simulations tend to be more accurate.

[19] The chapter uses the standard deviations instead of the variances because it is expressed in similar units as our data (it is based on distributions around the mean) and for ease of interpretation.

To search for the location of multiple break points, the efficient algorithm developed by Bai and Perron (2003a) is employed. The estimates of the model are obtained using the FGLS estimator, while the 95% confidence intervals for the break dates are computed using the block bootstrap method. Although distinct break points in the variances and correlations are allowed, it is, however, assumed that parameters within each component share common break points. If this assumption of common breaks is not imposed, then the break test may fail to detect breaks due to low power. Moreover, when the test is not based on this assumption, the estimated break dates may be biased. This assumption is useful even if each series has its own distinct break point (Bai, 2010). The confidence intervals for the break dates are also estimated. The coverage rate for these intervals will be adequate because the chapter allows the error processes to undergo regime switches.

3.4.3. Generalized Forecast Error Variance Decompositions

In the previous section, the methodology for the detection of contagion via breaks in the parameters of the model was discussed. However, contagion can also be detected using an alternative method known as spillovers of volatilities. This chapter follows Diebold and Yilmaz (2009, 2012) to compute spillover indices. Prior to the computation of these indices, the VAR model is first, applied to generate GFEVDs (Koop et al., 1996; Pesaran and Shin, 1998), which are generated without orthogonalization of shocks and ordering of variables. The GFEVDs are the share of the forecast error variance of variable i due to shocks to variable j at a h-step forecast. More explicitly, the error variance is split into components that are explained by different periods of shocks.

Let us consider the moving average representation of the VAR(p) model[20] which is given by:

$$\mathrm{y}_t = \sum_{i=0}^{\infty} \mathrm{A}_i \, \varepsilon_{t-i} \qquad (3.4)$$

[20] The moving average representation of the VAR(p) model is based on Diebold and Yilmaz (2012).

where A_i are the M x M coefficient matrices and $\mathrm{A}_i = SA^iS$ where $S = [I_M : 0 : \ldots : 0]$. Eq. (3.4) can be recursively represented as: $\mathrm{A}_i = \emptyset_1\mathrm{A}_{i-1} + \emptyset_2\mathrm{A}_{i-2} + \cdots + \emptyset_p\mathrm{A}_{i-p}$, with $\mathrm{A}_0 = I_M, \mathrm{A}_i < 0$ for $i < 0$ where I_M is an m x m identity matrix and $\emptyset_i(i = 1,2,3, \ldots, p)$ are the parameter matrices.

The impact of ε_t on the future values of y_t at horizon *h* is obtained by shocking the *jth* equation. The GFEVDs for the *h*-step ahead forecast period can then be defined as:

$$\varphi_{i,j}(h) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{h-1} \left(e_i' \mathrm{A}_h \Sigma e_j\right)^2}{\sum_{h=0}^{h-1} \left(e_i' \mathrm{A}_h \Sigma \mathrm{A}_h' e_j\right)} \qquad (3.5)$$

where σ_{jj} and Σ denote the standard deviation of the *jth* element and the variance matrix in ε_t. e_i is a n x 1 vector of random elements with ones as the *ith* element and zeroes as the other elements. The share of the *h*-step ahead forecast error variance of variable i due to shocks to variable j is accounted for by $\varphi_{i,j}$. The sum of the shares of own- and cross-variable generalized variance decomposition usually do not sum up to one, i.e. $\sum_{j=1}^{n} \varphi_{i,j}(h) \neq 1$. For it to sum up, each $\varphi_{i,j}(h)$ must be normalized as:

$$\tilde{\varphi}_{i,j}(h) = \frac{\varphi_{i,j}(h)}{\sum_{j=1}^{n} \varphi_{i,j}(h)}, \qquad (3.6)$$

to satisfy $\sum_{j=1}^{n} \tilde{\varphi}_{i,j}(h) = 1$ and $\sum_{i=1}^{n} \sum_{j=1}^{n} \tilde{\varphi}_{i,j}(h) = n$.

The chapter computes three measures of spillover indices: total, directional, and net. These measures show the extent and the direction of spillovers between markets.

The total spillover index $TS(h)$, which measures the shares of the total forecast error variance that is caused by shocks to other markets, is given as

$$TS(h) = \frac{\sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} \varphi_{i,j}(h)}{\sum_{i=1}^{n} \sum_{j=1}^{n} \varphi_{i,j}(h)} \text{ X } 100 \ \cdot \quad (3.7)$$

Typically, an increase in this index indicates the existence of spillover contagion.

The directional spillover index, which measures the spillovers sent from i to other markets, is given as

$$DS(h)_{\leftarrow i} = \frac{\sum_{j=1, j\neq i}^{n} \varphi_{i,j}(h)}{n} \text{ X } 100 \ \cdot \qquad (3.8)$$

Similarly, directional spillover index, which measures the spillovers received by market i from other markets, is given as

$$DS(h)_{\rightarrow i} = \frac{\sum_{j=1, j\neq i}^{n} \varphi_{i,j}(h)}{n} \text{ X } 100 \ \cdot \qquad (3.9)$$

The net spillover index by market i, which is calculated as the difference between directional spillovers, sent to others and received from others. It is the contribution of each market to the volatility of other markets, on a net basis and it is given as

$$NS_i(h) = DS(h)_{\leftarrow i} - DS(h)_{\rightarrow i} \ \cdot \qquad (3.10)$$

The measures of spillover indices are computed by taking into consideration breaks in VAR coefficients, variances, and correlations matrices. The value of the indices, which are the spillover effects, are associated with different breaks in the parameters of the matrices.

3.4.4. Data

Since the investigation involves determination of the extent of change and breaks in the correlations of returns across countries, cross-country comparability of the data is of great importance. Normally, global stock markets open on different days and at different times. These differences create a problem of non-synchronous trading across markets. To circumvent this problem, this chapter uses weekly data for analysis. Data with this sort of frequency have already been adjusted for weekend effects, making it less 'noisy'. The data for this chapter's analysis thus comprises mainly countries' weekly closing prices of stock. It spans from 03 January 1995 to 03 November 2016 and has a total of 1,140 observations. The span of the data is long enough for this chapter's analysis, and it even covers some major regional and global crisis episodes. The data is transformed to returns using the formula $r_{it} = ln(p_{it}/p_{it-1})$, $t = 1, 2, \ldots, T$, where r_{it} denotes the stock returns for country i at time t while p_{it} and p_{it-1} denote each countries stock prices for the periods t and $\mathrm{t} - 1$. ln represents the natural logarithm.

For checks on the robustness of results, data on the volatilities of stock returns[21] are used. Each market's volatility is computed using the formula: $\sigma(X_t) = \sqrt{\frac{\sum_{\tau=t-2}^{t+3}(X_i - \bar{X}_t)}{3}}$ where standard deviation of stock returns $\sigma(X_t)$ is based on a three-week rolling window, i.e., it is rolled over a three-week period, X_i are the returns at the country level. $\bar{X}_t$ is the mean of each market's return between $t-2$ and $t+3$.

The data come from the MSCI database on Bloomberg and includes twenty-six countries: the US, the UK, France, Germany, Belgium, the Netherlands, Portugal, Italy, Ireland, Spain, Brazil, Chile, Colombia, Mexico, Peru, Argentina, China, Hong Kong, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, Taiwan, and Thailand. The countries are grouped into three regions; developed Europe (nine countries), Pacific and emerging Asia (10 countries) and emerging Latin America (six countries) with the US featuring in each group. The US is included to act as the source of the global crisis. Table 3.1 presents the summary statistics for stock returns.[22]

[21] The structure of cross-market correlation has breaks in returns, but it is also possible that there are breaks in volatility (Chiang et al., 2007).
[22] A detailed summary statistic for volatility of stock returns is presented in Appendix 3.

Table 3.1: Summary Statistics, Stock Returns

	Average return	Maximum return	Minimum return	Std. Dev.	Skewness	Kurtosis
Panel A: DE markets						
UK	0.0009	0.1336	-0.2088	0.0235	-0.5684	10.9223
France	0.0013	0.1306	-0.2173	0.0291	-0.4502	6.7851
Germany	0.0014	0.1692	-0.2122	0.0314	-0.3527	7.0087
Belgium	0.0012	0.1247	-0.1954	0.0286	-0.8611	8.6755
The Netherlands	0.0013	0.1662	-0.2568	0.0292	-0.8287	9.9424
Portugal	0.0003	0.1255	-0.1729	0.0276	-0.5033	6.0929
Italy	0.0005	0.2026	-0.2221	0.0320	-0.4136	7.7106
Ireland	0.0006	0.1859	-0.3139	0.0343	-0.9451	12.3638
Spain	0.0016	0.1447	-0.2142	0.0321	-0.4430	6.0854
Panel B: PEA markets						
China	0.0008	0.2511	-0.2160	0.0443	0.0681	6.1687
Hong Kong	0.0013	0.1462	-0.1904	0.0322	-0.2324	5.9220
Indonesia	0.0029	0.3266	-0.2179	0.0457	0.5027	9.9092
Japan	0.0002	0.1012	-0.2000	0.0283	-0.4205	5.6721
Korea	0.0018	0.2070	-0.1926	0.0407	0.0879	6.5039
Malaysia	0.0009	0.3008	-0.1826	0.0299	0.8430	17.7223
Philippines	0.0010	0.1824	-0.1857	0.0334	-0.1869	6.8437
Singapore	0.0005	0.1882	-0.1921	0.0292	-0.0700	9.4374
Taiwan	0.0006	0.2136	-0.1341	0.0362	0.1635	5.6261
Thailand	0.0008	0.2700	-0.2487	0.0437	0.5311	8.2306
Panel C: ELA markets						
Brazil	0.0022	0.2919	-0.2814	0.0525	-0.0852	6.6123
Chile	0.0009	0.2108	-0.2929	0.0328	-0.6540	10.9766
Colombia	0.0018	0.1622	-0.2519	0.0391	-0.3772	6.5911
Mexico	0.0023	0.2529	-0.2641	0.0417	-0.0082	7.8526
Peru	0.0025	0.2467	-0.2544	0.0402	0.1258	7.5582
Argentina	0.0022	0.2885	-0.2857	0.0536	-0.0930	7.1467
Panel D: Crisis source market						
US	0.0016	0.1221	-0.1822	0.0240	-0.4994	8.2057

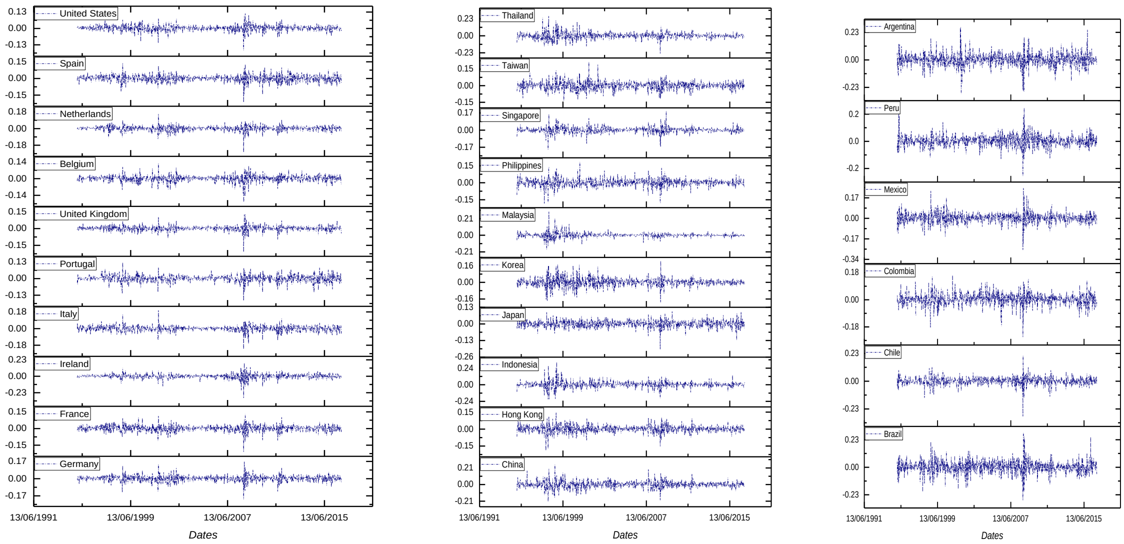
Source: Author's compilation

The second and fifth columns of Table 3.1 contains average and standard deviations obtained from data on stock returns. It reveals that average returns ranged between a low of 0.02% and a high of 0.29%. It also shows that, on an average basis, Indonesia has the highest return while Japan recorded the lowest return. With regards to standard deviations, it ranged between 0.024 and 0.046, implying that returns are fairly dispersed across markets. Column (6) contains the statistics for the skewness of returns, which are the tail distributions. It shows that about 81%

of the sample is left skewed implying that distributions cluster below their mean values while the remaining 19% are skewed to the right.

Figure 3.2 plots the evolution of stock returns for each market[23]. A visual inspection of the plots show that the pattern of returns varies across markets. However, during the GFC of 2007-2008, one can clearly see the comovement of returns across markets.

Figure 3.2: Stock Returns



Source: MSCI Bloomberg data and author's computation

Notes: The figure plots the weekly stock returns (three-week rolling window) across country and time. The *dashed* blue line in this figure depicts the stock returns.

3.5. Empirical Results

This section documents the main findings of the investigation on contagion in stock markets of DE, PEA, and ELA. However, prior to providing in-depth analysis, how the econometric model was set-up and implemented will be discussed in detail.

[23] The plots of the evolution of volatility of returns for each market are presented in Appendix 4.

The first step in the model set-up involves the trimming of the finite-sample ($T = 1{,}140$ observations). To accomplish this, a moderate trimming fraction of $\varepsilon = 0.05$ is adopted. This fraction is chosen because of the reasonably modest size of the sample. It is pertinent that the sample is trimmed in order to reduce the sensitivity of the sample to outliers. Besides reducing sensitivity to extreme values, trimming will allow us to have reasonable partition between successive breaks, i.e., regime intervals. Hence, following the trimming, each regime interval is going have a minimum partition period $h = [\varepsilon T]$ containing 57 observations.

The second step involves setting of the number of breaks (m) in the parameters of the model. The maximum number of breaks for the parameters of the conditional means, variances and correlations are set to three[24]. In the third step, the optimum lag length, p is determined and it is set to one because the Bayesian Information Criterion selects the lag order of one.

After this, the chapter proceeds to conduct the estimation of the multivariate VAR models in order to estimate breaks. This estimation will require the implementation of several sequential iterations of the simulation process until convergence is achieved. The significance level for all estimations are set to $\propto = 0.05$. The chapter sequentially searches for co-breaks in VAR coefficients, standard deviations, and correlation coefficients. Co-breaks are breaks that occur when there is a constant parameter. The chapter searches for up to three simultaneous co-breaks in all the $n(n + 1 + 2) = 754$ VAR coefficients. It also searches for up to three simultaneous co-breaks in $n = 26$ standard deviations, however these searches are conditional on breaks in VAR coefficients. It searches for up to three simultaneous co-breaks in $\frac{n(n-1)}{2} = 325$ correlation coefficients. These searches, however, are conditional on breaks in VAR coefficients and standard deviations. It obtains the corresponding upper (lower) 95% bootstrap confidence bands of all breaks and computes critical values using Monte Carlo bootstrapping simulation based on 100 replications.

[24] Bai and Perron (2003a) suggest that the maximum number of breaks should be set to 8 when $\varepsilon = 0.10$. However, they do not provide any economic explanation for this selection.

3.5.1. Changes and Breaks in Conditional Means and Variances of Returns

The results of changes in the estimated coefficients of the conditional means and variances, and their estimated break dates are provided in Panels A and B of Tables 3.2[25]. Changes in estimated coefficients are obtained by taking the difference between the coefficient estimates in two different regimes, i.e., the change in the estimated coefficients in the second column are the difference between the coefficient estimates between regime 1 and 2, and so on.

To evaluate whether breaks exist, the chapter compares the value of the maximum log-likelihood ratio tests with their equivalent 99% critical values. The corresponding *p*-values for the maximum log-likelihood ratio estimates are given in squared brackets. The results reveal some interesting evidence across markets.

The regressions of the conditional means for all sub-regions were found to yield statistically significant results. In all, the chapter detects three significant common or synchronous break points for each sub-region. This implies that markets within each sub-region had three dates that were identical. For the DE, the result shows that estimated common break points for markets in this sub-region are significant at 5% level, $[p - val = 0.00]$. The result shows that dates for the common break falls on 30 July 1999, 28 September 2007, and 10 February 2012, respectively. The initial break date might be associated with the build-up to the dot-com bubble of early 2000, which was prompted by the emergence of internet stocks. Several stock markets in the DE had previously experienced a protracted period of increased market exuberance in 1999. It thus shows the period of extremely high speculative activity in the trading of internet stocks in the DE. This speculative activity caused bubbles to form with its eventual bursting on 10 March 2000.

[25] More results on changes in coefficients of conditional means and variances but using data on volatility of returns are presented in Appendix 5.

Table 3.2: Results of Changes and Breaks in Conditional Means and Variances of Returns

Panel A: Conditional means			
max LR test	T.S [696.74]	C.V [381.76]	p-value [0.00]
Estimated break dates	30-Jul-99	28-Sep-07	10-Feb-12
95% confidence intervals	[28-May-99, 23-Aug-02]	[26-Dec-03, 28-Sep-07]	[10-Feb-12, 08-Jun-12]
Coefficients changes for the DE	Regime 1 to 2	Regime 2 to 3	Regime 3 to 4
Constant	-0.022	-0.045	0.041
GER_{t-1}	0.595	1.039	0.402
FRA_{t-1}	-1.125	0.099	0.568
IRL_{t-1}	-1.419	0.349	-0.347
ITL_{t-1}	-0.321	0.117	1.504
POR_{t-1}	-0.523	-1.587	-0.099
UK_{t-1}	1.082	-5.486	5.360
BEL_{t-1}	0.695	0.414	0.401
NET_{t-1}	0.121	0.501	-2.082
SPA_{t-1}	-0.821	-2.464	1.702
US_{t-1}	1.980	6.164	-7.514
max LR test	T.S. [723.05]	C.V [438.07]	p-value [0.00]
Estimated break dates	01-Oct-99	30-Jul-04	23-Jan-09
95% confidence intervals	[28-May-99, 17-Dec-99]	[13-Feb-04, 10-Sep-04]	[12-Dec-08, 09-Jul-10]
Coefficients changes for PEA	Regime 1 to 2	Regime 2 to 3	Regime 3 to 4
Constant	-0.004	0.020	-0.024
CHN_{t-1}	0.444	-0.211	0.198
HKG_{t-1}	-1.401	1.453	-0.437
IND_{t-1}	0.135	-1.083	1.334
JPN_{t-1}	0.492	-1.650	0.912
KOR_{t-1}	-1.267	0.747	0.676
MAL_{t-1}	-0.876	1.727	-0.723
PHI_{t-1}	-0.670	-0.374	4.871
SIN_{t-1}	1.824	0.177	-0.675
TAI_{t-1}	-1.039	1.057	-1.480
THA_{t-1}	0.575	-2.251	0.578
US_{t-1}	4.633	0.128	-2.145
max LR test	T.S [346.28]	C.V [207.29]	p-value [0.00]
Estimated break dates	20-Aug-99	20-Apr-07	09-Sep-11
95% confidence intervals	[28-May-99, 12-Oct-01]	[27-May-05, 27-Apr-07]	[02-Sep-11, 15-Jun-12]
Coefficient change for ELA	Regime 1 to 2	Regime 2 to 3	Regime 3 to 4
Constant	0.019	-0.015	-0.013
BRA_{t-1}	0.543	0.035	-0.281
CHI_{t-1}	-0.124	-2.144	1.261
COL_{t-1}	-0.120	-1.437	2.037
MEX_{t-1}	-0.397	-1.980	1.988
PER_{t-1}	-0.681	2.353	-1.443
ARG_{t-1}	-0.668	-0.759	0.723
US_{t-1}	1.111	3.695	-5.247

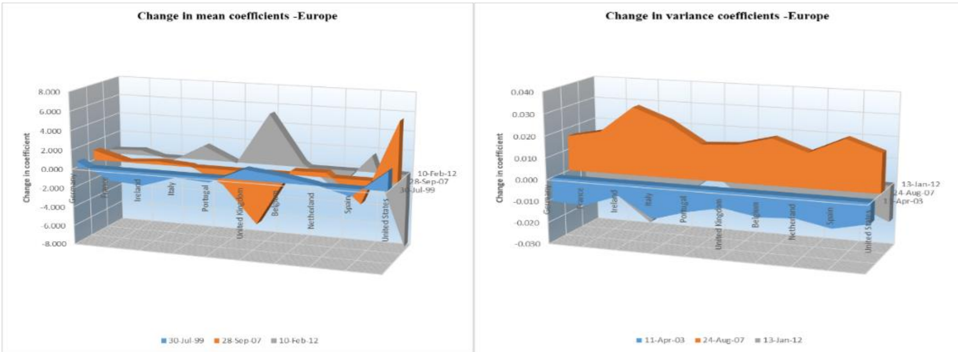
Panel B: Conditional variance			
max LR test	T.S [929.35]	C.V [304.47]	p-value [0.00]
Estimated break dates	11-Apr-03	24-Aug-07	13-Jan-12
95% confidence intervals	[27-Sep-02, 11-Apr-03]	[24-Aug-07, 31-Aug-07]	[06-Jan-12, 08-Jun-12]
Change in standard deviation for the DE			
	Regime 1 to 2	Regime 2 to 3	Regime 3 to 4
GER	-0.011	0.016	-0.014
FRA	-0.012	0.019	-0.015
IRL	-0.006	0.031	-0.027
ITL	-0.015	0.026	-0.012
POR	-0.011	0.016	-0.001
UK	-0.008	0.017	-0.014
BEL	-0.011	0.021	-0.015
NET	-0.010	0.016	-0.014
SPA	-0.013	0.023	-0.010
US	-0.009	0.018	-0.017
max LR test	T.S [2353.74]	C.V [561.15]	p-value [0.00]
Estimated break dates	11-Oct-02	13-Jul-07	02-Dec-11
95% confidence intervals	[05-Jan-01, 21-Feb-03]	[23-Feb-07, 20-Jul-07]	[25-Nov-11, 04-May-12]
Change in standard deviation for PEA	Regime 1 to 2	Regime 2 to 3	Regime 3 to 4
CHN	-0.023	0.016	-0.023
HKG	-0.018	0.014	-0.016
IND	-0.025	0.010	-0.015
JPN	-0.005	0.010	-0.005
KOR	-0.021	0.006	-0.020
MAL	-0.025	0.004	-0.009
PHI	-0.012	0.010	-0.017
SIN	-0.014	0.015	-0.019
TAI	-0.014	0.007	-0.015
THA	-0.027	0.006	-0.016
US	-0.009	0.017	-0.017
max LR test	T.S [433.56]	C.V [333.34]	p-value [0.00]
Estimated break dates	25-Apr-03	21-Sep-07	03-Feb-12
95% confidence intervals	[28-Dec-01, 02-May-03]	[07-Sep-07, 21-Sep-07]	[03-Feb-12, 15-Jun-12]
Change in standard deviation for ELA	Regime 1 to 2	Regime 2 to 3	Regime 3 to 4
BRA	-0.013	0.018	-0.019
CHI	-0.007	0.022	-0.021
COL	0.003	0.002	-0.008
MEX	-0.018	0.023	-0.022
PER	0.002	0.018	-0.024
ARG	-0.018	0.021	-0.007
US	-0.010	0.019	-0.017

Notes: The estimated break dates are the same for all countries in the sample. The dates in parenthesis are the 95% confidence intervals break dates. T.S and C.V denote test statistic and critical value, respectively.

The next break date corresponds with the period when markets showed signs of strong synchronous comovement. This comovement happened three months after the sub-prime mortgage crisis began in the US. The crisis is traceable to the securitization of sub-prime mortgage-backed assets and the failure of sub-prime mortgage borrowers in US to fulfil their repayment obligations. The growth in mortgage defaults by borrowers in the US increased the risk of some banks in the DE because of their high level of ownership of US mortgage-backed securities. These defaults by the US sub-prime lenders resulted in large losses on investments, which affected both markets and banks of the DE because of their high level of exposure to the US mortgage-backed securities. The final break date occurs around the period that the US market witnessed dramatic declines in stock prices post-GFC crisis. Interestingly, it appears that the date captures the period of significant regulatory change. It seems to coincide with the period of monetary policy shift, when the European Central Bank (ECB) announced policy prescriptions to address the sovereign debt crisis arising from huge defaults by periphery member countries in the Euro area. Part of the ECB's response included the long-term refinancing operations, which aimed at providing liquidity with extended maturities. Additionally, it coincided with the week when the Greek government passed an approval for new austerity measures as part of the European Union bailout plan. It is likely that these policies and the news effect quickly affected stock returns in the Euro area.

So far, the chapter has adduced reasons for breaks in the conditional means and variances for markets in the DE. Next, it analyses the results of changes in the coefficients of the conditional means and variances, which are presented in columns (1) – (3) of Tables 3.2. In addition, Figures 3.3 –3.5 graphically displays these changes alongside their respective dates of breaks. The sign of the coefficient changes reflects the change in estimated coefficients between successive regimes. A positive change in the mean coefficient signifies that cross-market dependence following a shock has strengthened whereas a negative change indicates it worsened. The result of changes in the estimated coefficients are analysed in relation to the three common break dates. During the first break of 30 July 1999, the result shows that markets in Germany and Belgium had strong positive changes in their conditional means whereas the remaining seven markets had either positive or negative changes.

Figure 3.3: Changes in Coefficients of Conditional Means and Variances for the DE



During the second break of 28 September 2007 markets which appear to have experienced substantial negative change in the conditional means include the UK (-5.486), followed by Spain (-2.464) and Portugal (-1.587). Contrariwise, Germany had the largest positive change in conditional mean of 1.039, followed by The Netherlands (0.501), Belgium (0.414), Ireland (0.349), Italy (0.117) and France (0.099).

The chapter now turns to examine the results of breaks in the conditional means and variances for the PEA. In this sub-region, the first identified location of common break in the conditional mean occurs around the late 1990's, precisely on the week of 01 October 1999. This result reveals that markets continued to co-move strongly almost two years after the East Asian crisis. The crisis, which was mainly confined to the countries within the region, influenced the dynamics of markets. This clearly is an evidence of strong regional equity market integration.

The result shows that the second estimated date of common breaks occurred on the week of 30 July 2004. It is associated with the period when many markets witnessed high volatility and a period of uncertainty. It is also linked to the burst of the internet bubble in 2004, which occurred two years after the dot-com bubble and seriously affected the performance of markets.

The result shows that the third estimated date of common breaks occurred on the week of 23 January 2009, which is linked, to the period after the emergence of the GFC. The break occurred several months after the collapse of Lehman Brothers in the US. Prior to their collapse, they had filed for bankruptcy, but the US government had refused to bail it out. The failure to rescue the investment bank later caused a financial crisis and eventually this crisis plunged into a new stage when global stock markets reacted to the negative news increasing market sentiments and resulting in the strong comovement of markets with the US market. Many markets witnessed extreme downturn precipitated by this crisis. The crisis dramatically worsened the already falling stock prices across global markets, which began in 2007 because of the housing market crisis, and this fall in prices persisted into 2009. The crisis seems to have adversely affected the performance of markets in the Asian region. This suggests that the role of shocks in the transmission of market contagion cannot be ignored.

The results show that during the first break of 01 October 1999 markets in China, Indonesia, Japan, Singapore and Thailand had positive changes in their conditional means whereas the other markets within the sub-region had negative changes. During the second break of 30 July 2004, the results show Hong Kong, Korea, Malaysia, Singapore, and Taiwan has positive changes while the remaining markets had negative changes. Finally, during the third break of 23 January 2009, the results show that markets in China, Indonesia, Japan, Korea, Philippines, and Taiwan had positive, the rest of the markets had negative changes.

Figure 3.4: Changes in Coefficients of Conditional Means and Variances for PEA

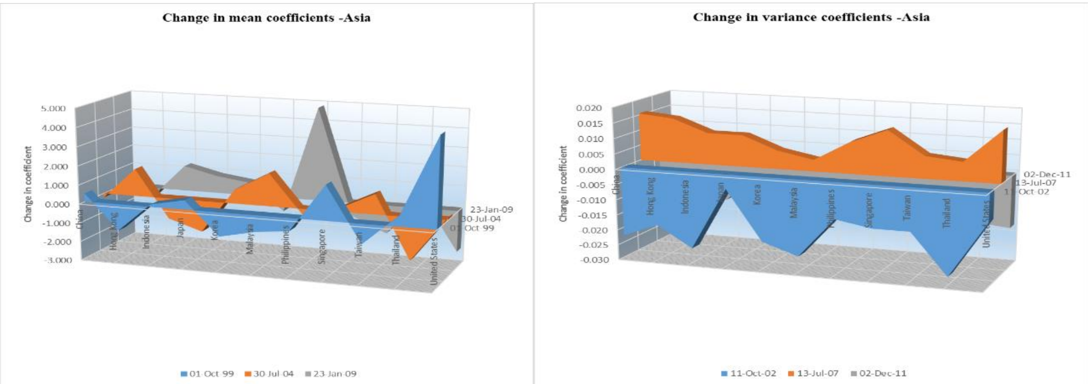
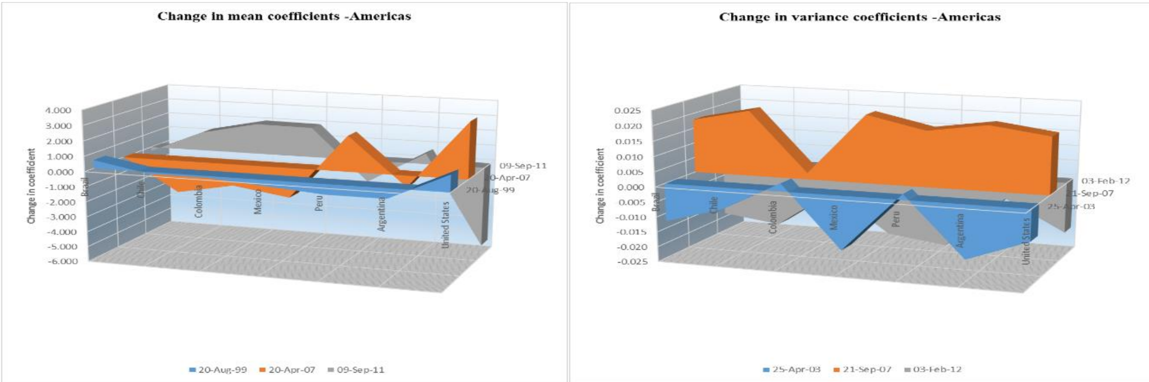


Figure 3.4 plots the changes in the coefficients of the conditional means and variances for PEA. The plot for the conditional means shows that the conditional mean of Thailand exhibits the highest negative change of -2.251. This is followed by Japan (-1.650), Indonesia (-1.083), Philippines (-0.374) and China (-0.211). Similarly, for positive changes, the result shows that it is higher for Malaysia (1.727) while Singapore (0.177) has the lowest positive change.

Finally, the chapter examines the results of breaks in conditional means and variances for the ELA. The result shows that the first break is detected in the week of 20 August 1999 for this sub-region. This date reflects the period prior to the technology bubble and its burst. It falls within the period of increased return and bullish market that lasted for over 17 years but ended in 10 March 2000 following the speculative bubble burst of internet stocks.

Figure 3.5: Changes in Coefficients of Conditional Means and Variances for ELA



The result shows that the second break date is detected in the week of 20 April 2007. Although this date does not coincide with the US housing market crisis, it falls within the period of market exuberance. The result shows that third break date occurred on the week of 09 September 2011. This date corresponds to the time when stock markets experienced considerable downturn following the aftermath of the GFC. The downturn is associated with the bear-market, which started in August 2011 and continued to the end of 2011.

Figure 3.5 plots the changes in the coefficients of the conditional means and variances for ELA. The plot for the conditional means clearly shows only two out of six countries this region has positive coefficient changes during the second break on the week of 20 April 2007. The positive change of coefficient associated with conditional mean is high for Peru (2.353) and quite low for Brazil (0.035) whereas the conditional mean of Chile (-2.144) has the highest negative coefficient change. This is followed by Mexico (-1.980), Colombia (-1.437) and lastly by Argentina with a significantly lower negative coefficient change of -0.759. The negative change in the coefficient indicates that cross-market dependence following a shock worsened.

3.5.2. Changes and Breaks in Conditional Correlation of Returns

In the previous sub-section, broad interpretations for the dates of breaks in the conditional means and variances are provided. It also provided discussions on changes in their coefficients. In this sub-section, our goal is to test for increases in conditional correlations and the existence of breaks in these correlations as well as to determine the dates of breaks. Typically, conditional correlations could change because of changes in interdependence across markets. Tables 3.3 – 3.5 present the results of the breaks in conditional correlations, the dates of breaks, and the changes in correlation coefficients for different country pairs. The Tables reveals the 10 x 10, 11 x 11, and 7 x 7 matrices of the bivariate relationship across markets in the DE, PEA and ELA, respectively. The upper triangulation of the matrices provides the results of the estimated pairwise correlations with their changes while the lower triangulation reports the estimated break dates. There are three possible outcomes for a change in correlations; First, a positive change in correlations implies that an increase in returns offered by a stock market results in a corresponding increase in returns in a counterpart market, which supports the contagion phenomenon. Second, the change in correlations can be negative which is in support of

Table 3.3: Changes and Breaks in Conditional Correlation of Returns for Markets in the DE

	GER	FRA	IRL	ITL	POR	UK	BEL	NET	SPA	US
GER		0.8443		0.5821		0.7460				0.6423
		0.0847 0.0150 −0.0166	0.6363	0.2483 0.0486 −0.1143	0.6241	0.0768 0.0920 −0.1409	0.7475	0.8623	0.7869	0.1383 0.1012 −0.1701
		0.9274		0.7648		0.7739				0.7117
FRA	01-Aug-03 [08-Feb-02, 01-Aug-03]		0.4994	0.6527	0.5873	0.6841	0.6733	0.8200	0.7586	0.6372
	14-Dec-07 [14-Dec-07, 21-Dec-07]		0.0303 0.2193 −0.0449	0.2068 0.0654 −0.0726	−0.0573 0.2617 −0.1015	0.2017 0.0636 −0.1289	0.1857 −0.0481 0.0013	0.0885 0.0247 −0.0179	0.0922	0.1587 0.0857 −0.1329
	04-May-12 [27-Apr-12, 15-Jun-12]		0.7041	0.8524	0.6901	0.8206	0.8122	0.9153	0.8508	0.7487
IRL	-	30-Jul-99 [28-May-99, 20-Oct-00]					0.4674	0.5398		
		04-Mar-05 [12-Dec-03, 28-Dec-07]		0.5649	0.4542	0.6067	0.2096	0.1850	0.5588	0.5538
		25-May-12 [17-Jul-09, 15-Jun-12]					0.6769	0.7249		

<table>
<tr><th></th><th>ITL</th><th>POR</th><th>UK</th><th>BEL</th><th>NET</th><th>SPA</th><th>US</th></tr>
<tr><td>ITL</td><td></td><td>0.4365

0.1207
0.2365
−0.1114

0.6823</td><td>0.5390

0.2909
0.0387
−0.2072

0.6615</td><td>0.6749</td><td>0.5813

0.2308
0.0717
−0.1096

0.7742</td><td>0.6600

0.1072
0.0455
0.0825

0.8954</td><td>0.5079

0.2026
0.1113
−0.1712

0.6506</td></tr>
<tr><td rowspan="3">POR</td><td>16-Jul-99
[04-Jun-99,
28-Mar-03]</td><td rowspan="3"></td><td>0.4553</td><td>0.5390</td><td>0.5035</td><td>0.6080</td><td>0.3437</td></tr>
<tr><td>10-Aug-07
[09-Jan-04,
10-Aug-07]</td><td>0.1146
0.1883
−0.1327</td><td>−0.1675
0.2807
−0.1006</td><td>−0.0081
0.2534
−0.1320</td><td>−0.0630
0.2573
−0.1062</td><td>0.1185
0.2211
−0.1195</td></tr>
<tr><td>23-Dec-11
[23-Dec-11,
15-Jun-12]</td><td>0.6256</td><td>0.5516</td><td>0.6167</td><td>0.6960</td><td>0.5639</td></tr>
<tr><td rowspan="3">UK</td><td>11-Aug-00
[25-Sep-99,
05-Apr-02]</td><td>11-Apr-03
[10-Sep-99,
20-Jun-03]</td><td rowspan="3"></td><td rowspan="3">0.7126</td><td rowspan="3">0.8136</td><td rowspan="3">0.7198</td><td>0.6385</td></tr>
<tr><td>10-Aug-07
[22-Apr-05,
26-Oct-07]</td><td>02-Nov-07
[24-Nov-07,
28-Dec-07]</td><td>0.1249
0.1309
−0.1003</td></tr>
<tr><td>23-Mar-12
[23-Dec-11,
15-Jun-12]</td><td>11-May-12
[16-Mar-11,
15-Jun-12]</td><td>0.7941</td></tr>
</table>

	BEL	NET	SPA	US
BEL		0.791	0.6734	0.4986 0.1524 0.0935 −0.0987 0.6458
NET	-		0.7638	0.6581 0.1790 −0.1044 0.7327
SPA	-	-		0.5407 0.1717 0.0627 −0.1166 0.6586
US	22-Aug-03 [11-Jun-99, 22-Aug-03]		28-Sep-01 [28-May-99, 28-Feb-03]	
	04-Jan-08 [04-Jan-08, 01-Feb-08]	17-Mar-06 [02-Nov-01, 02-Mar-07]	24-Aug-07 [10-Feb-06, 21-Sep-07]	
	15-Jun-12 [18-May-12, 15-Jun-12]	15-Jun-12 [18-May-12, 15-Jun-12]	03-Feb-12 [06-Jan-12, 15-Jun-12]	

interdependence. Finally, no change in correlations, confirming market interdependence and the decoupling of markets. Table 3.3 presents the result of the changes and breaks in conditional correlation of returns for markets in the DE. The results are quite remarkable as it shows that there are 28 significant pairwise correlation breaks out of a possible 45. The results also show that pairwise correlations between markets are of varying strengths. The result reveals that stock markets in the DE have higher pairwise correlations values, which are sometimes close to unity, than markets in other sub-regions. The estimated correlation values for the DE ranged from 0.3437 to 0.9274 while those for PEA and ELA ranged from -0.009 to 0.7700 and 0.1565 to 0.7064, respectively (see Tables 3.3 – 3.5). The higher correlation values for markets in the DE clearly reflects a high level of market integration between markets in the sub-region. Remarkably, the result of the pairwise correlations reveal the presence of strong comovements between stock markets in the DE even before the global panic caused by the collapse of Lehman Brothers on 15 September 2008.

Next, the chapter turns to analyse the result of the changes in correlation coefficients and estimated break dates for the DE. The result shows that the value of the change in correlation between the UK and Italy is 0.0387 and the estimated break date is located on the week of 10 August 2007. By the same token, the result shows a high change in correlation between Germany and the US, a positive change of 0.1012 and between France and the US, a positive change of 0.0857. Both breaks occurred on the week of 16 June 2006.

The chapter now proceeds to analyse the results for PEA. Table 3.4 presents the result of the changes and breaks in conditional correlation of returns for markets in PEA. The results show that out of a possible 55 country pairwise correlations only 34 are significant. Strikingly, in some instances, the results show positive changes in correlations during the second breaks which appears to support the phenomenon of contagion. It shows that the change in correlations between Indonesia and Taiwan is positive and that the pair had the highest coefficient change of 0.5179. The change in correlations between this country pair is over five times higher than that between China and Hong Kong. The result also reveals that Indonesia had the strongest comovement with the US with a positive coefficient change of 0.4115. This strong comovement with the US occurred on the week of 30 September 2005. The change in correlations for Indonesia and the US is over three time higher than that of Taiwan and the US. The result shows that Taiwan had the weakest comovement with the US, posting a coefficient change of 0.1321. It is interesting to observe the absence of comovement between the US market and those in Hong Kong, Korea, Singapore, and Thailand. This clearly suggests interdependence and the decoupling of these markets, which implies that not all crisis episodes can be considered contagious.

Table 3.4: Changes and Breaks in Conditional Correlation of Returns for Markets in PEA

	CHN	HKG	IND	JPN	KOR	MAL	PHI	SGN	TAI	THL	US
CHN		0.4566	0.2977	0.2394	0.1323		0.4493	0.3843	0.3817		0.1319
		0.2648 0.1039 −0.0552	−0.1130 0.3738 −0.6362	0.1635 0.2492 −0.2777	0.3609 0.1582 −0.1140	0.4274	−0.3200 0.3761 −0.4423	0.2362 0.1582 −0.2481	0.2482 −0.1184	0.3758	0.2313 0.2451 −0.2021
		0.7703	−0.0776	0.3745	0.5375		0.0632	0.5306	0.5115		0.4063
HKG	12-May-00 [28-May-99, 16-Jun-00]		0.4024	0.2380	0.2840		0.5774				
	29-Oct-04 [24-Sep-04, 01-Feb-08]		−0.1938 0.3671 −0.6387	0.2128 0.2321 −0.3044	0.2107 0.1576 −0.2019	0.4207	−0.4693 0.4609 −0.4957	0.6605	0.4924	0.4085	0.4622
	15-Jun-12 [13-Mar-09, 15-Jun-12]		−0.0630	0.3785	0.4504		0.0732				
IND	28-Jan-00 [28-May-99, 28-Jan-00]	06-Apr-01 [04-Jun-99, 20-Jul-01]		0.1953	0.2964	0.4058		0.4739	0.2686	0.4751	0.3292
	11-Jun-04 [11-Jun-04, 20-Apr-07]	02-Dec-05 [19-Aug-05, 20-Apr-07]		0.0604 0.2711 −0.5944	−0.1460 0.3665 −0.5260	−0.1258 0.3306 −0.6468	0.3649	−0.2789 0.3970 −0.6358	−0.2677 0.5179 −0.4745	−0.1721 0.2441 −0.6626	−0.2396 0.3767 −0.5567
	02-Sep-11 [31-Oct-08, 01-Jun-12]	02-Sep-11 [14-May-10, 08-Jun-12]		−0.0675	−0.0090	−0.0361		−0.0438	0.0442	−0.1155	−0.0903

	JPN	KOR	MAL	PHI	SGN	TAI	THL	US
JPN		0.2422	0.1913	0.2602	0.3503	0.2062		0.3368
		0.2256 0.1948 −0.3274	0.0881 0.2310 −0.3408	−0.1350 0.4325 −0.5290	0.2919 −0.2069	0.2465 0.1562 −0.3412	0.3504	0.1639 0.1952 −0.2155
		0.3353	0.1697	0.0287	0.4353	0.2678		0.4804
KOR	31-Dec-99 [28-May-99, 24-Mar-00]		0.1863	0.2370	0.2826	0.2079		
	06-Aug-04 [14-May-04, 28-Sep-07]		0.1341 0.2429 −0.2398	−0.0860 0.3474 −0.5168	0.2089 0.1875 −0.2485	0.4042 0.1105 −0.1843	0.4031	0.4374
	09-Mar-12 [20-Feb-09, 08-Jun-12]		0.3236	−0.0184	0.4305	0.5385		
MAL	13-Jul-01 [28-May-99, 03-Aug-01]	29-Dec-00 [28-May-99, 27-Sep-02]						0.2841
	16-Dec-05 [25-Nov-05, 20-Jul-07]	16-Mar-07 [20-May-05, 20-Jul-07]		0.3209	0.4761	0.3850	0.3753	−0.1650 0.2999 −0.1619
	02-Dec-11 [30-Apr-10, 08-Jun-12]	02-Dec-11 [29-Jul-11, 15-Jun-12]						0.2570

	PHI	SGN	TAI	THL	US
PHI		0.3752	0.32969 −0.1273 0.3043 −0.4907 0.0159	0.5614 −0.3087 0.2193 −0.3970 0.0749	0.3729 −0.2467 0.4115 −0.4053 0.1324
SGN	-		0.4810	0.4437	0.4815
TAI	02-Jul-99 [28-May-99, 15-Sep-00] 04-Feb-05 [14-Nov-03, 02-Dec-05] 23-Apr-10 [19-Jun-09, 15-Jun-12]	-		0.3647	0.2219 0.2244 0.1321 −0.1471 0.4314
THL	08-Sep-00 [28-May-99, 07-Dec-01] 28-Apr-06 [28-Jan-05, 09-Jun-06] 22-Oct-10 [10-Sep-10, 15-Jun-12]	-	-		0.3264
US	06-Oct-00 [04-Jun-99, 18-May-01] 30-Sep-05 [18-Feb-05, 09-Dec-05] 23-Apr-10 [19-Feb-10, 08-Jun-12]	-	25-Apr-03 [20-Aug-99, 25-Apr-03] 08-Sep-07 [07-Sep-07, 09-Sep-07] 20-Jan-12 [20-Jan-12, 15-Jun-12]	-	

Turning now to analyse the results for ELA. Table 3.5 presents the result of the changes and breaks in conditional correlation of returns for markets in ELA. The results show that 17 country pairwise correlations are significant out of 21 country pairwise correlations. The results show that most of the changes in correlations are positive, particularly during the second break. It shows that quite a number of countries in ELA experienced market comovements prior to the housing market crisis in the US. In contrast, negative changes in correlations appear to be more prevalent during the third break suggesting absence of contagion. The result shows that the change in correlation between Chile and Colombia is the highest, posting a value of 0.5084 and this change occurs on the week of 06 January 2006. With respect to changes in correlations between the US and markets in this region, the result shows that the highest change in correlations is between Argentina and the US. The strong positive change of 0.3984 between them occurred in the week of 26 February 2006.

Table 3.5: Changes and Breaks in Conditional Correlation of Returns for Markets in ELA

	BRA	CHL	COL	MEX	PER	ARG	US
BRA		0.6358	0.2163 0.0958 0.3940 −0.1433 0.5628	0.5730 0.1342 0.1498 −0.2121 0.6449	0.4317 0.1704 0.2254 −0.2298 0.5976	0.6573 −0.2601 0.3349 −0.3952 0.3370	0.4251 0.2562 0.1068 −0.3095 0.4786
CHL	-		0.2954 −0.1585 0.5084 −0.0531 0.5922	0.4478 0.1278 0.1308 0.7064	0.5241	0.4772	0.5115
COL	15-Feb-02 [23-Jul-99, 11-Mar-02]	22-Dec-00 [28-May-99, 10-Aug-01]		0.1565	0.2279	0.2040	0.1666
	14-Jul-06 [30-Jun-06, 12-Oct-07]	06-Jan-06 [06-May-05, 23-Nov-07]		0.2674 0.2778 −0.0946	0.0465 0.3581 −0.1371	−0.0979 0.4707 −0.2718	0.2386 0.2385 −0.1818
	24-Feb-12 [26-Nov-10, 15-Jun-12]	20-Apr-12 [28-May-10, 15-Jun-12]		0.6071	0.4953	0.305	0.4619

	MEX	PER	ARG	US
MEX		0.3288	0.6679	0.5314
		0.1529 0.3060 −0.3111	−0.2957 0.3533 −0.3449	0.2014 0.1350 −0.2006
		0.4767	0.3806	0.6673
PER	03-Dec-99 [04-Jun-99, 17-Jan-03		0.4940	0.2148
	21-Sep-07 [14-May-04, 30-Nov-07]		−0.3146 0.5050 −0.3690	0.1802 0.3232 −0.2364
	11-May-12 [03-Feb-12, 15-Jun-12]		0.3155	0.4820
ARG	14-Sep-01 [04-Aug-00, 05-Jul-02]	30-Mar-01 [18-Jun-99, 28-Sep-01]		0.4359
	22-Dec-06 [03-Feb-06, 07-Sep-07]	24-Feb-06 [02-Sep-05, 03-Aug-07]		−0.1935 0.3984 −0.1946
	20-Jan-12 [20-May-11, 15-Jun-12]	23-Dec-11 [27-Aug-10, 15-Jun-12]		0.4462
US	30-May-03 [25-Jun-99, 30-May-03]	21-Mar-03 [27-Aug-99, 04-Apr-04]	23-Mar-01 [29-Oct-99, 12-Oct-01]	
	12-Oct-07 [12-Oct-07, 07-Dec-07]	17-Aug-07 [03-Aug-07, 04-Jan-08]	26-Feb-06 [12-Aug-05, 07-Sep-07]	
	20-Apr-12 [24-Feb-12, 15-Jun-12]	18-May-12 [30-Dec-11, 15-Jun-12]	20-Jan-12 [13-Aug-10, 15-Jun-12]	

In addition, the result shows a high positive change of 0.3232 between Peru and the US which occurred on the week of 17 August 2007. Generally, it appears that all markets exhibited strong positive comovements with the US market. Interestingly, the result shows that the corresponding 95% confidence intervals of the break dates for all country pairs appear to be quite close. This implies that the dates are precisely estimated and largely can be viewed as the true dates.

Taken together, the chapter finds substantial changes in the conditional correlation of returns during the GFC. It also finds that stock markets in the DE exhibited higher pairwise correlations than markets in other sub-regions. Markets in the DE also exhibited higher changes in correlations with US than markets in counterpart sub-regions. In addition, it finds evidence of breaks in the conditional correlations for markets in all the different sub-regions. It thus presents evidence in favour of contagion phenomenon, but this evidence is true for more markets in the DE than in other sub-regions. It finds evidence consistent with interdependence and decoupling phenomenon for markets in PEA and ELA.

3.5.3. Distinct Breaks and Spillovers of Volatilities

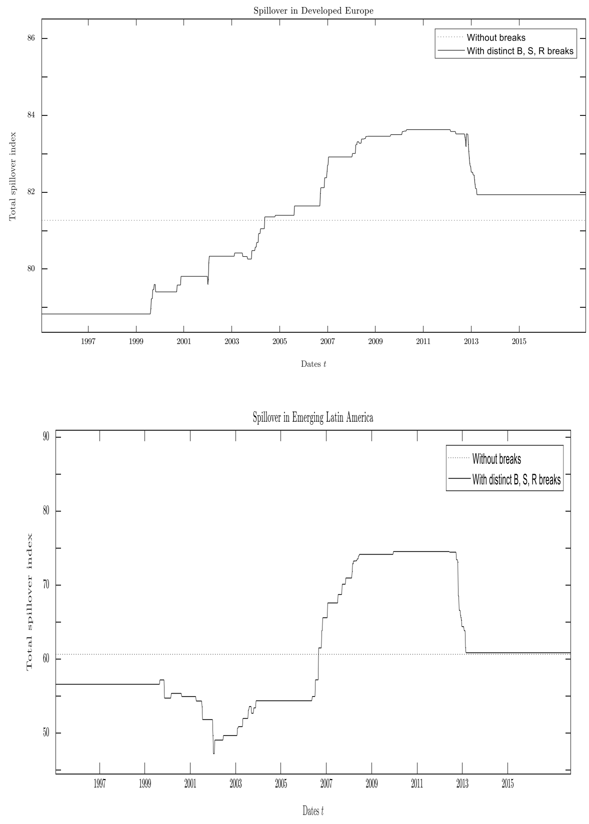
As discussed in the previous sub-sections, there are breaks in conditional mean, variance, and correlation of returns for markets in the DE, PEA, and ELA. Such evidence strongly suggests the need to account for these breaks in models on stock returns. In this sub-section, therefore, our goal is to determine whether these breaks are important for the computation of spillover indices. To determine this, two VAR models[26] are estimated; the first model is without any breaks while the second[27] one assumes distinct breaks in conditional means, variances, and correlations, and obtains these breaks using the SP. The indices are computed using GFEVDs obtained from the VAR models based on forecast horizon length of $h = 5 -$ weeks[28]. Then the indices obtained using the model with distinct breaks are compared to those obtained using the model without any breaks. The comparison of the two indices will allow us to demonstrate the importance of distinct breaks in the computation of spillovers. Figure 3.6 plots the total spillovers generated from other markets to one market for each of the different regions.

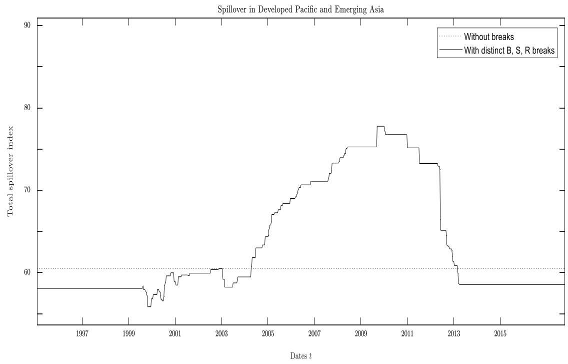
The chapter contrasts the two curves on total spillovers with (without) breaks and some interesting insights emerge. It is obvious to observe that the curve based on the model without breaks is a straight line, which does not show any evolution in spillovers over time. In contrast, it turns out that the other curve obtained with the model with distinct breaks shows time variation in the evolution of spillovers. This time variation arises from the large number of

[26] The method of modelling is time-varying parameter vector autoregression (TVP-VAR).
[27] Prior to the estimation of the second model, the chapter divided the sample into several regimes. This was done because of the evidence showing large number of breaks in the previous sub-section.
[28] The *h*-step-ahead rolling time horizon corresponds to over one month of trading.

distinct breaks and shifts in regimes. The curve based on the model without breaks in the first panel shows that over 80% of volatility shocks arising from other stock markets spills over to markets in the DE. In the middle and last panel, the plots show that a little above 60% of volatility from other markets spills over to markets in ELA and PEA. In contrast, the curve based on models with breaks in the first panel shows that the spillovers of volatilities from other stock markets to markets in the DE oscillates around 78% and 84%. In the middle panel, which displays spillovers to markets in ELA, the plot shows that it fluctuates between 49% and 71% while in the last panel which shows spillovers to markets in PEA it oscillates between 59% and 80%.

Figure 3.6: Total Spillovers, by Region





Notes: The figure reports the total spillovers by region. Spillover effects without breaks (dotted lines) and with sequences of breaks in the conditional means, variances, and correlations (dashed lines). The figures are drawn using 5-step-ahead rolling forecast horizon and isolates the contribution from own shocks.

Interestingly, from the plots one can visualize that the pattern of volatility spillovers appears to vary over time, i.e., the spillovers of volatilities are changing over time. There is a high degree of time variation in the spillovers of volatilities in markets across different regions. In each region, it is noticed that spillovers are initially constant, particularly in the 1990’s but soon after began to intensify. This intensification is because of the rise in transmitted market volatilities experienced across markets in the 2000’s. The figure shows long and sustained rise in spillovers for markets in the DE and PEA than in markets in ELA. It is also interesting to observe time-varying volatility, which is in response to shocks from the GFC. Besides, one can observe that prior to the GFC spillovers had been on the rise in all regions with the exclusion of those in ELA. Remarkably so, it was only in ELA that the rise in spillovers tapers out prior to the GFC, i.e., between 2005 and 2006 as seen in the middle panel of the figure. Figure 3.6 also shows that the strongest spillovers occurred between 2008 and 2013, which falls within the period of the GFC. During this period, spillovers jumped dramatically by almost over 10 percentage points from its pre-GFC level in markets of all the regions. However, during post-GFC, markets in all regions witnessed relatively stable spillovers from 2013 to end of 2016. The chapter now considers directional spillovers between markets within a region and thoroughly examine spillovers. Table 3.6 presents the direction of spillovers. It shows the transmission of spillovers from and to markets, and net spillovers with the signs of spillovers.

Table 3.6: The Direction of Spillovers

Country/Region	T_f	T_t	N_s
Panel A: Markets in the DE			
UK	+	+	-
France	+	+	+
Germany	+	+	+
Belgium	+	+	-
The Netherlands	+	+	+
Portugal	+	+	-
Italy	+	+	+/-
Ireland	+	+	-
Spain	+	+	+/-
US	+	+	-
Panel B: Markets in PEA			
China	+	+	+
Hong Kong	+	+	+/-
Indonesia	+	+	+/-
Japan	+	+	+/-
Korea	+	+	+/-
Malaysia	+	+	-
Philippines	+	+	+/-
Singapore	+	+	+/-
Taiwan	+	+	+/-
Thailand	+	+	+/-
US	+	+	-
Panel C: Markets in ELA			
Brazil	+	+	+
Chile	+	+	-
Colombia	+	+	-
Mexico	+	+	+/-
Peru	+	+	+/-
Argentina	+	+	+/-
US	+	+	-

Notes: T_f denotes transmission from or transmitting countries and T_t denotes transmission to or receiving countries. N_s indicates net spillovers.

Table 3.7 presents the transmission of spillovers. It sheds additional light on the directional spillovers for each country in terms of spillovers from transmitting country to other countries and vice versa, and the strength of spillovers transmission during the GFC. It shows that the transmission of spillover from the US to markets in the DE rose, though by a small margin. In contrast, it draws the reverse conclusions for spillovers from the US to markets in PEA and ELA. This is because spillovers to markets in these regions are substantially higher than spillovers to markets in the DE. Generally, the results show increases in contemporaneous correlations.

Table 3.7: Transmission of Spillovers

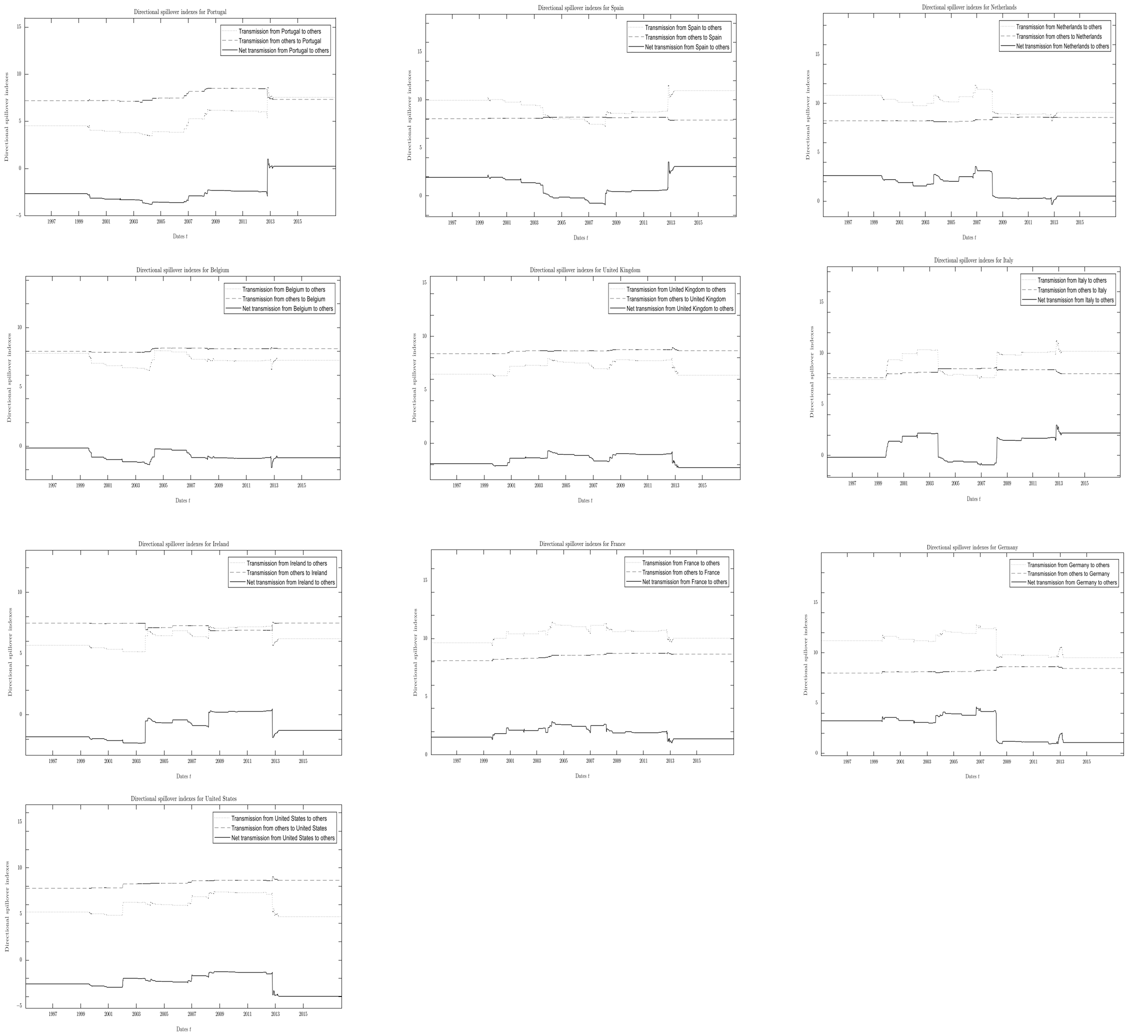
Country/Region	T_f	T_t	T_{fgfc}	T_{tgfc}
Panel A: DE markets				
UK	7	8	↑ M	↑ L
France	10	8	↓ L	↑ L
Germany	11	8	↓ H	↑ L
Belgium	7	8	↑ L	↓ L
The Netherlands	11	8	↓ H	↑ L
Portugal	7	6	↑ L	↑ L
Italy	9	8	↑ H	↓ L
Ireland	7	8	↑ H	↓ L
Spain	10	8	↑ L	↓ L
US	8	8	↑ L	↑ L
Panel B: PEA markets				
China	9	5	↑ H	↑ L
Hong Kong	7	7	↑ M	↓ L
Indonesia	6	5	↓ M	↑ M
Japan	4	6	↑ M	↑ L
Korea	8	5	↑ L	↓ L
Malaysia	4	6	↓ L	↑ M
Philippines	6	5	↓ L	↑ L
Singapore	7	8	↑ H	↓ L
Taiwan	6	6	↓ L	↑ L
Thailand	7	6	↓ M	↑ L
US	5	6	↑ H	↓ L
Panel C: ELA markets				
Brazil	15	9	↓ M	↑ H
Chile	7	10	↑ L	↑ L
Colombia	7	6	↓ L	↑ H
Mexico	13	9	↑ H	↑ L
Peru	8	9	↑ H	↑ L
Argentina	9	7	↑ L	↓ M
US	7	11	↑ H	↓ L

Notes: T_f and T_t denotes transmission from and to (averages for the entire sample period). T_{fgfc} and T_{tgfc} refers to transmission from and to (during the GFC). Spillover strength is categorized into three, where L corresponds to low spillover, M to moderate spillover and H to high spillover.

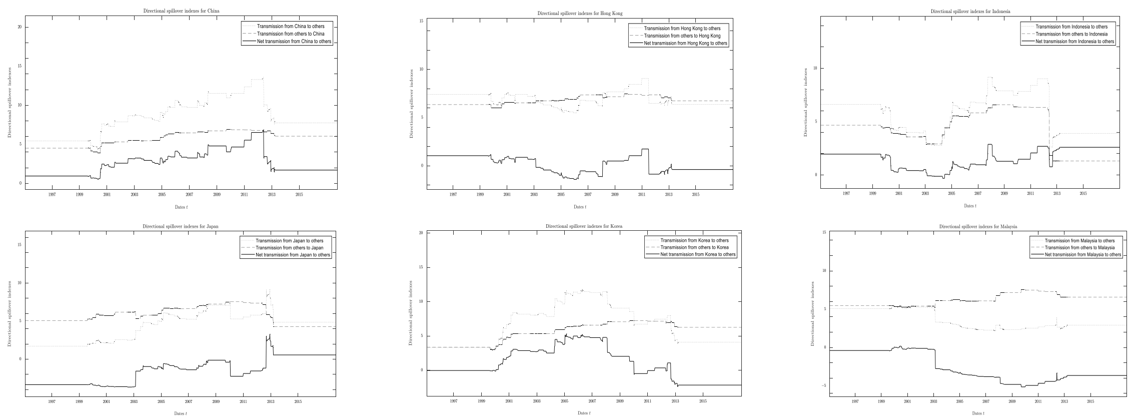
Figure 3.7 plots the directional spillovers for markets in regions across time. In Panel A of Figure 3.7, which plots the directional spillovers for markets in the DE, it is clearly seen that France, Germany and The Netherlands have positive net spillovers. This suggests that they transmit structural shocks to other markets in the DE and the US, which causes the spillovers of volatilities. In contrast, Belgium, Portugal Ireland, and the UK have negative net spillovers, which suggests that they receive structural shocks from other markets in the DE and the US. It also shows that in some periods Italy and Spain experience positive or negative net spillovers. The primary transmitters of volatility shocks in the DE are Germany and The Netherlands. Each of these markets transmit about 11% of their volatility to other markets in the DE.

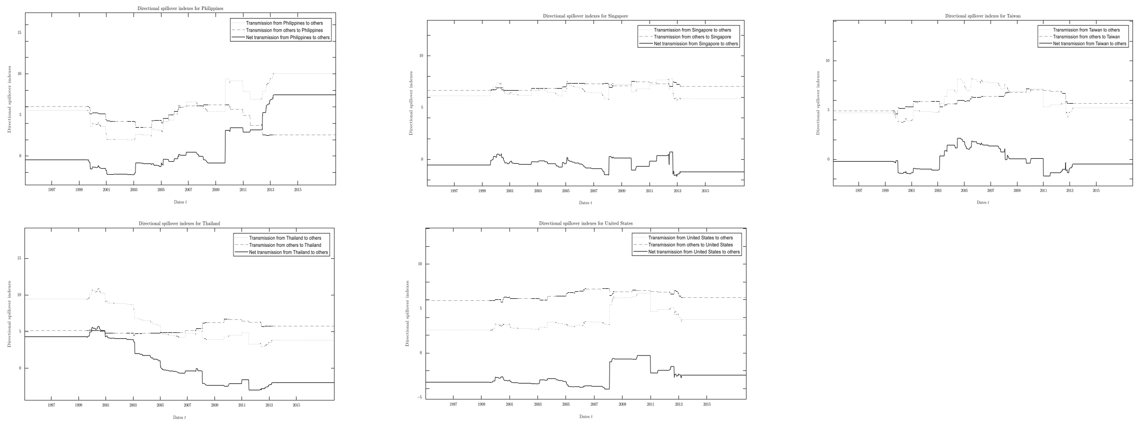
Figure 3.7: Directional Spillovers, by Country and Region

Panel A: DE

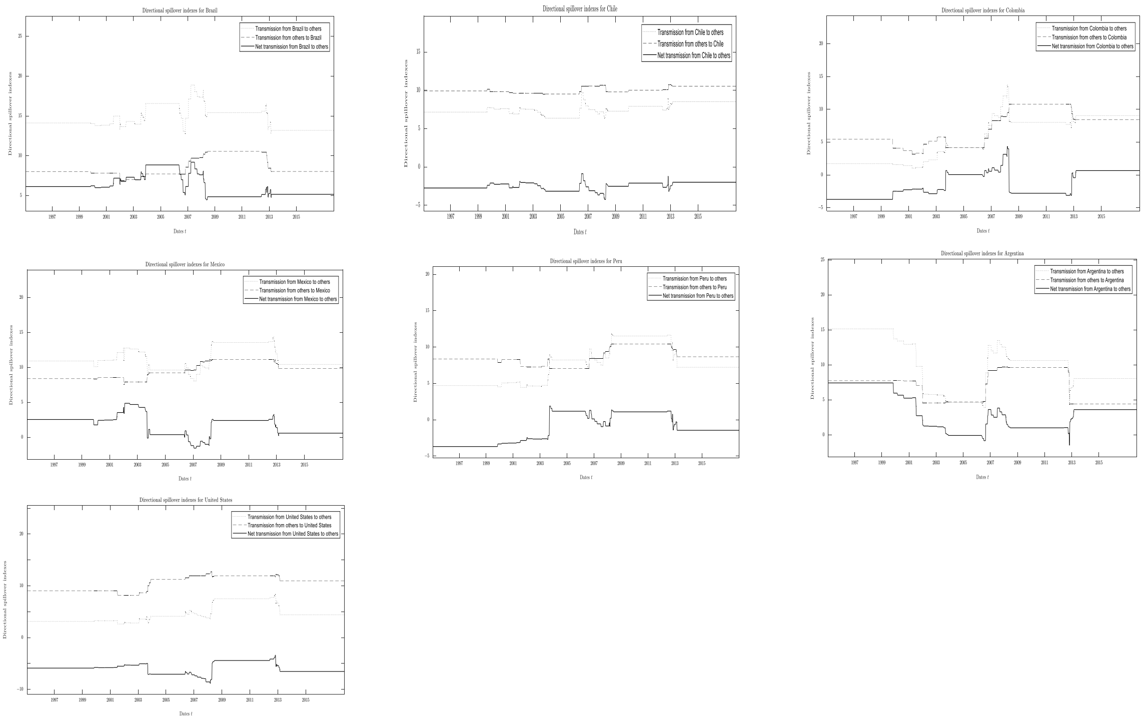


Panel B: PEA





Panel C: ELA



Notes: The figure displays the directional spillovers for each country across different regions (with the US). The figure shows the transmission from or transmitting countries (dotted lines), transmission to or receiving countries (dashed lines) and the net transmission (solid lines).

Panel B of Figure 3.7 plots the directional spillovers for markets in PEA. Surprisingly, China is the only one with positive net spillovers, while Malaysia is the one and only market with negative net spillovers. All the other markets in PEA switch between positive or negative net spillovers. China is the largest transmitter of volatility shocks within PEA. It transmits about 9% of its volatility to other markets in the region. In contrast, Singapore receives more volatility shocks than other markets in PEA.

As displayed in Panel C of Figure 3.7, which plots the directional spillovers for markets in ELA, it is obvious that only Brazil has positive net spillovers, while only Chile and Colombia have negative net spillovers. The remaining markets in ELA switch between positive or negative net spillovers. Brazil is the largest transmitters of volatility shocks in ELA. It transmits about 15% of its volatility to other markets in ELA. In contrast, Chile receives more shocks than other markets in ELA.

Overall, the chapter finds that volatilities spilled over across markets in all regions. It also finds that shocks caused by the GFC generated a substantial rise in volatilities, which spilled over markets and interpreted this as evidence of contagion. In addition, it finds that volatilities exhibited a high degree of time variation, which varies considerably across markets. The degree of time variation in volatilities is more pronounced for markets in ELA and PEA than those in the DE. Because the chapter allowed for distinct breaks during the estimation of the model, one was able to observe time-variation in the spillovers of volatilities. In addition, the model captures the timing of the GFC remarkably well. However, it is noticed that when the chapter did not allow for distinct breaks during estimation the spillovers of volatilities became time invariant. The chapter, thus, shows that allowing for distinct breaks in the conditional means, variances and correlations during estimation allows one to observe time variation in the spillovers of volatilities. In contrast, it shows that an alternative empirical model that does not allow for distinct breaks during estimation yields volatility spillovers that are time invariant. It also results in the over- and under-estimation of forecast error variances, which are required for the computation of spillover indices. To this end, it suggests the estimation of VAR models allowing for distinct breaks in structural innovations.

3.5.4. Robustness

This sub-section will use data on volatility of returns and explore the robustness of our results on changes and breaks in conditional correlations to this alternative data. Table 3.8 presents the result of changes and breaks in conditional correlations for markets in the DE. The results are largely consistent with our main result using data on stock returns. The result shows that changes in correlations ranges from 0.2331 to 0.8529 for markets in the DE. The result shows that the change in correlation between Ireland and the US is 0.4121 and this change occurred on the week of 22 August 2008. The result shows a high and positive change in correlation of 0.7139 between UK and the US. This change occurs on the week of 07 November 2008. The result shows a change of 0.4684 in the correlation between Belgium and the US which occurs on the week of 20 February 2009.

Table 3.8: Changes and Breaks in Conditional Correlation of Return Volatilities for Markets in the DE

	GER	FRA	IRL	ITL	POR	UK	BEL	NET	SPA	US
GER		0.6958 0.1302 0.0269 0.8529	0.4023	0.6281	0.4973 −0.3206 0.3154 −0.1151 0.377	0.6647	0.5481	0.6707	0.6295	0.5548
FRA	07-Mar-03 [18-Jun-99, 25-Jun-04] 07-Nov-08 [20-Jul-07, 08-Jun-12]		0.3686 −0.1428 0.1939 0.1219 0.5416	0.7149	0.387	0.5166 0.2627 0.0930 −0.2044 0.6679	0.4198 0.3102 −0.3411 0.2535 0.6424	0.6241 0.1752 0.0274 0.8268	0.6798	0.572
IRL	-	09-Jul-99 [28-May-99, 09-Jul-99] 21-Nov-03 [21-Nov-03, 07-May-04] 19-Sep-08 [30-May-08, 15-Jun-12]		0.3448	0.2331	0.3892	0.3507	0.4268	0.3451	0.4486 −0.2371 0.0191 0.1815 0.4121

	ITL	POR	UK	BEL	NET	SPA	US
ITL		0.3533 −0.0576 −0.0755 0.3302 0.5503	0.6166	0.4465	0.6273	0.6037 0.4465 0.7801	0.4359
POR	19-Nov-99 [28-May-99, 10-Dec-99]				0.3495	0.6328	
	23-Apr-04 [02-Apr-04, 07-May-04]		0.3287	0.3274	−0.2083 0.0785 0.2388	−0.3986 −0.0561 0.4208	0.2538
	19-Sep-08 [05-Sep-08, 08-Jun-12]				0.45862	0.5989	
UK	-	-		0.5055	0.6506	0.5507	0.4035 0.0653 0.2450 0.7139

	BEL	NET	SPA	US
BEL		0.5732	0.4396	0.3203 −0.0814 0.0785 0.1510 0.4684
NET	-		0.5738	0.4584
SPA	-	-		0.4246
US	28-May-99 [28-May-99, 28-May-99] 10-Oct-03 [10-Oct-03, 08-Oct-04] 20-Feb-09 [29-Feb-08, 08-Jun-12]	-	-	

In Table 3.9, the chapter reports the result for changes in correlations and their estimated breaks dates for markets in PEA. The result shows that changes in correlations ranges from -0.0025 to 0.5190 for markets in this region. The result shows that changes in correlations between China and the US is 0.3066 while changes between Korea and the US is 0.1411. It shows that both changes occur on the week of 14 November 2008. The result shows that changes in correlations between Taiwan and the US is 0.3220 and this change occurs on the week of 09 October 2009.

Table 3.9: Changes and Breaks in Conditional Correlation of Return Volatilities for Markets in PEA

	CHN	HKG	IND	JPN	KOR	MAL	PHI	SGN	TAI	THL	US
CHN		0.3086		0.0261	−0.0492		0.4493				0.1300
		0.3207 0.0805 −0.1909	0.1784	0.1990 0.2488 −0.3129	0.1591 0.2410 0.0661	0.4274	−0.3200 0.3761 −0.4423	0.2961	0.2508	0.2102	−0.1156 0.0607 0.2314
		0.5190		0.1611	0.417		0.0632				0.3066
HKG	28-Dec-01 [28-May-99, 07-Feb-03]			0.0901	−0.0094		0.4040			0.2056	
	28-Dec-07 [19-May-06, 18-Jan-08]		0.1265	0.2004 0.2129 −0.3200	0.2349 0.2016 −0.2809	0.2581	−0.5719 0.5982 −0.4178	0.4515	0.4924	−0.1026 0.3331 −0.4417	0.2075
	01-Jun-12 [11-May-12, 15-Jun-12]			0.1836	0.1461		0.0125			−0.0056	
IND				−0.0096	−0.0254	0.3116		0.3823	0.1047		
	-	-		0.0579 0.3133 −0.3758	0.1452 0.2175 −0.4520	−0.3282 0.4219 −0.4773	0.3036	−0.5032 0.5001 −0.4690	−0.2026 0.3798 −0.5139	0.1547	0.0272
				−0.0142	−0.1147	−0.0720		−0.0897	−0.2319		

	JPN	KOR	MAL	PHI	SGN	TAI	THL	US
JPN		0.0491 0.4459 −0.2088 −0.1113 0.1749	0.0302 0.1028 0.2522 −0.3112 0.0741	0.1333	0.1078 0.1674 0.2398 −0.1130 0.4021	−0.0833 0.4778 −0.1616 −0.1283 0.1045	0.1466	0.2186
	12-Nov-99 [12-Nov-99, 30-May-03]		−0.0982		0.1324	0.0269		−0.0931
KOR	19-Oct-07 [02-Feb-07, 07-Dec-07]		0.2743 0.2559 −0.2266	0.0627	0.1650 0.2031 −0.2261	0.39831 0.1489 −0.2098	0.1394	0.3165 0.0598 −0.1421
	20-Apr-12 [02-Mar-12, 15-Jun-12]		0.2053		0.2745	0.3643		0.1411
	07-Sep-01 [11-Jun-99, 16-Aug-02]	17-Sep-99 [28-May-99, 04-Oct-02]		0.3828				
MAL	26-Jan-07 [20-Jan-06, 23-Nov-07]	02-Mar-04 [06-Feb-04, 07-Dec-07]		−0.3887 0.3780 −0.4307	0.3158	0.2315	0.1554	0.0816
	06-Apr-12 [10-Jun-11, 15-Jun-12]	15-Jun-12 [15-Jul-11, 15-Jun-12]		−0.0586				

	PHI	SGN	TAI	THL	US
PHI		0.3780 −0.4028 0.4237 −0.4378 −0.0388	0.0463 0.2787 -0.4192 −0.0940	0.1153	0.0767
SGN	-		0.2911	0.1904	0.2624
TAI	30-Sep-05 [22-Oct-99, 13-Oct-06] 18-Mar-11 [26-Feb-10, 08-Jun-12]	-		0.1348	0.2737 −0.2785 0.1550 0.1723 0.3220
THL	-	-	-		0.0822
US	-	-	28-May-99 [28-May-99, 28-May-99] 10-Oct-03 [10-Oct-03, 27-May-05] 09-Oct-09 [21-Mar-08, 15-Jun-12]	-	

Table 3.10 provides the results for changes and breaks in conditional correlation for ELA. The change in correlations range from -0.0120 to 0.5525 for ELA. The result shows that only Colombia exhibits correlation with the US. The change in correlation between Colombia and the US is 0.2842 and this change occurred on the week of 13 March 2009.

Table 3.10: Changes and Breaks in Conditional Correlation of Return Volatilities for Markets in ELA

	BRA	CHL	COL	MEX	PER	ARG	US
BRA		0.3795	0.0395 −0.0606 0.3235 0.0930 0.3955	0.4565	0.3812	0.312	0.2984
CHL	-		0.0774 −0.1589 0.4483 0.0936 0.4605	0.3760	0.3103	0.2448	0.2206
COL	18-Jun-99 [28-May-99, 19-Jun-99]	25-Jun-99 [28-May-99, 25-Jun-99]		0.1107		0.0098	-0.0120
	31-Oct-03 [31-Oct-03, 23-Feb-07]	07-Nov-03 [07-Nov-03, 13-Apr-07]		−0.2117 0.4738 0.1110	0.1391	−0.1457 0.4039 −0.2288	−0.1464 0.3134 0.1292
	08-Jul-11 [02-Jan-09, 25-May-12]	23-May-08 [09-Sep-11, 15-Jun-12]		0.4839		0.0390	0.2842

	MEX	PER	ARG	US
MEX		0.2783	0.5525 −0.3862 0.1626 −0.3425 −0.0135	0.4597
PER	-		0.2500	0.1889
ARG	28-May-99 [28-May-99, 23-Aug-02] 12-Jan-07 [07-Nov-03, 04-May-07] 16-Sep-11 [27-May-11, 15-Jun-12]	-		0.1890
US	-	-	-	

In sum, the chapter finds that correlations considerably changed following the GFC shock. As before, the degree of change in correlations differs across markets in the different regions. It still finds that markets in the DE were strongly correlated with the US market than markets in counterpart regions. Generally, our results on changes and breaks in conditional correlations suggest the existence of contagion.

3.6. Conclusion

This chapter has measured changes in the returns of three components– conditional means, variances, and correlations between stock markets in the DE, PEA, and ELA with the US market in VAR models using data from 03 January 1995 to 03 November 2016. It examined the existence of breaks in the parameters of all these components separately and dated breaks using these models. It examined the existence of breaks by employing SP and assumed that the breaks are distinct. In addition, it evaluated the role of structural breaks in volatility spillovers among markets. To assess the relevance of structural breaks for estimating models of volatility spillovers, it compared volatility spillovers obtained by incorporating structural breaks that were obtained by employing the SP (where it assumed distinct breaks in conditional means, variances, and correlations) against those without breaks.

In recognition of the fact that VAR models with measurement problems can potentially yield incorrect inferences, which may be of no use to policy design, our study goes beyond the prior literature. The previous research has tested for breaks in correlations using unconditional correlations under the restrictive assumption of constant correlation (the parameters of a model are constant overtime). Relying on this assumption could potentially affect the precision of the estimates of breaks as opposed to using conditional correlations under the assumption of changing correlations (parameters of a model are allowed to change). In addition, the previous research estimates the timing of break points in a model with known break points (exogenously) and estimate models by treating the location of all break points simultaneously. Such models rely on the assumption of common breaks in covariances. Relying on this assumption is likely to lead to misleading conclusions about contagion as opposed to assuming distinct breaks and estimating the break points sequentially. These differences in assumption may likely affect the estimation and tests for break points. Another important issue with the previous research is that the break dates are not consistently estimated. Failing to construct the confidence intervals for the estimates of the break dates could indicate that the break dates are not precisely estimated. It is important to ensure that the break dates are reliably estimated by computing their confidence intervals. Finally, in the previous research, the degree of changes in correlations and other components are evaluated by applying the 2SLS as opposed to using the FGLS estimation procedure. These were all in an attempt to avoid measurement errors, provide better inference and richer implications.

This chapter yielded four main results. First, it presented evidence of changes in correlations of returns of varying degrees between markets in the different regions. Specifically, it found that the markets in DE exhibit higher correlations than markets in counterpart regions, perhaps in part due to high level of market integration. Second, it found that the sequential test detects break points in conditional correlations, which are associated with significant increases in the correlation of returns following the recent financial crisis shock. It found that the estimated break dates of all break points are consistently estimated based on the constructed confidence intervals. This suggests that the estimated break dates are likely to be true dates. It provided substantial support for the existence of contagion from the evidence of breaks in conditional correlations and the significant increases in the correlation of returns following the recent financial crisis. The chapter finds overwhelming evidence in favour of contagion for more markets in the DE than other regions. Third, the findings support interdependence and decoupling for markets in PEA and ELA. Fourth, it finds that volatility spillovers are directly affected by distinct breaks. Specifically, it detected time-variation in volatility spillovers through the inclusion of breaks in conditional means, conditional variances, and conditional correlations. It finds that allowing for distinct breaks in VAR models to obtain the spillover effects leads to time-variation in the volatility spillovers than models without breaks. It also finds that the VAR models that accounted for structural breaks by assuming distinct breaks captured the periods of significant increases in volatility, even the GFC period. It documented that it is difficult to observe the time variation in spillovers in the absence of distinct breaks. It finds that not accounting for distinct breaks when estimating models for volatility spillovers may results in the over- or under- estimation of the degree of spillovers.

Our result of breaks in conditional correlations suggests the true DGP for returns undergoes shifts in conditional correlations. Our result on breaks in conditional correlations is robust to alternative data on stock returns. Specifically, our result is robust to using data on volatilities rather than returns. Our results show the relevance of structural breaks, which are obtained by employing the SP, and assuming distinct breaks in correctly identifying the timing of abrupt changes from one regime to another and in detecting contagion. Our results indicate that the detection of breaks is improved by applying the SP due to the higher power of the test.

Our findings also highlight the relevance of structural breaks (obtained by assuming distinct breaks) for estimating models of volatility spillovers. The measurement of spillover effects across markets can be improved by allowing for distinct breaks. By allowing for distinct breaks, one can capture changes in volatility between markets and uncover the time variation in volatility spillovers. Allowing for structural breaks that are obtained by assuming distinct breaks is not only important for the detection of the time variation in volatility spillovers, it is also important for generating more precise estimates of spillover effects. This assumption allows us to observe time-variation in the evolution of spillovers. Accordingly, earlier studies that do not allow for structural breaks that are obtained by assuming distinct breaks when estimating spillover effects may have over- or under- estimated these effects. It is important to allow for structural breaks because when one does so, it introduces dynamics into the measurement of spillovers. Thus, incorporating structural breaks that are obtained by assuming distinct breaks in models might be a plausible way to improve the estimation of spillovers. In all, our findings suggest that the presence of structural breaks that are derived under the assumption of distinct breaks does matter for understanding volatility spillovers.

Our findings are particularly relevant to both investors and policy makers concerned about contagion. One important implication of these findings that confirm contagion is that at the regional level, regional portfolio diversification benefits would be smaller or even disappear. It is often sensible for investors to diversify their portfolio in the international markets when returns are highly correlated, but some investors may be reluctant to do so in countries that are less financially developed or markets outside their region due to high country risks and their adverse consequences for stock markets. For instance, when countries in the DE experience negative shocks, the size of change in the correlation of returns were found to be larger compared to those of its counterparts in other regions. Hence, when there is existence of contagion within the DE, it is quite unlikely that investors from this region would want to diversify their portfolio in a country with high risks, even when returns are highly correlated. This is because it runs contrary to their motive, which is to hold portfolios that reduce their risk of losses. This suggests that countries, particularly those from this region, might want to consider carefully policies that could be used to insure against adverse shock transmission or limit exposure to global shocks, mitigate market risks, and increase resilience in the markets or the speed with which the returns recover from shocks. Overall, our result may be useful to help investors make better decisions on portfolio diversification and the management of their portfolio risks.

Our results suggest that researchers should avoid the use of unconditional correlations, because stock returns tend to vary overtime and so, the assumption of constant correlation may be too restrictive. Our results also suggest the use of SP whenever possible since the test has the ability to detect the location of break points more precisely. Furthermore, our findings suggest that breaks in conditional means, variances, and correlations are important sources of time variation in the spillovers of volatilities across markets. Researchers should therefore consider accounting for breaks in all these three components when estimating spillovers.

Our study suggests several possible interesting directions for future research. One important direction would be to extend our analysis to the sector level using the empirical strategy in this chapter. Our investigation tells us nothing about which economic sectors would have significant changes in the correlation of returns following a shock. The extension should help in uncovering which specific sectors of the stock markets would be subject to contagion, but also recommend useful suggestions aimed at addressing this phenomenon. Two, the chapter did not study contagion across asset classes but within an asset class. The study could easily be extended to understand inter-market contagion in general linear multivariate models. Thus, the analysis can be extended to other contexts, which are related to the stock market, and markets where returns are feasible, but this is beyond the scope of this chapter. Three, a SP to determine the number of breaks, that is, where the number of breaks are unknown, such as the one proposed by Kejriwal and Perron (2010) could be used to examine whether our results could be affected by the selected number of breaks.

Chapter 4: Crisis Date Determination and Stock Market Contagion through Coskewness

4.1. Introduction

Analyses of contagion during the global financial crisis (GFC) has been based on changes in correlations (Samarakoon, 2011; Syllignakis and Kouretas, 2011; Aloui et al., 2011; Bekaert et al., 2014). Several of these have endogenously determined the date the GFC started (Dimitriou et al., 2013; Dungey and Gajurel, 2014; Luchtenberg and Vu, 2015; Kenourgios and Dimitriou, 2015), while others have exogenously determined this date (Lee, 2012; Hemche et al., 2016). Only recently have the literature on contagion begun to test for the existence of contagion in higher-order moments such as coskewness (Fry, et al., 2010). This recent literature focuses on the coskewness for two reasons. Firstly, the distributions of returns are not only characterized by the mean and variance of returns, but also by the coskewness of returns. Secondly, when investors want to choose their portfolio, their preferences are beyond the mean and variance of returns of an asset. They also prefer the coskewness of return of an asset. Indeed, they even prefer assets that increase the skewness (right-skewed) of their portfolios to those that decrease it (left-skewed) (Harvey and Siddique, 2000a; Caccioli, et al., 2014). This preference is as a result of their risk aversion behavior.

Prior to testing for contagion among stock markets, however addressing some challenging issues is crucial. One of such issues is the demarcation of the crisis from the non-crisis period (Dungey et al., 2005). This demarcation allows for testing of cross-market relationships during a stable period and testing for significant increases in these relationships after a shock in order to determine whether contagion occurred. Demarcation is of critical importance because the length of the crisis and non-crisis periods could considerably affect test of contagion and the accuracy of estimates (Serwa and Bohl, 2005). Typically, the date that a crisis starts is required for this demarcation. This date, however, has to be determined. It can be either exogenously determined using the sequence of crisis events/ex post observation of events, or endogenously determined via empirical procedures. In this respect, Dungey et al. (2015) have shown that dates exogenously determined often under- and over-estimates the date of transition between different phases of crisis. The approach adopted in selecting the demarcation date, therefore, is of critical importance because if an inexact date is chosen, the length of time and the set of observations that will be drawn upon for estimation will not reflect the actual crisis and non-crisis periods. The date chosen could have a direct impact on estimates of contagion models and affect inferences (Dungey and Zhumabekova, 2001; Dungey 2005; Baur, 2012).

A few papers have exogenously determined this date for the analysis of contagion in the context of coskewness (Chan et al., 2018) (hereafter CFH), while others have endogenously determined this date (Fry-McKibbin et al., 2019). However, does it really matter whether this date is exogenously or endogenously determined for the analysis of contagion measured using higher-order comoments like coskewness? Even though studies have exogenously and endogenously determined the date, as of yet, no study exists as to the sensitivity of contagion estimates to the choice of the crisis start date. Since this chapter cannot assume that the approach used to determine the date does not affect estimates of contagion. This chapter argues that depending on the approach adopted, the magnitude of contagion estimates can change. It is, therefore, important to evaluate quantitatively the relative importance of endogenously versus exogenously determined crisis dates by ascertaining whether the choice of the crisis date could possibly affect estimates of higher-order comoments. This chapter endogenously determines the start date of the GFC across stock markets in DEE and adopts the exogenously determined start date in CFH. It carefully evaluates the magnitude of coskewness estimates obtained from contagion model with endogenously determined date and gauges them against those obtained from contagion model with CFH's exogenously determined date. This comparison uncovers the extent of differences in estimates. This chapter fills the gap in the empirical literature by being the first to examine the sensitivity of estimates of contagion measured through coskewness to the way the demarcation date is chosen.

The empirical investigation in this chapter focuses on the contagion during the GFC. This crisis is particularly interesting to study because it was prominent and prolonged, and it generated substantial turmoil in global markets. A great deal of empirical work has documented that the dramatic movement of returns in the US stock market following the crisis had a strong impact on other markets across the globe (Guo et al., 2011; Aloui et al., 2011; Bekaert et al., 2014; Mollah et al., 2016). Baur (2012) points out that the global dimension of the GFC could make it difficult for one to detect the date the crisis began. In addition, the empirical research in this chapter is carried out for a set of markets in DEE, i.e., markets in the DE, PEA and ELA regions, respectively[29]. These markets are examined because the phenomena of contagion could impact differently on markets in different regions. Moreover, contagion may not be global in nature. As pointed out by Calvo (1999) and Kaminsky and Reinhart (2000), contagion tends to be more of a regional phenomenon than a global one. Based on this view, the chapter expects that contagion should have different important implications for the dynamics of market returns in different regions.

While there is a growing literature that investigates contagion through coskewness, these investigations have focused on fewer stock markets in DEEs. Investigating more stock markets in DEEs is crucial for having a better understanding of the changing behaviour of correlation and coskewness of returns for the analysis of contagion and for rich comparisons of contagion results. This chapter adds to this growing literature by focusing on a broader set of markets within DEEs. To obtain the start date of the crisis period, country-level data on stock returns has been used for this purpose. Due to the large number of markets in our dataset, the chapter argues that the use of this data would result in the estimation of too many break dates. It is meaningful to use the GDP-weighted average of stock returns in order to obtain a single date for countries within a region. To date, no such data has been used for analysis in this context; this chapter is the first to do so.

For the analysis of contagion through coskewness, a few models and empirical tests have been applied to endogenously determine the start date of the GFC. Some of these models and empirical tests are known to suffer from a number of shortcomings such as the non-fulfilment of some standard regularity conditions needed for the estimation of parameters for the detection of transitional behaviour and strong prior beliefs about the break date (Hansen, 2001). The chapter argues that if these shortcomings are not avoided or mitigated, it could bias estimates of contagion. This study econometrically differs on tests used to determine the start date, in order to avoid empirical shortcomings inherent in models and tests applied, and to obtain consistent estimates. This chapter avoids potential empirical shortcomings and uses the Quandt-Andrews (QA) and Bai and Perron (BP) test procedures in linear regression model to determine the date with the expectation of avoiding these shortcomings. The use of these test procedures is a convenient way to obtain the true date. They allow breakpoints to occur at

[29] The US is included in the data set of each region to act as the source of idiosyncratic shocks.

unknown break date, i.e., they are endogenously detected from data, and they do not treat the date of breaks as *known* a priori, but rather assume that the date is endogenous within the breakpoint model[30]. No study has used these test procedures to determine the dates for the analysis of contagion in the context of coskewness across markets of DEE.

The chapter tests for the existence of contagion for the different regions, individually and jointly. To do this, it relies on an extension of the regime switching model and assumes that the distributions of the model are skew normal[31]. It is advantageous to use this model because the switching processes are well suited for capturing the influence of both linear and non-linear time-varying changes in stock return behaviour. In addition, the switching processes can avoid possible heteroscedasticity problems and control for the effect of asymmetry on the distribution of returns. Finally, it allows the parameters to change across different regimes. These switches across regimes allows for consistent estimation of the parameters. The chapter adopts a Bayesian estimation approach for estimating the parameters of the model. This approach offers several attractive features such as allowing for the inclusion of uncertainties in our estimates in view of limited data or hidden factors. In addition, it allows one to incorporate prior information into our estimates. It is based on the MCMC Gibbs sampling technique, which allows one to draw accurate probabilistic inference about parameters. A key advantage of this technique is that it readily accommodates data with high dimensionality, and it is efficient at sampling a high dimensional vector of variables. It utilizes the posterior distributions during estimation to provide efficient estimates, which makes it particularly suitable and convenient for the joint estimation of parameters. Moreover, it provides a satisfactory performance because it does not suffer from the problem of non-convergence. The model is, thus, estimated with greater flexibility using this approach.

The remainder of this chapter is organized as follows: Section two discusses the theoretical background. Section three reviews existing studies on contagion through coskewness and the determination of the crisis date. Section four describes the data and presents the empirical

[30] In this chapter, the breakpoint model is a linear regression model, which is consistently estimated using least squares estimators.
[31] This chapter relies upon this assumption because stock returns normally exhibit skewness and tail behaviour.

methodology. Section five reports the results on the identified dates, the estimation results for analysis of contagion, and summarizes the sensitivity analysis. Section six concludes.

4.2. Theoretical Background

This section presents a critical review of conventional capital asset pricing theory. This widely accepted theory has given sufficient attention to the role of covariance in expected returns. However, capital asset pricing theory has gradually evolved with the shifting risk preferences of investors and the subsequent unfolding characteristics of the distribution of asset returns. Researchers have now pursued and outlined new economic theories of capital asset pricing with a view to reflecting these changes. One area of recent theoretical development in the theory of capital asset pricing was the introduction of the role of higher-order moment in explaining expected returns and the incorporation of higher-order risk. This "new" capital asset pricing theory has provided the formal basis for much of the recent work that relates to contagion measured by higher-order comoments such as the coskewness of returns, which is characterized by asymmetries in distributions or extreme outcomes. During crisis, contagion could also occur if there are significant changes in these extreme outcomes across markets.

4.2.1. Capital Asset Pricing Model

Capital Asset Pricing Model – Alternative Theoretical Framework?

The basic premise of the theory of asset pricing is to understand the risk factors that explain variations in the cross section of expected returns, i.e., it focuses on the determinants that contribute to the expected returns of an asset. The theory is based on the standard two-moment capital asset pricing model (CAPM) developed by Sharpe (1964) and Lintner (1965). In this model, cross-sectional change in asset returns is only explained by the asset's joint variability with the market portfolio. As a result, the model can only provide effects of asset covariances (asset betas) on expected returns. In view of this, assets with higher covariances would cause larger changes in the variance of the market portfolio than those with lower covariances. Thus, assets with higher covariances should have greater systematic risk than those with lower covariances. Hence, they would require higher risk premium from investors. The theory shows, in principle, that it is possible for investors to determine their expected returns.

The standard two-moment CAPM has arguably played a fundamental role at providing the framework for the understanding of cross-sectional variation in asset returns behaviour. However, a number of studies have seen it as inherently flawed and have criticized the use of this simple model for determining the pricing of assets. The model suffers from three shortcomings. Firstly, it does not allow assets covariances to vary with time. Secondly, it assumes that covariance risk alone is sufficient to explain asset valuation (Campbell et al., 1997; Campbell, 2000). Thirdly, it neglects the influence of potential non-linear dynamics in the pricing of assets, i.e., it rules out possible asymmetries in the distribution of returns such as coskewness. Put differently, the role of non-linearity or asymmetries in the distribution of returns is ignored by the standard model. As pointed out by Merton (1973), the model assumes that investors select their portfolios subject to the mean-variance criterion of Markowitz (1959)[32]. In addition to this, the model has to be subjected to large number of necessary conditions in order to meet the criterion and for its validity[33].

Arrow (1971) and Pratt (1964) have provided compelling theoretical justification for the importance of asymmetries in distributions. The so-called Arrow-Pratt theory posits that the utility function of an investor exhibits absolute risk aversion (ARA). This notion is consistent with investors who reduce the absolute amount invested as their wealth increases. The theory defines the ARA as,

$$\mathrm{A}(c) = -\frac{u''(c)}{u'(c)}, \tag{4.1}$$

where $\mathrm{A}(\cdot)$ is the ARA while $u'(c)$ and $u''(c)$ represent the first and second order derivatives with respect to c, respectively.

[32] The CAPM assumes that returns are normally distributed. Thus, the mean-variance criterion is when this assumption holds or when investors' preferences are quadratic (Fung and Hsieh, 1999).

[33] Due to these criticisms, several extensions of the standard framework have been proposed to overcome these drawbacks (see, e.g., Harvey and Siddique, 2000a; Dittmar, 2002; Guidolin and Timmermann, 2008; Chabi-Yo, 2012; Chabi-Yo et al., 2014).

A necessary condition that should be satisfied is that a rational utility function should exhibit a non-increasing ARA. This desirable property indicates that investors with a globally greater risk aversion would prefer skewness that is more positive and as investors' wealth increases, there would be a concomitant growth in their demand for risky assets. The theory is, thus, important for understanding how the risk aversion behaviour of investors influences their preference for skewness and the resultant effect of this behaviour on asset pricing. Arditti (1967) also demonstrates that non-increasing ARA reflects investor's predisposition in favour of positive skewness.

Alternative Framework

Some theoretical studies extend the standard CAPM framework to incorporate the role of asymmetries in the distribution of returns. The seminal contribution of Kraus and Litzenberger (1976) is one of such extension. They recognized the importance of distributional asymmetries in returns and assumed that higher-order moments of risk premia also account for the pricing of assets. They address the misconception that asset pricing is conditional on the joint variability of assets alone and thus extend the standard model to develop a three-moment pricing model, which incorporates the role of non-linearity. They embedded a systematic skewness[34] term within the CAPM framework for asset pricing and showed that systematic skewness adds to the risk premium of an asset. In general, their version of CAPM is related to investors' preference. In this context, they postulate that the preference of all rational investors that are averse to market risk would be to hold assets with positive return skewness in their portfolio. Investors who favour holding assets with this sort of skewness would have portfolios with lower market risk premiums or expected returns. The effect of strong preference for this sort of skewness is that it causes many investors to hold similar assets which makes assets to become over-priced, leading to low expected returns.

A modified version of the three-moment CAPM, which accounts for asymmetric risk in asset return, exists. Harvey and Siddique (2000a) build this modified version and incorporate conditional coskewness into the standard model. Their model captures both variability and

[34] The systematic skewness is used by many studies to capture coskewness to circumvent scale problems (Jiang et al., 2016). A negative systematic skewness is, thus, equivalent to a positive coskewness and vice versa.

skewness risks in the cross-section behaviour of asset returns. They define the coskewness of an asset as the excess return, which is measured by the covariance of returns and the squared return of the market. To them, coskewness indicates how much an underlying asset contributes to the skewness of the market portfolio. Typically, an asset with higher coskewness should be more desirable to hold because it contributes more to the systematic skewness of market portfolio. Because of this, the expected return on assets with this sort of coskewness would be lower. By linking the coskewness of an asset with market portfolio, it is assumed that the price of an asset with high coskewness risk would be negative in the cross-section of expected returns. They show that the unconditional distribution of coskewness does not account for asymmetric risk, but the conditional one does, and it is of relevance in portfolio selection and hedging. For instance, an asset with positive coskewness can be used as a "hedge asset" in times of market volatility.

The general representation of the three-moment CAPM is given by

$$E(\tilde{r}_i) = \lambda_1 \beta_i + \lambda_2 \gamma_i, \qquad (4.2)$$

where

$$\tilde{r}_i = \left(\frac{\tilde{R}_i - r_f}{r_f}\right),$$

$$\beta_i = \frac{\mathrm{Cov}(\tilde{r}_i, \tilde{r}_m)}{\mathrm{Var}(\tilde{r}_m)}, \text{ and}$$

$$\gamma_i = \frac{E\left[\left(\tilde{r}_i - E(\tilde{r}_i)\right)\left(\tilde{r}_m - E(\tilde{r}_m)\right)^2\right]}{E\left[\left(\tilde{r}_m - E(\tilde{r}_m)\right)^3\right]},$$

where R_i is the excess return of the *ith* asset's which equals one plus the expected return of the *ith* asset. r_f is the risk-free return or excess return on the risk-free asset. It is measured as one plus the risk-free asset return. β_i is the beta of asset, which accounts for systematic risk. γ_i denotes higher-order systematic skewness risk (conditional standard deviation of coskewness) of the individual asset. λ_1 and λ_2 are the risk premiums coefficients for both systematic risk and higher-order systematic skewness risk, respectively.

These risk premiums are the expected excess returns rewarded to investors for taking on market risks. The higher-order systematic skewness risk reflects the market premium for an asset's coskewness with the market. A positive λ_1 implies that investors are compensated with a positive risk premium for bearing risk and so they expect higher returns from assets with positive systematic risk. Conversely, a negative λ_2 implies that investors are compensated with a positive risk premium because they expect the higher-order systematic skewness to be positive. In general, if the skewness of market returns is positive (negative), an asset's co-skewness with the market (λ_2) would have a market premium that is negative (positive).

Asymmetries in the Distribution of Returns

When selecting a portfolio, investors usually have a preference for the mean (expected value) and variance (value of risk) of returns. Markowitz (1952) developed a mean-variance analysis for the selection of a portfolio of stocks. His analysis is based on utility functions that are quadratic, i.e., an investor reduces the nominal amount invested in risky assets as his wealth increases. One of the conditions required for this analysis is that the distributions of returns must be normal. Moreover, he assumes that all portfolio selection problems have the same objective function (Markowitz and Todd, 2000). He showed that a mean-variance efficient portfolio is one that provides: (1) less variance compared to any other portfolio with the same expected return and (2) more expected returns compared to any other portfolio with the same variance. More explicitly, minimizing risk for any feasible of expected return and maximizing expected return for any feasible level of risk. However, some studies criticise the use of the mean-variance analysis of portfolio selection (see, e.g., Borch, 1969; Feldstein, 1969).

Some studies have documented that most financial returns are not normally distributed. Hence, the mean and variance may not be sufficient measures of risk. In the context of stock returns, several studies have shown that its distributional form departs slightly from normality due to the existence of extreme observations (Officer, 1972; Peiró, 1994; Cont, 2001). Specifically, stock returns exhibit skewness like characteristics or asymmetry, particularly positive skewness, vary with time and have significant tail behaviour. These attributes of stock returns could preclude the use of the mean-variance analysis for portfolio selection. Thus, selecting a portfolio with this analysis may be unacceptable by investors because the distributional properties of stock returns somewhat deviates from normality. Due to this distributional form, it means that other risks besides the variance of returns such as risks related to higher-order moments might be plausible for portfolio selection.

A few studies have shown that higher-order moments such as skewness are relevant to an investor's decision on portfolio selection (Lai, 1991; Chunhachinda, et al., 1997). These studies show that investors prefer skewness when selecting a portfolio and hence, assume that the objective function to maximize the expected value of an investor's utility function has a non-linear form (polynomial) to incorporate this preference. Since the skewness of a portfolio is important to investors, it must be that the coskewness risk could also be rewarded. For example, Barone Adesi et al. (2004) and Ang et al. (2006) show that the risk of coskewness is becoming increasingly relevant to investor's decision because the risk is separately priced from the mean-variance risks. They argue that existence of coskewness risk arises because investors consider asymmetries in asset return by evaluating right (highly positive returns) skewed assets separately from left (highly negative returns) skewed assets. Moreover, it is documented that investors normally prefer right-skewed assets than left-skewed ones (Harvey and Siddque, 2000a; Smith, 2007) in comparison with the market portfolio. This indicates the existence of asymmetric preferences for coskewness by investors. They are willing to receive a lower average return during periods of high market volatility reflecting their preference for right-skewed assets. By contrast, assets, which makes investor's portfolio to be more left-skewed, can cause the overall portfolio's return to fall making such assets less attractive to hold by investors because of the asset's high susceptibility to downside losses. Accordingly, investors who hold left-skewed assets need to be compensated with higher average returns for bearing a greater coskewness risk (Ang et al., 2006). By providing justification for the importance of coskewness in returns, since returns are non-normal and coskewness is of importance to investors concerned about extreme outcomes, it might therefore be necessary for us to consider testing contagion in this context.

From the foregoing, the distributional form of returns has to reflect its characteristics. This is of crucial importance, particularly when modelling asset returns. If the assumptions made about the form of distribution is incorrect, it could be a potential source of error. Typically, the estimates of models on asset returns relies heavily on the assumptions made regarding the shape of distributions. In this view, MacKinlay and Richardson (1991) and Badrinath and Chatterjee (1988) point out that statistical inference depends greatly on distributional assumptions. The shape that the distribution of asset returns takes, therefore, is of great importance in order to improve model accuracy.

It is, therefore, important to determine the stable distribution that fits asset returns. In the context of stock returns, there is ample evidence in the prior literature that its distributions are non-normal (Mandelbrot, 1963; Fama, 1965; Praetz, 1972; Richardson and Smith, 1993) but rather it exhibits skewness, particularly positive skewness (Brunnermeier et al., 2007; Bessembinder, 2018), changes with time (Singleton and Wingender, 1986; Harvey and Siddique, 2000b), and has significant tail behaviour (Bollerslev, 1987; Kearns and Pagan, 1997; Cont, 2001).

Typically, skewness in stock returns is adduced to asymmetries caused by extreme events. These extreme events are the outliers in the distribution of returns that lead to asymmetries. Since the attributes of returns are skewed, the Gaussian assumption that distributions are independently and identically distributed, which is commonly used, will be inappropriate for modelling such returns. A handful of studies have shown that return distributions do not converge to normality (Peiró, (1994, 1999); Aparicio and Estrada, 2001). According to these authors, due to their non-convergence, such an assumption will not provide the best fit with observed returns data. There are studies that have even shown that the distributions of returns observed on daily frequency are not entirely normal (Officer, 1972; Fama, 1976; Brown and Warner, 1985; Akgiray and Booth, 1988; Mills, 1995; Harris and Küçüközmen, 2001; Wen and Yang, 2009). The evidence from these studies, therefore, invalidates the use of Gaussian assumptions for the modelling of returns. This is because the standard assumption of normal distributions does not provide a reasonable model fit and it cannot accommodate asymmetries like skewness and fat-tails.

Due to these evidences, a wide variety of alternative forms of distribution for stock returns has been proposed (Blattberg and Gonedes, 1974; Kon, 1984; Bookstaber and McDonald, 1987;

Gray and French, 1990; Linden, 2001), including skew-normal distributions. This type of distribution has been the focus of a few studies (Azzalini, 1985, 1986; Azzalini and Valle, 1996; Azzalini and Capitanio, 1999, 2003; Gupta et al., 2004). In these studies, it has been shown that stock returns follow a skew-normal distribution, and it provides a better fit than the normal distribution. As a result, modelling of returns based on this type of distribution is becoming increasingly popular (Sahu et al., 2003; Adcock and Shutes, 2005; Harvey et al., 2010).

Skew-normal distributions are normally distributed but have attributes of skewness, i.e., they are a mixture of normal distribution. It is a skewed extension that nests the density of Normal and Student t-distributions. The model for estimating such distributions contains distinct parameters accounting for non-normalities such as skewness and fat tails. In the model for determining this type of distribution, which is useful in handling possible outliers or both positive and negative skewness, there are three key skewness parameters, namely, location, scale and correlation.

This type of distribution which has been studied in the case of univariate models is extended to a multivariate case with n-dimensional dataset (Adcock and Shutes, 2005; Harvey et al., 2010). The multivariate model has been particularly popular in financial studies and Azzalini (1985, 1986) and Genton (2004) have extensively studied its key properties. This popularity is mainly because it provides a better fit than purely symmetric models like multivariate normal models. For example, Sahu et al. (2003) demonstrate that the model can be fitted without much difficulty by applying Bayesian methods and MCMC approximations. The model has other attractive features, which include high flexibility in capturing both asymmetric and symmetric processes in one probability density function, and the tractability of analysis. This type of distribution is derived by transforming the standard normal distribution. The distributions are then generated by an approximation procedure. This chapter uses this model to compute the distributions of stock returns for the analysis of contagion.

4.3. The Study of Stock Market Contagion in Empirical Literature

This section focuses on the empirical literature on contagion among stock markets. This chapter draws on and contributes to two main strands in the literature on contagion. The first strand of literature focuses on the issue of coskewness of returns for understanding the phenomenon of contagion. The second strand of literature concentrates on the issue of determining the start date of crisis period for the analysis of contagion. It, thus, reviews existing studies in these strands of empirical literature and contrasts these studies with the investigation conducted in this chapter in order to highlight the differences between them.

4.3.1. Literature Review on Contagion through Coskewness

The global transmission of shocks from one stock market to another one during a financial crisis is not new. Changes in the transmission mechanism which cause a significant increase in the comovement of stock returns – a phenomenon often labelled contagion (Forbes and Rigobon, 2002; Pericoli and Sbracia, 2003) has received considerable attention over several years in the academic literature because of its implications for portfolio diversification. The areas investigated include changes in the mean and variance between market stock returns (Baur, 2003). Finally, many authors have analysed contagion between markets through the changing behaviour of correlations of market returns across crisis and non-crisis periods (Baig and Goldfajn, 1999; Billio and Pelizzon, 2003, Billio et al., 2005; Billio and Caporin, 2010; Hon et al., 2004; Chiang et al., 2007; Kenourgios et al., 2011; Syllignakis and Kouretas, 2011; Dimitriou et al., 2013; Hemche et al., 2016). As Forbes and Rigobon (2002) point out, they are relatively straightforward to use in examining the existence of contagion. Moreover, the authors have further highlighted that it is particularly suited for the analysis of linear dependence between markets. Within the context of the recent GFC, some studies show a significant increase in correlation between market stock returns. Many of these authors confirm the existence of contagion through correlations during this crisis (Guo et al., 2011; Aloui et al., 2011; Bekaert et al., 2014; Mollah et al., 2016).

However, some authors argue that tests for contagion based on the correlations are an inadequate measure of market linkages because of the bias arising from heteroscedasticity or changing market volatility of returns (Boyer et al., 1997; Longin and Solnik, 2001; Forbes and Rigobon, 2002). Bae et al. (2003) have highlighted that contagion is linked with extreme returns because small return shocks transmit in a different way from large-return shocks. Based on this, the authors argue that correlations may be inappropriate if contagion is characterized by non-linear changes of market linkages. Due to this well recognized empirical characterization of stock returns, correlations are incapable of fully capturing market linkages. This because it is assumed that return realizations in the left and right tail of the distribution are generated by closely similar processes (Cappiello et al., 2014). Moreover, in the computation of correlations, returns are equally weighted. Although there are obvious concerns highlighted in the literature about the use of correlations, the empirical literature almost exclusively tests for contagion within this context.

However, as shown by Fry et al. (2010), a deeper insight of contagion might be gained from an analysis of significant changes in the higher-order comoments of stock returns during crisis periods like coskewness. They have highlighted that a natural point of departure in testing for contagion is to focus on correlations, but it is possible that there are additional contagious channels operating through higher-order comoments during a financial crisis through which contagion can manifest, which require examination. When compared with the large body of work on contagion through correlation, the analysis of such a phenomenon through coskewness is still relatively limited. Even though coskewness is an important characteristic of stock returns, it is largely ignored. Harvey et al. (2010) have highlighted that one reason coskewness is overlooked is that simple descriptions of asset returns often show scanty evidence of higher-order comoments. More recently, however, a small but growing literature investigates the importance of coskewness of stock returns covering aspects such as the role of coskewness in the pricing of assets (Harvey and Siddique, 2000a; Barone Adesi et al., 2004), asset allocation and portfolio selection (Guidolin and Timmermann, 2008; Harvey et al., 2010), return predictability (Martellini and Ziemann, 2010), linkage between coskewness of stock returns and liquidity risk (Nguyen et al., 2007), among others. Harvey and Siddique (2000a) have documented that coskewness is important in explaining stock returns and it considerably increases the explanatory power of pricing models. In addition, Potì and Wang (2010) and Lambert and Hübner (2013), among others, provide compelling evidence that coskewness of returns are priced in stock markets. In this vein, Smith (2007) shows that the price of coskewness appears to be large. In general, these authors note the importance of coskewness in stock returns.

With regards to tests of contagion by means of coskewness based analysis, Fry et al. (2010) note that these are typically tests for changes in coskewness between the crisis and non-crisis periods, which mainly arise from changes in the interaction of volatility, and the average returns across markets. Most of the studies that have considered the analysis of contagion through coskewness show that cross-market coskewness significantly increased after a crisis, which in turn indicates that the transmission mechanism between markets reinforced after the crisis. Evidence of such an increase has been interpreted as the occurrence of contagion across markets through coskewness. In general, studies on contagion through coskewness have highlighted that there are other important channels for the transmission of contagion besides correlations. For example, Fry et al. (2010) have pointed out that tests of contagion based on coskewness detected linkages across markets stemming from contagion, which tests based on correlations, failed to identify. In addition, Fry-McKibbin et al. (2014) have highlighted that during a crisis, significant changes in linkages are transmitted through all channels of contagion and that, most countries experience contagion through a combination of channels.

The existing studies have been conducted on different crises, markets with different structures and sizes in different countries. For example, Fry-McKibbin et al. (2014) focus on changes in the dependence structures of stock markets through coskewness to examine the phenomena of contagion during nine crises in OECD and emerging markets. The authors show evidence of manifestations of the phenomena through the coskewness channel for some of the crises. Similarly, CFH test for the existence of contagion through coskewness between four DE markets and the US during the GFC. The authors' document increased coskewness of returns across stock markets, which they interpret as evidence of contagion. In addition, they interpreted it as additional comovements in returns which are only present in the crisis period but not in the non-crisis period.

More recently, Fry-McKibbin et al. (2019) developed joint contagion tests for coskewness and apply the test to Eurozone stock markets with the US as the crisis source country. The authors tested for contagion during three distinct crisis periods namely the subprime, the GFC, and the

European debt crises. The authors provide evidence that strongly supports contagion through coskewness from the US to countries in the Eurozone. However, these studies investigate the contagion phenomena across markets through coskewness mainly from the perspective of Europe, rather than DEEs. The literature notes the changing dependence of returns across stock markets, but there is no recognisable empirical consideration of how this changing behaviour of returns between crisis and non-crisis manifests as a phenomenon of contagion through coskewness for DEEs.

4.3.2. Literature Review on the Determination of the Crisis Date

The determination of the start date of a crisis period, which is an important requirement prior to testing for contagion between markets, is of crucial importance. As already discussed, this date, which has to be determined, is used for the demarcation of the full sample into non-crisis and crisis periods.

Carefully determining this date is crucial otherwise there might be sample selection bias[35]. Dungey et al. (2015) argue that one of the most widespread difficulties in the contagion literature is the demarcation of the crisis period from the non-crisis period preceding them. Broadly speaking, there are two main approaches for determining the crisis dates for the studies of contagion among stock markets: exogenous and endogenous.

The use of exogenous approach is more widespread. This is mainly due to the ease of obtaining the date by the researcher as it is mostly obtained through use of sequence of events rather than the underlying processes, which generate market returns. The crisis date is determined using exogenous approach by Forbes and Rigobon (2002), Billio and Pelizzon (2003), Chiang et al. (2007), Kenourgios et al. (2011), Gallegati (2012), Dimitriou et al. (2013) among others. For example, in a recent study by CFH they examine contagion through changes in the correlations and coskewness of returns between four DE countries and the US during the GFC using daily stock return data from 2005 to 2014. They separate the non-crisis and crisis periods using an

[35] There are several potential biases that one should overcome to accurately measure contagion, and these include heteroscedasticity or volatility bias which occurs due to the changing volatility of returns at times of crisis (Boyer et al., 1997; Forbes and Rigobon 2002; Dungey and Renault, 2018), endogeneity bias (Pesaran and Pick, 2007), and omitted variables (Corsetti et al., 2005) amongst others. See Dungey et al. (2005) for a survey of the common methodologies and empirical biases in contagion studies.

exogenously determined start date for the GFC. They ignored the true process that generates the return series, but instead they set the start date of the GFC to March 3, 2008, which corresponds, to the date of the bailout of Bear Stearns. They find evidence that supports that correlations and coskewness of returns significantly increased during the crisis. The evidence of contagion, however, is hard to rationalise as their analysis may have been subjected to bias from the selection of samples and their estimates may have been influenced by the date chosen.

Although the use of exogenous approach gives reliable information about timing of the crisis, it may be inappropriate, particularly when the true DGP for stock returns exist. Failure to allow the true DGP determine the date i.e., to search for points of breaks in the data on stock returns series, even with sufficiently large amount of data at high frequency,[36] could result in estimation issues. This is because the underlying processes that generate the series could exhibit abrupt change at some point in time and that point could be associated with the start date of the crisis.

Given these studies, one can state that the use of exogenously determined crisis date has two serious potential drawbacks. Firstly, it is subjective, as it requires one to decide the date by oneself (self-selection) or derives from author’s independent judgement. This could confound attempts to demarcate the sample accurately. Secondly, it may lead to sample selection bias. This bias is likely to result in substantial estimation errors for the parameter estimates of contagion models due to the unrepresentativeness of the sample. From an empirical standpoint, these drawbacks are enough to allow us to raise a question on the accuracy of the parameter estimates from contagion models that have previously used this approach and to question the validity of their inferences.

The use of the endogenous approach to the determination of the crisis date, has been the focus of attention in the more recent literature, though still to a limited extent. Dungey and Gajurel (2014) have shown that that this approach generates more accurate dates than the other approach previously discussed. The approach is used by a few of papers which, utilizing the returns generating processes in econometric models, identify the crisis date and carry on to present evidence of contagion (Samarakoon, 2011; Syllignakis and Kouretas, 2011; Dimitriou

[36] Most studies on contagion are conducted using this sort of data and data frequency.

et al., 2013; Luchtenberg and Vu, 2015; Fry-McKibbin et al., 2014; Fry-McKibbin et al., 2019). In this vein, few models and empirical tests have been applied in the literature to endogenously determine the crisis date. There are, of course, few shortcomings to the use of these models and tests applied. For example, Dungey et al. (2015) endogenously determined the start date of the GFC for the US market. They used smooth transition models, which uses time threshold procedure for this purpose and simultaneously measured contagion effects with a multivariate structural GARCH model. They searched for breakpoints using the transition speed for regime changes. They employed quasi-maximum likelihood estimators, which are consistent and asymptotically normal, thereby making inference straightforward. This estimator is only consistent and asymptotically normal under a set of standard regularity conditions. However, often these conditions, which are crucial and necessary for the estimation of this type of model, are neither guaranteed nor likely to be always fulfilled. Thus, it may not be feasible for one to expect that these conditions would hold all the time.

Similarly, Fry-McKibbin et al. (2014) employed the regime switching model to date a number of crisis periods. The model is applied to data on stock returns for all markets and it is estimated using Bayesian techniques. Typically, prior information on the period of trigger event is required to conduct the estimation and to determine the crisis date, which may be subjective. In a more recent study by Fry-McKibbin et al. (2019), they used a multivariate generalization of Diebold and Chen's (1996) endogenous break test to determine the timing of the start of the crisis period. The test is conducted in a dynamic model with multivariate processes, which allows for interconnections among markets. It is, therefore, robust for understanding the transmission of crises across markets unlike univariate processes or a model with single regressor. However, the test itself is the standard chow test, which is based on strong prior beliefs about the timing of potential breakpoints in regression models, i.e., it cannot be implemented if the possible location of breakpoints are not assumed known *a priori*. In addition, for each sub-sample that will be estimated, the number of observations must not be less than the number of parameters or else the test will be indeterminate.

The studies discussed above provide important empirical insights into the different models and empirical tests applied by researchers to determine the crisis date. They, however, do not use models nor apply empirical tests that generate true dates. Moreover, as stressed above, they do not know the degree to which the choice of their dates might affect the magnitude of their estimates. This chapter directly turns to the evidence from the above laid out literature, while complementing and extending it in several ways. Firstly, all the previous studies discussed above focus on a few stock markets in DEE. This chapter, in contrast, uses a database that comprises a large sample of stock markets from DEEs situated in different regions. This, in turn, allows for rich and meaningful country/regional comparisons of the contagion results. By investigating a broader set of markets, one can have a better understanding of the changing behaviour of correlation and coskewness of returns for the analysis of contagion.

Secondly, fundamentally important, this chapter is interested in the models and tests applied in endogenously determining the crisis start date. While the previous studies use models and empirical tests whose shortcomings have already been discussed above. This chapter, in contrast, econometrically differs on tests used to endogenously determine the date. In particular, this chapter uses two different types of endogenous dating test procedures proposed in the literature: QA and a variety of BP tests.

Thirdly, this chapter has argued that depending on the approach adopted, the magnitude of contagion estimates can change. Differences in estimates of contagion might arise due to differences in the approaches used to determine the date. Rather than ignoring the sensitivity of estimates to the selected date, this work focuses primarily on the choice of date and the extent to which it might affect the magnitude of contagion estimates. This, in turn, requires a comparative analysis of the magnitude of contagion estimates obtained using an exogenously determined date to those obtained using an endogenously determined date.

Fourthly, this chapter is interested in GDP-weighted average of stock returns over time (in log), which is the regional index of stock returns. This chapter uses weighted averages in a manner similar to studies on trade, see, for example, Feenstra et al. (2013) and Kovak (2013). The data is used to test the hypotheses of no breaks in the underlying process that generates returns. This data and the hypothesis will be used to address the economic research question of endogenously determining the start date of crisis for higher-order comoment. Using this data will allow us to obtain a common break date for markets within a region. This has not been done in the literature before. In contrast, much of the previous studies have mostly used data on country-level stock returns for testing this hypothesis. It makes sense, however, to consider using data on GDP-weighted average of stock returns over country-level stock returns for two reasons. Firstly, it will allow us to estimate less break dates. The use of each country's return series would eventually result in the estimation of too many models. In addition, testing for breaks separately for each country may result in too many estimates of break dates due to the large number of countries in our dataset. Secondly, since the analysis on contagion would be based on countries within a region, it is meaningful to consider using the GDP-weighted average of stock returns. The use of this data would not affect the size of our parameter estimates.

4.4. Data and Empirical Methodology

This section is divided into three sub-sections. The first sub-section presents the econometric model based on regime switching. The second sub-section presents test procedures for breaks. Finally, the last sub-section describes the data.

4.4.1. Regime Switching Model

The model used is an extension of the popular seminal work based on the constancy of regime switching probabilities proposed by Hamilton (1989). In our case, the switching probabilities are allowed to vary across regimes; in particular, they are allowed to switch between two regimes over time. Correlation and coskewness processes are allowed to be affected by changes in regimes. Given that all the correlation and coskewness parameters of the model, Z_t follow a two-regime Markov process s_t, by extension the behaviour of correlation and coskewness of returns will be regime-specific. The model takes a similar functional form to CFH for regime switching in contagion models.

The underlying empirical specification for y_t, which is representing stock returns, dependent upon s_t is given by:

$$y_t = \mu_{s_t} + \Omega_{s_t} Z_t + \varepsilon_t, \tag{4.3}$$

$$\varepsilon_t \sim i.i.d.\ N\left(0, \Sigma_{s_t}\right), \tag{4.4}$$

$$Z_t \sim i.i.d.\ N(c1_m, I_m)\ 1\left(Z_{jt} > c, j = 1, \dots, m\right). \tag{4.5}$$

where $y_t = (y_{1t}, \dots, y_{mt})'$ and and $Z_t = (Z_{1t}, \dots, Z_{mt})'$ are m -dimensional matrices of random vectors based on period $t = 1, \dots, T$, respectively. μ is an m x 1 vector of constants, Ω is an m x m skewness-coskewness matrix due to the skew-normal distribution, ε_t is an m x 1 error disturbances vector which are $i.i.d.$ across t, Σ denote the m x m matrix of the variance-covariance, 1_m is an m x 1 column vector of m ones and I_m is the m x m identity matrix. By incorporating the vector Z_t, skewness is allowed in the distribution which improves the dependency structure between the underlying components of matrix y_t. Z_t, $1(\cdot) = 1$ if Z_{jt} holds true and 0 otherwise, i.e., it is true when Z_{jt} (sample test statistics) exceeds c (associated MCMC Bayesian statistics). The subscript s_t denotes the time-varying switching regime s at period t.

The distribution of the skew-normal variable y_t has a joint probability density function (P.D.F) given by:

$$f_{(SN)}\ (y_t; \mu, \Sigma, \Omega) = \frac{2^m}{det(\Sigma + \Omega)^{1/2}} f_{(N)} \left((\Sigma + \Omega^2)^{-\frac{1}{2}} (y_t - \mu) \right) \Pr\ (V\ > 0), \tag{4.6}$$

where

$$V \sim N(\Omega(\Sigma + \Omega^2)^{-1}(y_t - \mu), I_m - \Omega(\Sigma + \Omega^2)^{-1}\Omega). \tag{4.7}$$

$\Pr\ (V\ > 0)$ indicates that the P.D.F is a non-negative function that generates finite positive probabilities. $f_{(N)}(y_t)$ is the P.D.F of the conventional Gaussian distribution with the mean taking on value $\mu = 0$ while it requires the covariance matrix I_m to be positive definite and conditional upon y_t. If the sample space of the skew-normal distribution is set to 0, i.e., $\Omega = 0$ then Eq. (4.3) to (4.5) collapses to that of a joint P.D.F for the Gaussian distribution given by

$$f_{(G)}\ (y_t; \mu, \Sigma) = \frac{1}{det(\Sigma)^{1/2}} f_{(N)} \left(\Sigma^{-\frac{1}{2}} (y_t - \mu) \right). \tag{4.8}$$

There are two-regime variables in the model taking on values $s_t \in \{0, 1\}$. The two regimes, which captures the behaviour of economies during the non-crisis and crisis periods, allows for parameter switches. Specifically, the two possible regimes of s_t is defined as

$$s_t = \begin{cases} 1, & \text{if } s_t = \quad \text{crisis} \\ 0, & \text{if } s_t = \quad \text{non} - \text{crisis} \end{cases}$$

In Eq. (4.3) and (4.4), there are three switching parameters, $\{\mu_{s_t}, \Sigma_{s_t}, \Omega_{s_t}\}_{s_t=0,1}$ which represents the means, μ_{s_t} cross-variances, Σ_{s_t} and coskewness, Ω_{s_t}. These parameters are allowed to change in regime 0 and 1. A switch in s_t is, thus, expected to bring about a change in these parameters. Once there are changes in the parameters of correlation and coskewness during $s_t = 1$, it is assumed that contagion has occurred because they are measures of dependence.

For ease of estimation, it is computationally convenient to rewrite Eq. (4.3) to (4.5) as

$$y_t = X_t \beta_{s_t} + \varepsilon_t, \tag{4.9}$$

$$\varepsilon_t \sim i.i.d.\ N\left(0, \Sigma_{s_t}\right), \tag{4.10}$$

where

$$X_t = (I_m, I_m \otimes Z_t'), \qquad \beta_{s_t} = \left(\mu_{s_t}', \omega_{s_t}'\right), \qquad \omega_{s_t} = \text{vec}\left(\Omega_{s_t}'\right).$$

where $\otimes$ is the kronecker product for the matrix operation. As previously defined, y_t has mean μ_{s_t}', variance, ω_{s_t}' and sample space, Ω_{s_t}'. m, k and $(m + k)$ with $k = m^2$ are respectively the matrix dimensions of μ_{s_t}, ω_{s_t} and β_{s_t}.

The time-varying switching parameters, which are conditionally regime-dependent, are

$$\Theta = (\beta_0, \beta_1, \Sigma_0, \Sigma_1), \tag{4.11}$$

These parameters, $(\beta_0, \beta_1, \Sigma_0, \Sigma_1)$ switch regimes via an unobservable Markov process. For model completeness, the time-varying Markov switching conditional probability of s_t is given by

$$p_{it} = \Pr\,(s_t = 1|s_t = i) \text{ for } i = 0 \text{ and } 1. \qquad (4.12)$$

where p_{it} are conditional probabilities. These probabilities are seen as fixed constants that vary over time.

In what follows, it is more convenient to stack up the data for given variables (observable and hidden) at T as: $y = (y_1', \dots, y_T')'$, $Z = (Z_1', \dots, Z_T')'$ and $s = (s_1, \dots, s_T)'$. And for ease of implementation, the log-likelihood function, l is used. Henceforth, the chapter defines the mean by $\mu_{i,l}$ whose ith element is $\mu_l = l = 0, 1$ and denote the sample covariance and sample space as $\Sigma_{ij,l}$ and $\Omega_{ij,l}$, respectively. For convenience, it estimates the correlations instead of the covariances. Specifically, the correlation ρ_{ij,s_t} (often denoted as $\rho_{ij,l}$ with $l = 0, 1$) to be evaluated over $s_t = 0, 1$ is given by

$$\rho_{ij,s_t} = \frac{\Sigma_{ij,s_t}}{\sqrt{\Sigma_{ii,s_t}}\sqrt{\Sigma_{jj,s_t}}}, \;\; for\ all\ i \neq j. \qquad (4.13)$$

In this chapter, the regime switching model employs the Bayesian approach to estimate the model parameters. This approach is based on the MCMC Gibbs sampling technique, which allows us to draw accurate probabilistic inference about the parameters of correlation and coskewness. The technique readily accommodates data with high dimensionality and utilizes the posterior distributions during estimation to provide efficient estimates. In addition, it provides a satisfactory performance because it does not suffer from the problem of non-convergence, and it allows for the possibility of modelling parameter uncertainty.

There are several potential empirical biases that the model in Eq. (4.9)[37] controls for during estimation. First, it controls for possible heteroscedasticity using adjusted standard errors to ensure that the estimates are robust. Second, it allows for capturing both the influence of linear and non-linear time-varying changes in market dependence of returns. Third, the effect of asymmetry on the distribution of returns is taken into consideration. Fourth, the parameters of interest are allowed to change across different regimes. However, the model does not provide the crisis start date to demarcate the two-regime variables $s_t \in \{0, 1\}$, even though there are important in the model. Hence, researchers are required to determine the date of the switch in regime from a non-crisis to a crisis one. If this date is not correctly determined, one could conclude that there were significant increases in the parameters of correlation and coskewness during $s_t = 1$ when, in fact, there were none and vice versa. Thus, an outstanding issue that needs to be addressed is the determination of the date where the regime switches. The test procedures used in determining this date will be discussed in the next section.

4.4.2. Tests Procedures for Determining the Dates – Breaks at Unknown Dates

As mentioned above, the regimes are an inherent part of the model to be estimated and the date that will be used to separate these regimes has to be determined. In this sub-section, therefore, the test procedures for determining this date will be discussed. Two test procedures are used to determine this date: Quandt-Andrews (QA) and Bai and Perron (BP). These procedures allow for breaks at *unknown* points in time, i.e., the possible location of break points and the estimation of their dates are treated as endogenous.

Quandt (1960) proposes the QA test procedure, but Andrews (1993) provided the approximate asymptotic distributions of the supremum (Sup) test statistics. The procedure is a generalization of the standard chow test. It is employed for testing whether there exist one or more *unknown* break points in the sample for a specified equation. The test procedure is based on the supremum of the individual Wald statistics, which have a non-standard distribution. Hansen (1997) computes the approximate asymptotic *p*-values for the test. Andrews and

[37] The empirical strategy, i.e., implementation steps, for estimating the model using Bayesian inference methods, the procedure to perform tests for contagion is presented in Appendix 6 while the methods for hypothesis evaluation for these tests and decision rules are presented in Appendix 7 and 8.

Ploberger (1994) developed stronger optimality properties for the test, namely the exponentially weighted $(ExpF)$ and average $(AveF)$ test statistics.

When the break date, k lies in the range $[k_1, k_2]$, the relevant test statistics that can be computed are the

Quandt test statistic

$$SupF_n = \sup_{k_1 \leq k \leq k_2} F_n(k)$$

and the Andrews and Ploberger (1994) test statistics

$$ExpF_n = \ln\left(\frac{1}{k_2 - k_1 + 1}\sum_{t=k_1}^{k_2} \exp\left(\frac{1}{2}F_n(k)\right)\right),$$

$$AveF_n = \left(\frac{1}{k_2 - k_1 + 1}\sum_{t=k_1}^{k_2} \left(F_n(k)\right)\right).$$

Moving next to the BP test procedures. Various BP testing procedures have been proposed by Bai and Perron (1998, 2003a). These procedures are $SupF_T\ (m)$, "double maximum" and $Sup\mathrm{F}_T(\ell + 1|\ell)$ test statistics. They have been employed extensively in several applications and are particularly useful because they allow for multiple breaks in linear regression models.

The $SupF_T\ (m)$ test statistic

Consider the linear regression model[38] with multiple breaks, m (and $m+1$ regimes) given by

$$y_t = x_t'\beta + \varepsilon_t \qquad t = T_{j-1}+1, \dots, T_j, \quad \text{for } j = 1, \dots, m+1 \qquad (4.14)$$

The regression specification employed is

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \qquad (4.15)$$

where y_t is dependent variable at time t. x is the vector of covariates. β is the vector of regression coefficients. ε_t is the error at time t. T denotes the total sample size. j are the different regimes defined by the m-partition $(T_1, \dots, T_m)$ or break points. These break points are explicitly dealt with as *unknown* and the convention that $T_0 = 0$ and $T_{\mathrm{m}+1} = 1$ is adopted. The aim, here, is to estimate β alongside the break points using the available T observations on (y_t, x_t). Eq. (4.15) has the following matrix form given by

$$Y = X\beta + E \qquad (4.16)$$

where $Y = (y_1, \dots, y_T)'$, $X = (x_1, \dots, x_T)'$ and $E = (\varepsilon_1, \dots, \varepsilon_T)'$. Let $(T_1^0, \dots, T_m^0)$ denote the true break points so that the true DGP is assumed to be

$$Y = X\beta^0 + E \qquad (4.17)$$

[38] In our case, the chapter considers three models: one for each of the three regions in our study. The dependent variable of each model is the regional index of stock returns (log) while the regressor in each model is the U.S. stock returns (log).

The estimation of Eq. (4.15) is based on the least-squares principle. The corresponding least-squares estimates of β for each of the m-partition $(T_1, \ldots, T_m)$ are obtained by minimizing the sum of squared residuals (SSR) function, $S_T(T_1, \ldots, T_m) = (Y - X\beta)'(Y - X\beta)$ given by

$$S_T(T_1, \ldots, T_m) = \sum_{i=1}^{m+1} \sum_{t=T_{i-1}+1}^{T_i} \left[y_t - x_t'\beta\right]^2 \qquad (4.18)$$

In terms of notation, let us denote all the m-partition $(T_1, \ldots, T_m)$ as $\{T_j\}$ and let $\hat{\beta}(\{T_j\} \quad)$ denote all the estimates of the vector of parameters. $\hat{\beta}(\{T_j\}$ is relevant for estimating the break points. Hence, substituting $\hat{\beta}(\{T_j\}$ into the objective function given by Eq. (4.18) $S_T(T_1, \ldots, T_m)$ and minimizing this function, the estimated break points $(\hat{T}_1, \ldots, \hat{T}_m)$ obtained are given by

$$(\hat{T}_1, \ldots, \hat{T}_m) = \arg \quad \min_{(T_1, \ldots, T_m)} S_T(T_1, \ldots, T_m),$$

where the minimization of the objective function is taken over all m-partitions $(T_1, \ldots, T_m)$ such that $T_i - T_{i-1} \geq q$, where q denotes the degrees of freedom. From Eq. (4.18), the estimators for the break point are global minimizers of the objective function. One can use the efficient algorithm developed by BP, which is based on the principle of dynamic programming to compute the estimates of the break points as global minimizers of the SSR. This algorithm draws upon at most a number of SSR of order $O(T^2)$ for any number of m, as opposed to a standard grid search procedure, which uses SSR operations of order $O(T^{\mathrm{m}})$[39]. Hereafter, the parameter estimates of the least squares regression, i.e., $\hat{\beta} = \hat{\beta}(\{\hat{T}_j\} \quad)$, which are the estimates

[39] Break points can only take a finite number of values because they are discrete parameters. These break points can be estimated by a grid search. However, Bai and Perron (2003a) argued that the estimation by a grid search can becomes rapidly computationally excessive when m > 2. They developed an alternative and more efficient method to compute the break points using a dynamic programming algorithm.

belonging to the m-partition $\{\hat{T}_j\}$, can be computed. The number of breaks (m) can then be tested using several testing procedures developed by Bai and Perron (1998)[40].

The $SupF_T\ (m)$ test is carried out under the null hypothesis of no structural breaks $m = 0$ versus the alternative of a fixed number of breaks $m = k$ breaks, where k is the pre-specified number of breaks. Let $T_1, \ldots, T_k$ be a partition such that $T_i = [T\lambda_i]\ (i = 1, \ldots, k)$, where T_i is the time index and λ_i are the possible break fractions in T. Let us define any generic stochastic matrix R such that $(R\beta)' = (\beta_1' - \beta_2', \ldots, \beta_k' - \beta_{k+1}')$. The F-statistic associated with this test given by

$$F_T(\lambda_1, \ldots, \lambda_k) = \frac{1}{T}\left(\frac{T-(k+1)2}{2k}\right)\hat{\beta}'R'\left(R\hat{V}\left(\hat{\beta}\right)R'\right)^{-1}R\hat{\beta},$$

where $\hat{\beta}$ corresponds to the vector of least-squares coefficient estimates. Meanwhile $\hat{V}\left(\hat{\beta}\right)$ is the estimate of the variance-covariance matrix for the parameter estimates, $\hat{\beta}$ that is robust to violations of the normality assumption, i.e., it is robust to both heteroscedasticity and serial correlation.

Bai and Perron (1998) follow Andrews (1993) and others, and consider the supremum F-statistic to test the null hypothesis of no structural breaks which takes the form,

$$SupF_T(k) = F_T\left(\widehat{\lambda}_1, \ldots, \widehat{\lambda}_k\right),$$

where $\widehat{\lambda}_1, \ldots, \widehat{\lambda}_k$ is used for the global minimization of the SSR. The asymptotic distribution, which can be used for testing of breaks, is based on a trimming parameter, τ through the imposition of a minimal length h for each sample segment (regime), namely $\tau = h/T$. Thus, a restriction that no less than τ proportion of T should be included in each segment is imposed on the objective function, i.e., $S_T(T\lambda_1, \ldots, T\lambda_k)$ is under restriction of $\left(\hat{\lambda}_1, \ldots, \hat{\lambda}_k\right) \in \Lambda_\tau$,

[40] In this chapter, the SP is employed to estimate the number of breaks.

where $\Lambda_\tau = \{(\lambda_1, \dots, \lambda_k); |(\lambda_{i+1} - \lambda_i) \geq \tau, \lambda_1 \geq \tau, \lambda_k \leq 1 - \tau\}$ and Λ_τ denotes the set of allowable segments that satisfy this restriction.

Double maximum statistics

Double maximum statistics are used to test the null hypothesis of no breaks against the alternative of an unknown number of breaks for some given upper bound/maximum of the number of multiple breaks allowed, M. The first double maximum statistic, $UDmax\mathrm{F}_T(M)$ is an equal weighted statistic where the weights[41] on all residuals are all set equally. The second statistic, $WDmax\mathrm{F}_T(M)$, which is also a weighted statistic, applies the weights to the individual test statistics such that the p-values are equal across values of m, these statistics are given by

$$UDmax\mathrm{F}_T(M) = max_{1\leq m\leq M} supF_T(\lambda_1, \dots, \lambda_m),$$

$$WDmax\mathrm{F}_T(M) = max_{1\leq m\leq M} \frac{c(q,\alpha,1)}{c(q,\alpha,m)} supF_T(\lambda_1, \dots, \lambda_m).$$

where c, q and α respectively denotes the critical value, degrees of freedom and significance level. $c(q, \alpha, m)$ is the asymptotic critical value of the $SupF_T(\lambda_1, \dots, \lambda_m)$ test.

The $SupF_T(\ell + 1|\ell)$ statistic

The $Sup\mathrm{F}_T(\ell + 1|\ell)$ statistic is used for testing the null hypothesis of a number of changes, say ℓ breaks versus the alternative hypothesis that an additional break exists, $\ell + 1$ breaks. This procedure is applied to test for additional breaks if the null hypothesis of breaks is rejected by the "double maximum" statistics. The implementation of the test starts with the global minimization of the SSR in a regression model with ℓ breaks. Each of the segments defined by the ℓ breaks are tested for the presence of additional breaks. Next, from all the segments where

[41] These weights possibly will reflect the imposition of some priors on the likelihood of several numbers of breaks.

an additional break is included, the segment that minimizes the SSR the most is chosen as the model with breaks. Finally, the $Sup\mathrm{F}_T(\ell+1|\ell)$ statistic is applied to test whether allowing for an additional break will result in a significant reduction in the SSR. This process is continued by increasing ℓ in a sequential way, starting with $\ell = 0$, $\ell = 1$,... until the test fails to reject the null hypothesis of ℓ breaks.

The test statistic is of the form

$$F_T(\ell+1|\ell) = \left\{S_T(\hat{T}_1, \dots, \hat{T}_l) - \min_{1\le i\le \ell+1} \inf_{\tau\in\Lambda_{i,\varepsilon}} S_T\left[\left(\hat{T}_1, \dots, \hat{T}_{i-1}, \tau, \hat{T}_i, \dots, \hat{T}_\ell\right)\right]\right\} \quad /\hat{\sigma}^2$$

where

$$\Lambda_{i,\varepsilon} = \left[\tau; \hat{T}_{i-1} + \left(\hat{T}_i - \hat{T}_{i-1}\right)\varepsilon \le \tau \le \hat{T}_i - \left(\hat{T}_i - \hat{T}_{i-1}\right)\right]$$

The test[42] rejects the null hypothesis in favour of a model with $(\ell+1)$ breaks if the SSR has an overall minimal value that is sufficiently smaller than the SSR from the model with ℓ break. The break date that would be selected is the one that corresponds with this overall minimum. This test procedure has some appealing features. Firstly, the appropriate number of breaks in the data are consistently determined because it allows for a specific to general modelling approach. Secondly, the general specifications for computing the test statistics allows for different serial correlation in the errors and data with different distributions. In addition, it allows for different types of errors. The errors can differ across segments or have a common error structure. Thus, estimated break dates will still be consistent even when the errors have serial correlation.

4.4.3. Data

The analysis in this chapter uses data on stock returns (all denominated in US Dollar). The chapter proceeds to compute country-level data on stock returns using daily data on stock

[42] Bai and Perron (2003b) provide relevant conventional critical values for this test.

prices. The data on stock prices come from Bloomberg's MSCI database. The stock prices data begin in January 4, 2005 and end October 17, 2018, which provides us with T=3450 daily observations. There is a problem that researchers confront when using stock data. This problem presumably arises from the non-synchronization of trading hours across global stock markets. However, this chapter does not have any concern about this problem because it has already been addressed by the source of the data. Therefore, there is no need to adjust for time-zone differences nor to resort to the use of lead and lag indices in the dataset.

Following standard practice, the chapter defines stock returns as the log difference of daily stock prices expressed in percent and this is given by:

$$r_{it} = 100 \text{ x } \left(ln(p_{it}) - ln(p_{it-1})\right) \; t = 1, 2 \dots T, \qquad (4.19)$$

where r_{it} denotes stock returns in market i at day t. p_{it} and p_{it-1} represents the stock price of market i at close of day t and $t-1$, respectively. (ln) denotes natural logarithm.

To test for breaks and to estimate break dates, the GDP-weighted average of stock returns over time (in log) is used. This return series will be constructed using data on a broad set of DEE countries, twenty-four in total. The countries which include Belgium, Brazil, Chile, China, Colombia, France, Germany, Hong Kong, Indonesia, Ireland, Italy, Japan, Korea, Malaysia, Mexico, the Netherlands, Peru, Philippines, Portugal, Singapore, Spain, Thailand, the UK will be grouped into 3 main regions, namely, the DE (nine countries), PEA (nine countries), and ELA (five countries). Within each region, the US will be included to act as the crisis source country.

To construct the dataset on the GDP-weighted average of stock returns (in log) the chapter proceeds as follows. Firstly, data on nominal GDP and consumer price index (CPI) (in the base year 2010) are obtained for the period 2005 to 2018 from the database of the World Bank. Next, to compute their real GDP, each country's nominal GDP are divided by their respective CPI. Secondly, the real income level share for each country in a region are obtained. It derives these by dividing country's real GDP with the total value of real GDP for all countries in a particular region. Each country is then weighted by its share of GDP, i.e., according to the size of its economy. Thirdly, the average weight for each country is obtained by dividing the sum of country's real income share with the total number of years. Finally, the weighted stock returns for each country is computed by multiplying their average weight by their daily stock returns. The average of the weighted stock returns of all countries in a particular region is then the GDP-weighted average of stock returns for that region.

The GDP-weighted average of stock returns R_t can be expressed as

$$R_t = \sum_{i=1}^{n} \omega_i \, r_{it} \qquad (i = 1, \dots, n) \qquad (4.20)$$

where R_t denotes the GDP-weighted average of stock returns for region i at time t, r_{it} is the stock return in market i, the weights for each country is defined as $\omega_i = \frac{x_{it}}{\sum_{i=1}^{n} x_{it}}$. x_{it} is the real income level of country i and $\sum_{i=1}^{n} x_{it}$ is the total real income for all countries in a region.

In general, to determine the crisis date using break tests, this chapter uses data on the GDP-weighted average of stock returns. To estimate the contagion model, however, it uses data country-level on stock returns.

Tables 4.3 presents some basic summary statistics for the sample of stock returns at country level during the period, January 4, 2005 to October 17, 2018. Panel A of Table 4.3 pertains to sample characteristics for stock markets in ELA while Panels B, C and D concern markets in PEA, the DE, and the crisis source market, respectively. For markets in ELA, the average returns ranged between 0.0067 and 0.02 percent, respectively. In the markets within PEA, the lowest and highest average returns are 0.0043 and 0.02 percent, respectively. The average returns are in the range of -0.0084 and 0.0084 percent for markets in the DE.

The degree of dispersion around the mean as measured by the standard deviation shows that stock return series are quite far from their mean. This is particularly so for stock markets situated in ELA. This is because the standard deviations of their returns are relatively higher

Table 4.1: Summary Statistics, Country-level Stock Returns

	Average return	Maximum return	Minimum return	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
Panel A: Markets in ELA								
Brazil	0.0084	9.8283	-7.9576	0.9823	-0.1613	12.4964	12978.73	0.0000
Chile	0.0067	9.6184	-5.0453	0.6094	0.4206	27.4857	86287.21	0.0000
Colombia	0.0122	7.1632	-5.6324	0.7331	-0.3146	12.1241	12024.13	0.0000
Mexico	0.0082	6.6824	-4.7331	0.7122	-0.1546	10.6969	8529.85	0.0000
Peru	0.0204	6.2880	-7.1670	0.8283	-0.3581	10.9357	9126.511	0.0000
Panel B: Markets in PEA								
China	0.0054	6.6979	-3.9695	0.4756	0.2465	20.4302	43708.17	0.0000
Hong Kong	0.0084	4.9907	-5.4549	0.5567	-0.2576	14.3001	18394.09	0.0000
Indonesia	0.0201	4.4015	-6.1272	0.6904	-0.4719	10.4132	8027.92	0.0000
Japan	0.0047	5.6725	-4.5322	0.6149	-0.4265	11.0515	9423.56	0.0000
Korea	0.0117	5.0907	-4.7651	0.5691	-0.3623	11.7036	10965.16	0.0000
Malaysia	0.0058	2.2588	-2.5558	0.4060	-0.1767	7.0948	2428.36	0.0000
Philippines	0.0143	4.0645	-5.9375	0.5828	-0.5274	10.4263	8087.83	0.0000
Singapore	0.0043	3.6417	-4.2698	0.4981	-0.2106	10.8514	8887.02	0.0000
Thailand	0.0104	5.7331	-7.8538	0.6222	-0.7019	20.2596	43106.03	0.0000
Panel C: Markets in the DE								
UK	0.0042	4.7365	-3.9772	0.4955	0.0233	12.9040	14100.65	0.0000
France	0.0048	5.7178	-4.0404	0.5852	0.0403	11.2971	9897.01	0.0000
Germany	0.0072	5.7747	-3.6625	0.5805	0.0409	11.1799	9619.58	0.0000
Belgium	0.0013	4.5434	-4.8478	0.5607	-0.4700	10.4066	8012.84	0.0000
The Netherlands	0.0084	5.8183	-4.0172	0.5454	0.0089	12.5173	13020.77	0.0000
Portugal	-0.0074	6.2179	-4.6794	0.5619	0.0489	12.4145	12742.51	0.0000
Italy	-0.0070	6.4208	-5.9052	0.6797	-0.1337	10.4537	7996.73	0.0000
Ireland	-0.0084	5.8110	-7.7081	0.7695	-0.6091	12.8133	14056.61	0.0000
Spain	0.0001	6.3059	-6.0596	0.6641	-0.0521	12.1818	12120.63	0.0000
Panel D: Crisis source market								
US	0.0108	4.4918	-4.1319	0.5121	-0.4920	14.8093	20186.78	0.0000

Source: Author’s compilation

than standard deviations of the returns of other regions. Skewness, which measures the degree of asymmetry in the distribution of returns, shows both left and right skew of varying degree for markets in the DE. Whereas for markets in PEA and ELA, many of them have return distributions that are mostly left skewed. This is possibly due to falling returns over a long time in our sample for some markets in these regions. The return distributions in the crisis source market is also left skewed. Kurtosis, which are informative about the peakedness of the distribution, shows that the returns data for all markets have distributions that are leptokurtic, i.e., positive kurtosis. Under the null hypothesis of a normal distribution, the residuals in the returns for all markets fail the Jarque-Bera normality test. All the test statistics are highly statistically significant at the 5% level of significance. Overall, our sample of country-level stock returns largely have non-symmetrical distributions. This gives further indication that the distributional assumptions that accommodates the skewness of the return distributions should be considered for analysis.

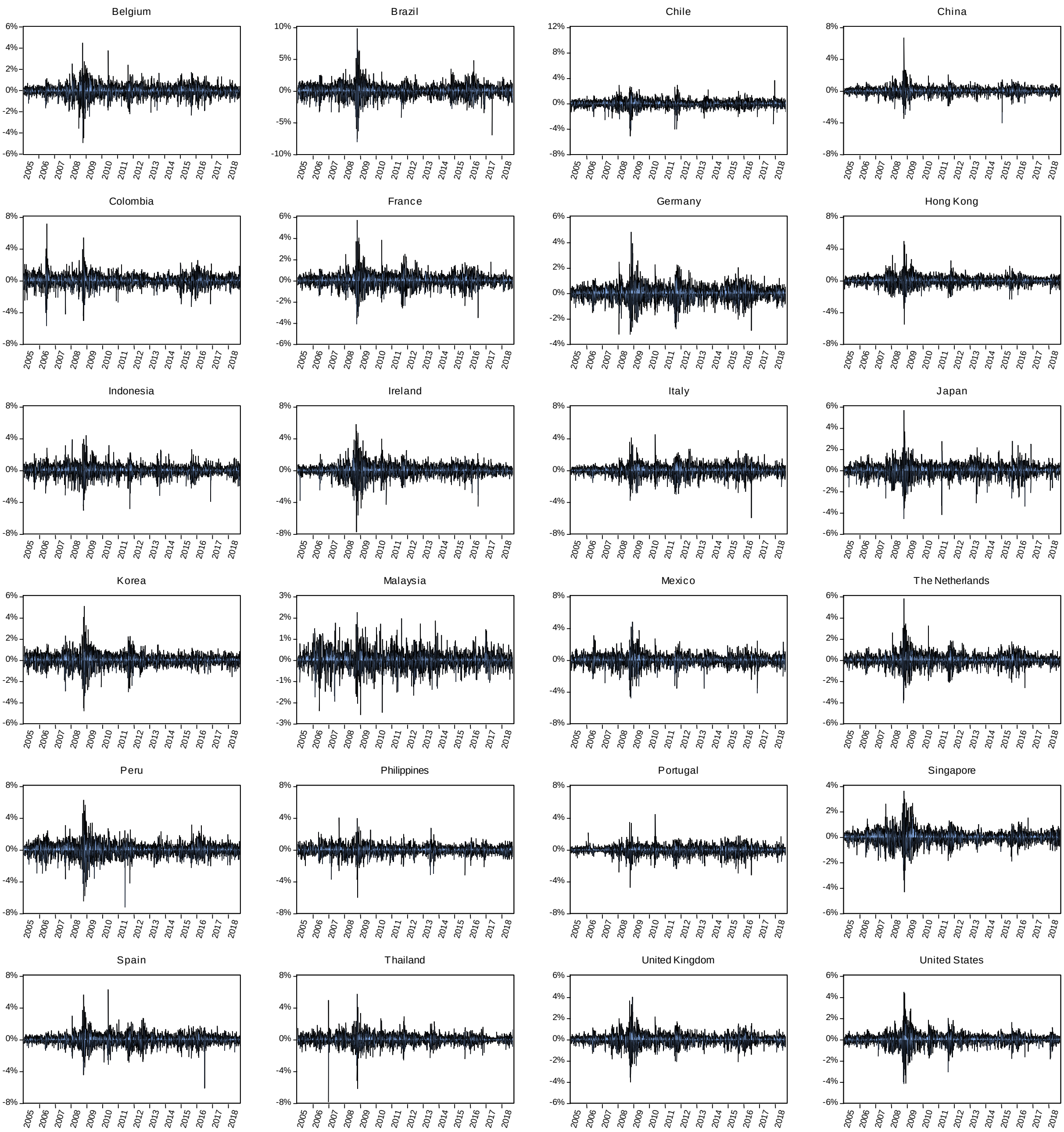
Table 4.2: Summary Statistics, GDP-Weighted Average of Stock Returns

	ELA	PEA	DE
Average return	0.0027	0.0012	0.0002
Maximum return	2.0628	0.9458	0.5578
Minimum return	-1.5689	-0.6023	-0.3806
Std. Dev.	0.1896	0.0730	0.0584
Skewness	-0.2875	-0.2851	-0.1024
Kurtosis	13.6486	19.0380	10.7526
Jarque-Bera	16347.75	37021.91	8645.86
Probability	0.0000	0.0000	0.0000

Table 4.2 reports summary statistics for the GDP-weighted average of stock returns for ELA, PEA, and the DE. Markets in ELA have the largest average stock return of 0.0027 percent. This is followed by markets in PEA with an average of 0.0012 percent and by markets in the DE with the least average return of 0.0002 percent. Skewness in the daily return of stocks weighted by GDP is left skewed for all regions. The Jarque-Bera test statistic are all statistically significant at the conventional significance level (p-value of 0.00). It, thus, rejects the normality hypothesis for markets in all regions.

Figure 4.1 plots the evolution of country-level stock returns for each of the market in our sample. Clearly, it can be seen from the figure that the behaviour of stock returns differs across markets. The figure shows that all markets experienced sharp declines in their respective returns in 2008. There is a strong possibility that the fall in returns across markets are associated with the GFC, but one cannot fully claim that this crisis is responsible for the decrease in returns.

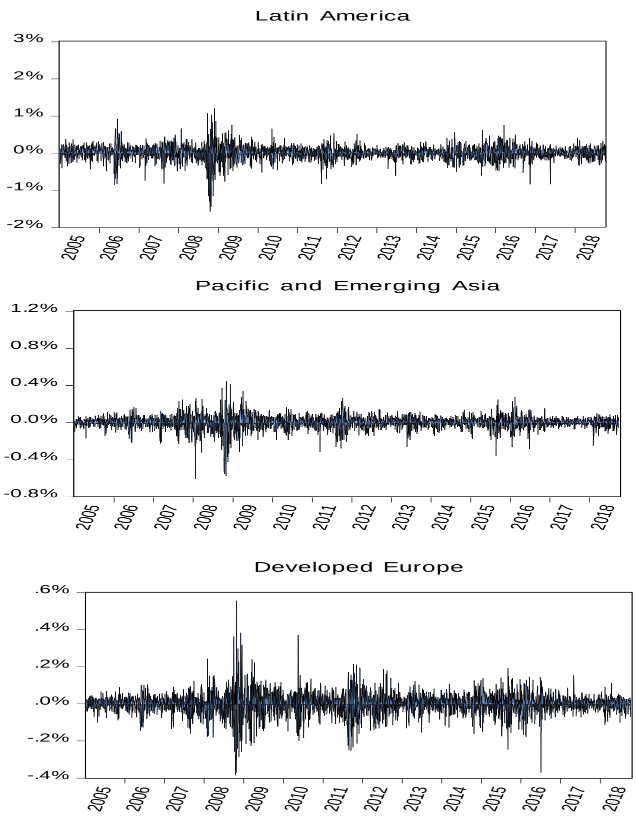
Figure 4.1: Country-level Stock Returns



Notes: The figure plots the evolution of stock returns (log) for all markets.

Figure 4.2 plots the GDP-weighted average of stock returns across three regions. The figure shows a dramatic rise and fall in returns during the sample period. There are differences in returns across regions, which continues to a large degree over the years. Stock returns in the DE exhibit substantially more variability (changeability) than in PEA and ELA. Returns have fallen even more rapidly in this region than in PEA and ELA. In 2008, however, stock markets in all regions exhibited quite similar patterns.

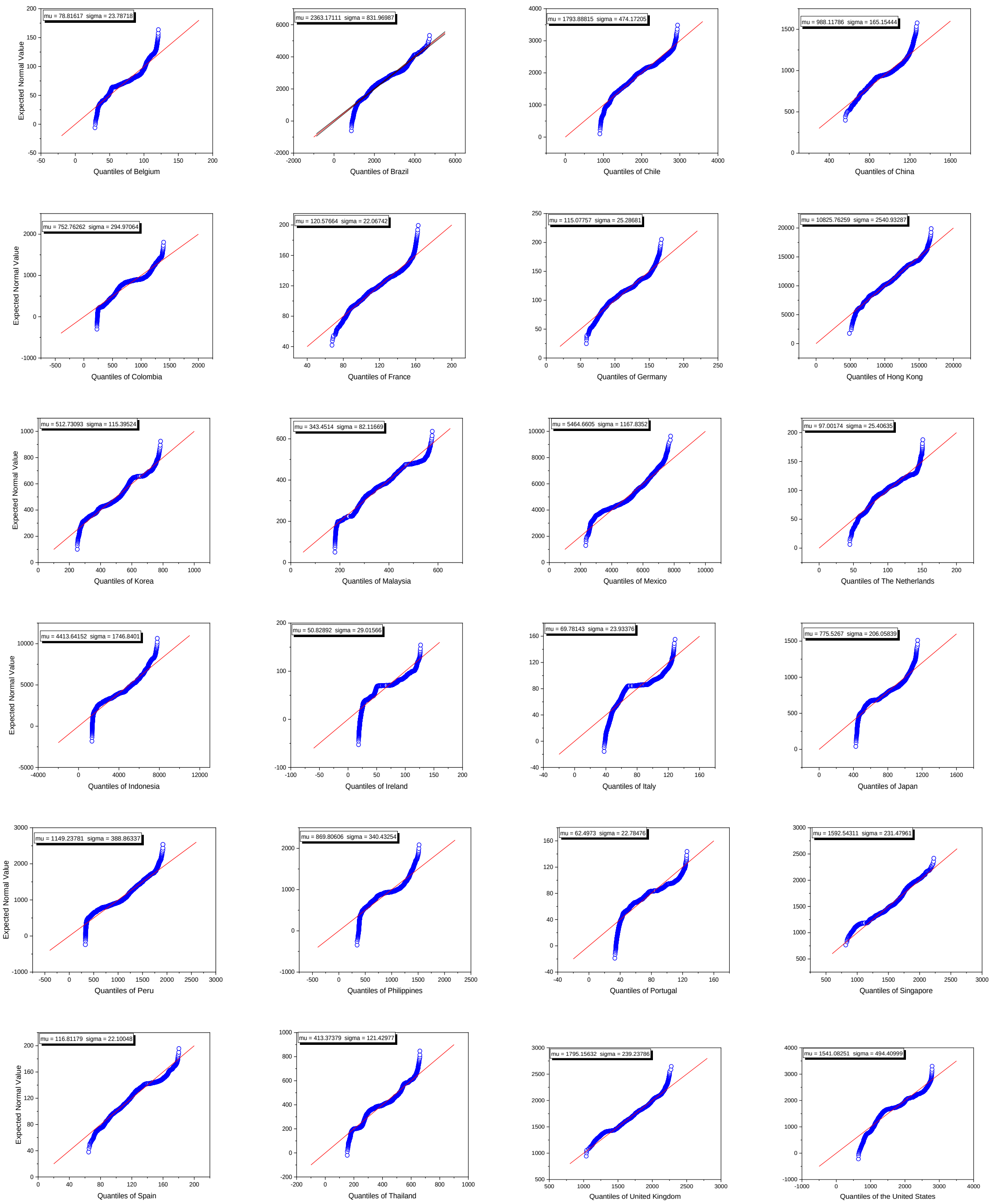
Figure 4.2: Plot of GDP-Weighted Average of Stock Returns across Regions



Relative to markets in other regions, returns declined sharply by almost 0.4 percent in the DE. However, it declined by over 0.6 and 1.5 percent, respectively in PEA and ELA. The timing of the sharp decline in returns across all regions appears to have occurred during the GFC. The magnitude of the decline in returns becomes less pronounced from 2009 forward in all the regions.

To motivate the type of distributional form that would govern stock returns, the chapter graphically illustrates how observed stock return distributions differ from normal approximations. Figure 4.3 depicts the Q-Q plot of stock returns (log) by country with superimposed normal distributions. It compares the distribution of returns (shown by the blue curve) with the fitted normal distribution (solid red line).

Figure 4.3: Q-Q Plot of Stock Returns (log) by Country and their Normal Approximations



Notes: The distribution of the normal density function (solid red line). The finite-sample size n= 3450.

A closer observation of the figure shows that there are extreme observations in the data on returns. Further, the graphical illustration suggests that returns have distributions that are not consistent with normality. The finite-sample distribution of the returns does not fit normal distributions well even though the series are log transformed data and not in levels, i.e., it is not well approximated by a normal distribution. The plots in the figure are quite similar for most of the countries and quite informative.

The figure reveals three interesting stylized facts about the precise properties of stock returns. Firstly, it is evident from the figure that the distribution of returns exhibits departures from normality with noticeably fatter tails. Secondly, one observes that the distributions have higher peaks than normal indicating excess kurtosis. Thirdly, there is evidence of asymmetry in the distribution of returns. This is because the distributions seem to exhibit slight left or right skewness. The distributional differences between the returns and the normal distributions indicates that our finite-sample data on stock returns are not completely consistent with normality assumption.

Based on these characterizations revealed from our data, it is obvious that the chapter must use a different distributional form, which does not fully rely on the underlying assumptions of normality during estimation in order to obtain reliable parameter estimates. Therefore, to allow for all these characterizations, it would use a mixture of normal distribution such as the skew-normal distributions for the estimation of our contagion models. Moreover, this distribution would help us to overcome the lack of fit. Overall, this illustration is informative about the behaviour of the returns and that non-normal distributions may provide a good fit for stock returns. This chapter relies on distributions derived from a skew-normal model for its empirical estimations. This model captures the conventional behaviour of returns including heavy tails, excess kurtosis, and asymmetry, thereby correcting for them in our analysis.

4.5. Empirical Results

This section is divided into four sub-sections. The first sub-section presents the results of the different test procedures based on least square estimation that were used to determine the start date of the GFC. The second sub-section provides the benchmark results of the regime switching model for contagion using endogenously determined crisis date and estimated by the

Bayesian estimation approach. The third sub-section contrasts the benchmark results of the model against the results of an alternative model using exogenously determined crisis date. The fourth sub-section reports the results of the sensitivity analysis.

4.5.1. Crisis Date Determination using Test Procedures

This sub-section is on crisis date determination using test procedures of QA and BP. As already mentioned, these procedures are used to locate break points in the underlying processes, which generate returns, and to estimate the dates of these break points with the goal of determining the crisis start date. Determining the location of break points involves two steps. Firstly, estimating the regression model in Eq. (4.17) separately for each of the different regions and using the least squares method of estimation to obtain the parameter estimates of the model. Secondly, relying on the regression results obtained from the first step, break tests at unknown points in time using the various procedures are conducted in order to estimate the break dates. However, before these tests are performed, the trimming of the distribution is required[43]. The trimming allows us to set the minimum length for each sample segment (regime or sub-sample), h. For test based on the QA procedure, the chapter imposes a trimming parameter, $\tau = 0.15$. This implies that the minimum length for each sample segment is 15% of T days. Tests based on BP procedures also requires trimming, so it again considers a trimming of $\tau = 0.15$. These tests, however, are carried out at $\alpha = 0.05$ significance level for $m = 5$ maximum number of breaks[44].

Table 4.5 reports the results of the break tests at unknown points in time[45]. It reports the test statistics and their corresponding p-values. It also reports the estimated break dates. The chaptere assesses whether these test statistics would reject the null hypothesis of no structural break at the conventional 5% significance level using the p-values for these test statistics. Panel A of Table 4.5 presents the results of the QA test procedure using $Sup\ LR$, $Exp\ LR$ and $Ave\ LR$

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[43] If the break is too near the top or bottom of the distribution, the test might be misleading.

[44] Bai and Perron (2003a) suggested that larger values of the trimming parameter should be considered to achieve break test with correct size in finite samples as small values may lead to tests with substantial size distortions. Moreover, larger values are required when allowing for serial correlation in the errors or heterogeneity across segments. They demonstrated that when $\tau = 0.15$ the maximum number of breaks permissible is 5. This chapter follows this recommendation and so, the trimming percentage that it adopts will not affect consistency of the test.

[45] The results of the QA and BP tests along with the estimated break dates when it uses the country-level data on stock returns are presented in Appendix 9.

test statistics. The test rejects the null hypothesis when using the $Sup\ LR$ test statistic for all the different regions. The p-value of the break points associated with the DE and ELA are essentially zero. With respect to $Exp\ LR$ and $Ave\ LR$ test statistics, the results are mixed for the various regions. For PEA, the null hypothesis cannot be rejected when using the $Exp\ LR$ test statistic. It can only reject the null for the DE and ELA using this tests statistic. In addition, the $Ave\ LR$ test statistic strongly rejects the null hypothesis for the DE and ELA but fails to reject the null hypothesis for PEA. The evidence in the $Sup\ LR$ test statistic is not fully supported by $Exp\ LR$ and $Ave\ LR$ test statistics, especially for PEA.

The estimated break dates using the QA test based on $Sup\ LR$ test statistic for all regions coincides remarkably well with the period of the GFC. For instance, in the DE and ELA regions, the dates identified by this test are 30/3/2009 and 13/11/2008, respectively. In PEA region, the break occurred earlier than that of the DE and ELA. More specifically, this break occurred on the 19/9/2008 for markets in this region.

Panel B of Table 4.5 reports the results of the BP tests for ELA, PEA, and the DE. It reports test statistics of $SupF_T\ (m)$, double maximum, and $SupF_T\ (\ell + 1/\ell)$ tests. It also reports the estimated break dates. For all the regions, the $SupF_T\ (m)$ test rejects the null hypothesis of no structural breaks at the 5% level of significance. The test detects a total of 5 break points each for the DE and ELA while it detects a total of 4 break points for PEA. The double maximum tests based on $UDmax\mathrm{F}_T(M)$ and $WDmax\mathrm{F}_T(M)$ statistics rejects the null hypothesis of no structural breaks for all the regions. The rejection of the null suggests that there is at least one break point. Finally, the $SupF_T\ (\ell + 1/\ell)$ test detects 2 break points each for the DE and ELA and 1 break point for PEA.

Next, the chapter analyses the results of the estimated break dates for both $SupF_T\ (m)$ and $SupF_T\ (\ell + 1/\ell)$ tests. In the case of ELA, the first break occurred on 31/7/2007. This break date falls within the first phase of the GFC, which occurred, from July 2007 to June 2008. It is associated with the reversal in the housing market coupled with the deterioration of the balance sheets of financial institutions, which lead to a contraction in supply of credit. The second break date occurs on the 13/11/2008, which corresponds to a similar date earlier identified using, the

QA test. Subsequent breaks occurred on 24/5/2010, 09/09/2011, 30/7/2012, 18/08/2014, 22/08/2014 and 23/9/2016, respectively.

Table 4.3: Results of the Break Tests at Unknown Points in Time

Tests	ELA	PEA	DE
Panel A: QA test			
Sup LR Statistic	28.4340***	8.4957**	41.5236***
p-value	(0.000)	(0.004)	(0.000)
Break dates	13/11/2008	19/9/2008	30/3/2009
Exp LR Statistic	8.0406***	0.8707	16.5056**
p-value	(0.000)	(0.238)	(0.001)
Ave LR Statistic	6.1466***	1.0494	10.8719***
p-value	(0.000)	(0.357)	(0.000)
Panel B: BP tests			
$SupF_T\ (m)$ *statistics*			
Sequential F-statistic determined breaks	5	4	5
Break: 1 **	28.4340	8.4957	41.5236
Break: 2 **	18.3917	5.7938	29.0883
Break: 3 **	13.8103	4.5242	20.3140
Break: 4 **	10.8852	3.6763	15.8434
Break: 5 **	6.7552		12.8995
Double maximum statistics			
UDmax Statistic[a]	56.8680**	16.9914**	83.0473**
WDmax Statistic[b]	56.8680**	16.9914**	83.0473**
$SupF_T\ (\ell + 1/\ell)$ *statistic*			
Sequential F-statistic determined breaks	2	1	2
Break test: 0 vs. 1 **	28.4340	8.49571	41.5236
Break test: 1 vs. 2 **	8.2301		15.8442
Estimated break dates			
	31/10/2007	19/09/2008	27/02/2007
	13/11/2008	13/11/2008	30/03/2009
	24/05/2010	15/12/2010	01/06/2009
	09/09/2011	11/08/2014	30/08/2011
	30/07/2012	28/05/2015	02/10/2013
	18/08/2014	07/09/2016	24/08/2016
	22/08/2014		
	23/09/2016		

Notes: Reported tests for breaks include the QA and BP tests, respectively. These tests are based on a linear regression model for each region log of GDP-weighted stock return indices with the US stock index. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. The figures in the parentheses are the probability values (p-values). The p-values for the tests are calculated using the method in Hansen (1997). [a] 5% UDmax critical value is 11.70. [b] 5% WDmax critical value is 12.81. For the $SupF_T\ (m)$ test, the critical values for breaks 1, 2, 3, 4, and 5 are 11.47, 9.75, 8.36, 7.19 and 5.85, respectively. For the $SupF_T\ (\ell + 1/\ell)$ test, the critical value for break test: 0 vs. 1 is 11.47 and the critical value for break test: 1 vs. 2 is 12.95.

In the case of PEA, the first break date occurs on 19/09/2008, which falls in the second stage of the GFC. This break occurs shortly after the Lehman Brothers bankruptcy filing in September 2008. The second and third break date occurs on 13/11/2008 and 15/12/2010, respectively. The chapter also finds evidence in favour of break points on 11/8/2014, 28/5/2015 and 07/09/2016, respectively.

In the DE, the first break date occurs on 27/7/2007. This date is linked to the period of turmoil in the credit market, which occurred in the summer of 2007. The second break date occurs on 30/3/2009, which is consistent with the date identified by the QA test. The third break date occurs almost two years after the initial break date on 01/06/2009. For this region, the remaining breaks occur on 30/8/2011, 02/10/2013 and 24/8/2016, respectively. Since our interest is in the start date of the GFC, the chapter only selects the first break date that falls within the 2007 - 2009 period for each of the different regions. It uses these estimated dates in our regime switching model to demarcate the non-crisis regime from the crisis one.

4.5.2. Benchmark Results from the Contagion Model

This sub-section presents benchmark results from the contagion model. The purpose of determining the crisis dates using a variety of test procedures in the previous section is to obtain the start dates of the GFC for each of the regions in our sample and to incorporate these dates in the regime switching model before performing individual and joint tests of contagion. The tests of contagion are based on changes in the correlation and coskewness of returns in the crisis regime $s_t = 1$ as opposed to non-crisis regime $s_t = 0$. Significant increases in the parameters governing market dependence, i.e., correlation and coskewness of returns during the crisis regime implies contagion.

Table 4.6 present the benchmark results of the estimation for the contagion model.[46] It provides the changes in correlation and coskewness between the US market and markets in each of the different regions. The probability value (P) is used to evaluate the results of the tests of contagion through correlation, where a value of 1 indicates evidence of contagion. In contrast,

[46] Plots of probability values and log of Bayes factor for the benchmark results are presented in Appendix 10.

the log of the Bayes factor (BF) is used to evaluate the tests of contagion through coskewness, where a value that is more than -4.6 provides decisive evidence in favour of contagion. The more negative the value, the stronger the contagion.

As mentioned above, to assess whether there are estimation errors arising from the choice of date, the magnitude of estimates of changes in the correlation and coskewness for benchmark model will be compared to those of the alternative model. This chapter takes the difference between the probability values or the log of the Bayes factor of these models in order to conduct this assessment. If the difference is positive, then the alternative model overestimates the probability values and vice-versa. Also, if the difference is positive, then the alternative model underestimates the log of the Bayes factor and vice-versa. An overestimated value or factor might substantially exaggerate the occurrence of contagion while an underestimated value or factor might understate its existence.

Panel A of Table 4.6 reports the results of the test for contagion between the US and markets in ELA region. The individual test results reveal four out of five countries in this region exhibit changes in correlation during the GFC. This is because the values of their probabilities of correlations are 1, i.e., 100%, providing strong evidence in support of the occurrence of contagion through correlation. It is only in Colombia that there is no evidence in favour of contagion through correlation. When all the markets are jointly considered, there is still strong evidence of contagion through correlation; this is because their probabilities are 100%. This result confirms the findings of a recent study by Mollah et al. (2016) that estimate contagion models and highlights that the dynamic correlations between the US market and markets in ELA were high during the GFC. This is also consistent with the findings of Dungey and Gajurel (2014) and Aloui et al. (2011) that find correlations between the US and ELA markets during this crisis.

Turning now to the test for contagion through coskewness, the individual test results show that there is no evidence of contagion occurring through coskewness between the US and markets in ELA, except for Chile. This lack of evidence is because the values of the log of the Bayes factor for other markets all fall outside the scale for evidential support for contagion. Since the result shows that most of the markets in ELA did not exhibit changes in coskewness during crisis, these findings suggest that the coskewness of returns either remained stable or declined during the crisis. When the chapter considers the result of the joint test for contagion through coskewness between the US market and markets in ELA, it shows that the log of the Bayes factor has a value of -456.55. This indicates that there is decisive evidence in favour of contagion through coskewness between the US market and markets in ELA.

The row at the bottom of Panel A of Table 4.6 reports the result of the individual and joint tests for the joint occurrence of contagion through both correlation and coskewness. For the individual test, the result shows that the log of the Bayes factor between the country pairs Brazil-US, Chile-US, Colombia-US, Mexico-US, and Peru-US are -15.60, -150.23, -6.47, -81.89 and -34.00, respectively. These findings suggest there is decisive evidence of contagion through both correlation and coskewness. The dependence between Chile-US and Mexico-US are particularly stronger than between the US and other markets in the region. Similarly, for the joint test, the log of the Bayes factor with a value of -677.66 provides decisive evidence of contagion jointly occurring through correlation and coskewness.

Panel B of Table 4.6 presents the results for the individual and joint tests for contagion between the US and PEA. The individual tests for contagion in correlation between the US and markets in PEA reveals evidence of contagion in six out of the nine country pairs. These country pairs include China-US, Japan-US, Indonesia-US, Philippines-US, Singapore-US, and Thailand-US. There is evidence of contagion because the probabilities for these individual tests are all 100%. In contrast, probabilities of correlation for individual tests for the following country pairs, Hong Kong-US, Korea-US, and Malaysia-US are 99%, 88% and 99%, respectively. These results suggest that the stock markets in Hong Kong, Korea and Malaysia are largely not affected by the crisis of the US. This is in line with the findings by Mollah et al. (2016) who document that Asian markets were partially affected by the GFC. Nonetheless, when the chapter jointly tested for contagion through correlation between the US and markets in PEA, it finds that correlation has a probability of 100%, this finding provides evidence in support of contagion through correlation between the US market and markets in PEA.

In terms of the coskewness, the individual test results show that only one country out of nine exhibits changes in coskewness of returns during the crisis. In particular, the result shows that there is decisive evidence in favour of contagion between the US market and the market in the Philippines. With respect to the joint test for contagion through coskewness, the chapter finds that the log of the Bayes factor for the coskewness has a value -1359.5. This result indicates that there is decisive evidence in favour of contagion through coskewness between the US and all markets in PEA.

In the context of joint occurrence of contagion through correlation and coskewness, the individual test results show that eight out of nine markets in this region exhibit changes in both correlation and coskewness of returns during the crisis. These countries include China, Japan, Hong Kong, Indonesia, Korea, Philippines, Singapore, and Thailand. The log of the Bayes factor for all these markets falls within the scale of decisive evidence in support of contagion. With respect to the joint test, the results show that all markets in this region exhibit changes in both correlation and coskewness of returns during the GFC. This is because the log of the Bayes factor has a value of -1405.2, which falls within the scale for decisive evidence.

Panel C of Table 4.6 presents the contagion test results between the US market and markets in DE. From the results individual tests, it is striking to find that all nine markets in the DE exhibit changes in correlation during the crisis that favours contagion with the US market. The results show that the probabilities of correlation between the US market and markets in the DE are all 1, i.e., 100%. This finding suggests that following the GFC, the level of dependence between the US market and markets in this region increased. Now when the chapter turns to the joint test, the result clearly shows that the probabilities of correlation are all 100%. This result further suggests that movements in US returns strongly affected markets in the DE. This is consistent with a previous finding by Dungey and Gajurel (2014) who attributed the greater contagion effect in markets of the DE to panic among investors about the effect of the US crisis on European markets. In general, it is not surprising that it finds all markets in the DE being correlated with the US market during crisis. It simply reflects the regions integration with the global capital markets, which might explain why it exhibits strong comovement with the US market even during crisis.

When the chapter individually tests for contagion through coskewness, the results show that seven out of the nine markets in the DE exhibit changes in coskewness during the crisis. It shows that the value of the log of the Bayes factor for these seven markets exceeds -4.6. Thus, except for markets in Portugal and Ireland, it cannot rule out decisive evidence in favour of contagion. Next, when it jointly tests for contagion through coskewness, the results show that the value of the log of the Bayes factor for the joint test for the coskewness is -975.12. Thus, it still concludes that there is decisive evidence of contagion through coskewness.

Finally, the chapter carried out individual and joint tests for the joint occurrence of contagion through correlation and coskewness for this region. The results for these tests are reported in the last row of Panel C in Table 4.6. The results show that the log of the Bayes factor for all markets have values that suggest decisive evidence in favour of contagion through both correlation and coskewness. It reaches similar conclusions when the joint tests are conducted. This is because the log of the Bayes factor with a value of -6280.4 provides the decisive evidence in support of this conclusion.

Overall, the results of the individual and joint tests for contagion through the correlation and coskewness were considered. In addition, tests for the joint occurrence of contagion were also considered. These tests have been evaluated using either the probability value or the log of the Bayes factor. The analysis provides several findings. First, one observes that evidence in favour of contagion occurring through correlation is strongest for markets in the DE than their counterparts in other regions. Second, within the context of coskewness, interestingly the chapter finds decisive evidence in favour of contagion through coskewness for more markets in DE than in ELA and PEA regions. These findings suggest that there may be comovements in extreme returns during the GFC and strong dependence between the US market and other markets. The findings reveal that this dependence is stronger for markets in the DE than other regions. It seems reasonable to conclude that contagion through correlation dominates, although this does not diminish the importance of contagion through coskewness. Overall, it provides evidence of contagion through both correlation and coskewness.

4.5.3. Exogenously or Endogenously Determined Crisis Date for Analysis of Higher-order Comoments

The analysis, so far, has focused on the benchmark results of the model with endogenously determined crisis date. This sub-section aims to compare magnitude of estimates from this model with those from an alternative model where the dates were exogenously determined[47]. This direct comparison allows us to assess whether there are estimation errors arising from the approach used, i.e., whether the choice of this date is a potential source of estimation error in the measurement of contagion and whether the choice of the crisis date affects the magnitude of correlation and coskewness. Panels A, B and C of Figure 4.4 plot the differences in the probability value of correlation, differences in the value of the log of the Bayes factor for coskewness and differences in the value of the log of the Bayes factor for both correlation and coskewness. In each panel, the plots show with solid pyramids these differences in values. The chapter plots these differences in values for only markets where it found evidence of contagion. Since our focus is on this notion, it would make sense to evaluate whether there are any differences between the benchmark and alternative model results only when it can present evidence of contagion.

The results in Figure 4.4 are striking and it is evident from these figures how sample selection bias due to the inaccurate identification of the crisis date affects the test of contagion through correlation and coskewness. Clearly, one can see that the figure reveals considerable differences in the magnitude of estimates between the benchmark model and the alternative one. This is because employing contagion models with different crisis dates fails to yield similar magnitudes.

In Panel A of Figure 4.4, the chapter displays the differences in the probability of correlation for all three regions. In ELA, the probability of correlation for both Chile and Mexico appear to have been underestimated. For these two countries, the benchmark results show evidence of contagion through correlation. However, when the alternative model where an exogenously determined date is used for the demarcation of the non-crisis and non-crisis periods, it finds

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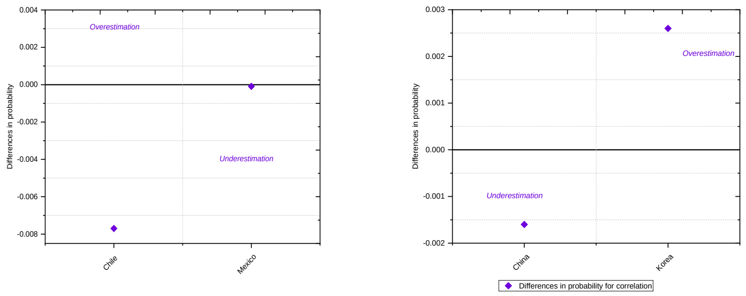
[47] The exogenously determined crisis date of March 3, 2008 used in the study by CFH is adopted.

that there is no evidence of contagion through correlation for these two countries. For PEA, the figure shows that the probability of correlation is underestimated for China but overestimated for Korea. Finally, when it considers the DE, the chapter does not find any differences between the results of the two models. Since it obtained identical results, it does not have any evidence to suggest differences in magnitude of estimates for correlation for only this region.

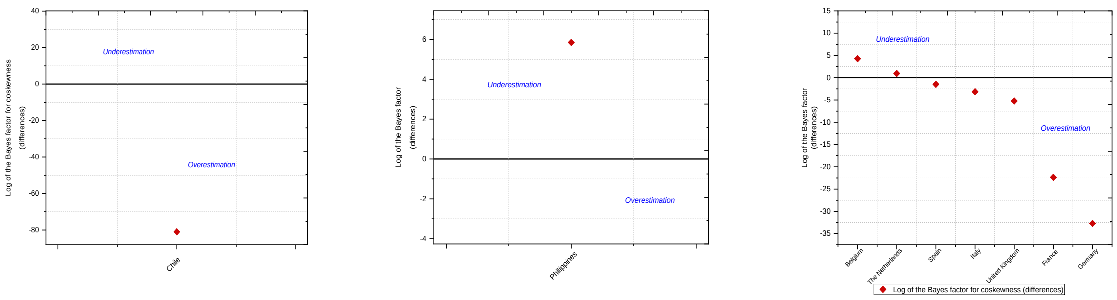
Of interest also is whether there are differences in the values of the log of the Bayes factor regarding tests for contagion through coskewness. Panel B of Figure 4.4 explores this as it displays the magnitude of differences between the results of the benchmark model and the alternative one. In the first plot of Panel B, which corresponds to the plots of differences in the values of the log of the Bayes factor for ELA, one can see that the value of the log of the Bayes factor is overestimated for Chile alone.

Figure 4.4: Differences in Magnitude of Estimates

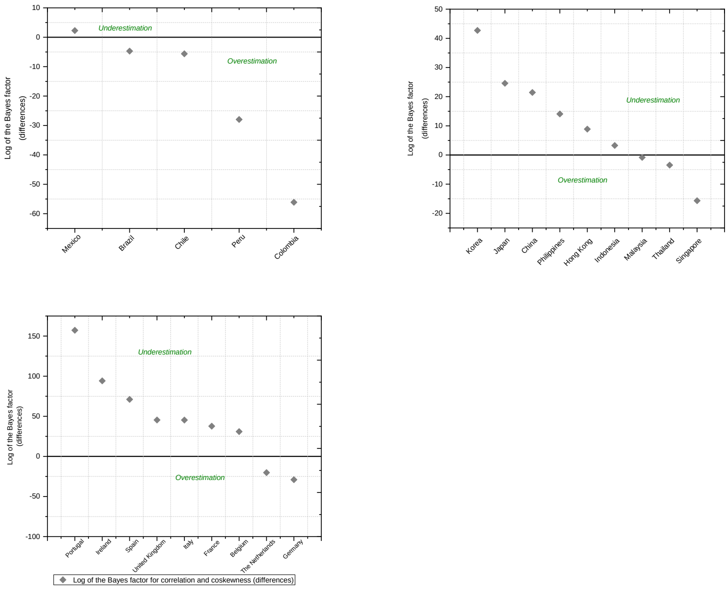
Panel A: Differences in the Probability for Correlation



Panel B: Differences in the Log of the Bayes Factor for Coskewness



Panel C: Differences in the Log of the Bayes Factor for Correlation and Coskewness



This shows that the estimated value of the log of the Bayes factor is higher for the alternative model (in absolute value) than the benchmark model. The value of the log of the Bayes factor is estimated as being larger than it really is. This suggests that a contagion model that uses an exogenously determined start date may exaggerate the extent of change in coskewness. Conversely, one can clearly see that for PEA region, i.e., in the middle plot, the value of the log of the Bayes factor is underestimated for only Philippines. This suggests that a contagion model that uses exogenously determined dates could also understate the extent of change in coskewness.

In the last plot of Panel B, which displays the differences between the values of the log of the Bayes factor obtained by the benchmark and alternative models for the DE, the chapter finds that the number of overestimates exceeds the number of underestimates. In particular, the values of the log of the Bayes factor are overestimated for Spain, Italy, UK, France, and Germany. Further, one can see that Germany and France have considerably larger magnitude of differences than Spain, Italy, and the UK. In contrast, the plot shows that the values of the log of the Bayes factor are underestimated for only Belgium and The Netherlands. It is obvious that the magnitude of differences in the value of the log of the Bayes factor is much larger for Belgium than The Netherlands. This suggests that the extent of change in coskewness may be understated. This is likely to happen when contagion models use exogenously determined dates.

The chapter now turns to examine whether there are differences in the values of the log of the Bayes factor for the joint occurrence of contagion through correlation and coskewness. As seen in the first plot of Panel C, which shows the plot of differences in the magnitude of estimates for contagion through both correlation and coskewness for ELA, the values of the log of the Bayes factor are largely overestimated for most markets in the region, with the exception of Mexico. It is striking to observe that the value of the log of the Bayes factor for Peru is highly overestimated. The difference in magnitude is even more pronounced when it considers Colombia. Obviously, the plot suggests that the observed differences in the values of the log of the Bayes factor for the joint occurrence of contagion through correlation and coskewness is mainly due to differences in the start date of the crisis period, which have been determined differently.

In the case of PEA, one can clearly observe from the middle plot of Panel C that the number of underestimates far exceeds that of overestimates. The values of the log of the Bayes factor for the joint occurrence of contagion through correlation and coskewness are underestimated for Korea, Japan, China, Philippines, Hong Kong, and Indonesia. Japan has the greatest difference in value of the log of the Bayes factor. The estimate of the benchmark model is almost 20 times larger than the estimated value obtained with the alternative model. Moreover, the value for the log of the Bayes factor obtained using our benchmark model supports the finding of contagion for Japan but this conclusion is not supported when the alternative model is used. In contrast, the values of the log of the Bayes factor for the joint occurrence of contagion through correlation and coskewness are overestimated for Malaysia, Thailand, and Singapore. The lowest and highest difference in value of the log of the Bayes factor occurs for Malaysia and Singapore.

The chapter also plots differences in the magnitude of estimates for the DE. One can see from the last plot in Panel C that there are far more underestimates than overestimates. Of the nine markets in the DE, seven of them have the values of the log of their Bayes factor understated while only two are overestimated. These values are grossly underestimated for Portugal, Ireland, Spain, UK, Italy, France, and Belgium. For instance, the difference in magnitude is so large for Ireland that for the estimated value of our benchmark model to match the alternative model, it would have to decrease by almost half. On the other hand, the plot shows that the value of the log of the Bayes factor for the joint occurrence of correlation and coskewness are overestimated for The Netherlands and Germany. This reveals that the alternative model arguably exaggerates the value of the log of the Bayes factor for the joint occurrence of contagion through correlation and coskewness.

In general, it is harder to find evidence of contagion through correlation using the alternative model as opposed to the benchmark model. This is because the chapter finds that the number of underestimates in the probability value for contagion through correlation exceeds the number of overestimates. On the other hand, it is easier to find evidence of contagion through coskewness using the alternative model versus the benchmark model. It attributes this to the fact that the number of overestimates in the value of the log of the Bayes factor for contagion through coskewness is much more than the number of underestimates. Thus, the alternative model seems to favour the existence of contagion through coskewness where there is none and thus, erroneously attribute changes in coskewness during crisis to the notion of contagion. In fact, even when it considers the joint occurrence of contagion through correlation and coskewness, it finds that it is much easier to find evidence in favour of contagion when it uses the alternative model as against the benchmark model. This finding is attributed to the fact that the number of overestimates in the value of the log of the Bayes factor for contagion through coskewness is greater than the number of underestimates.

Taken together, the results suggest that there are substantial differences in the magnitude of estimates of contagion depending on whether estimations are based on the alternative or benchmark model. It is straightforward to see that when the start date of the crisis period used to split the full sample into regimes is exogenously determined it is likely to lead to the overestimation (underestimation) of the values of correlation and coskewness. Overstating the values of correlation and coskewness would suggest exaggeration of the extent of contagion and vice versa. Our results suggest that previous works of contagion through correlation and coskewness are likely to suffer from estimation errors due to sample selection bias when the start dates of the crisis period are not endogenously determined. There is no paper, yet which shows this result, this chapter is the first to show this result.

In particular, the estimation error in correlation is trivial, although at times opposite conclusions are reached. It is, however, enormous for coskewness. Thus, the estimates are likely to be affected by selection bias arising from the choice of the crisis date. If there is no sample selection bias due to the choice of the start date for the crisis period, then the magnitude of estimates of the benchmark and alternative models should not have differed. By and large, from our comparison, the magnitude of estimates for correlation and coskewness seems to depend crucially on how the crisis start date is determined. One might conclude that the choice of the crisis date can bias the estimates. Hence, it can make an enormous difference whether an exogenously or endogenously determined crisis date is adopted. A crisis date that is endogenously determined might provide more accurate estimates due to correct sample split into non-crisis and crisis periods. In addition, the analysis suggests that the approach used to determine the crisis start date might be an important avenue through which the magnitude of contagion estimates are affected. Thus, accurate determination of this date should be an important consideration when modelling contagion.

Table 4.4: Contagion Test: Correlation and Coskewness

Panel A: ELA									
Contagion tests (i=j)	Contagion model	Method (DR)	**Individual Tests**						**Joint Tests**
			BRA	CHL	COL	MEX	PER	US	**for all**
Correlation	Exogenously determined date (CFH)	P	1	0.9923	0.9998	0.9999	1		1
Correlation	Endogenously determined date	P	1	1	0.9999	1	1		1
Coskewness	Exogenously determined date (CFH)	BF	-1.7211	-87.3098	1.4496	1.2754	1.6284		-812.905
Coskewness	Endogenously determined date	BF	1.0608	-6.3063	0.7919	1.0816	-1.771		-456.552
Correlation & coskewness	Exogenously determined date (CFH)	BF	-20.3224	-155.868	-62.574	-79.6233	-61.9661		-1063.900
Correlation & coskewness	Endogenously determined date	BF	-15.6014	-150.236	-6.4793	-81.8931	-34.0022		-677.664

Panel B: PEA													
Contagion tests (i=j)	Contagion model	Method (DR)	**Individual Tests**										**Joint Tests for all**
			CHN	JPN	HKG	IND	KOR	MAL	PHI	SGN	THL	US	
Correlation	Exogenously determined date (CFH)	P	0.9984	1	1	1	0.8848	0.9992	1	1	1		1
Correlation	Endogenously determined date	P	1	1	0.9999	1	0.8822	0.9992	1	1	1		1
Coskewness	Exogenously determined date (CFH)	BF	-1.0217	1.6086	0.6235	-0.1424	1.6664	1.2828	0.5151	1.0478	0.7583		-1202.300
Coskewness	Endogenously determined date	BF	0.3927	-1.4778	1.2264	1.1364	1.4456	1.453	-5.3315	1.7622	1.675		-1359.500
Correlation & coskewness	Exogenously determined date (CFH)	BF	-11.7703	-1.3471	-7.2677	-12.844	-4.5671	1.1383	-3.9817	-28.32	-9.6353		-1227.800
Correlation & coskewness	Endogenously determined date	BF	-33.2178	-25.944	-16.146	-16.111	-47.283	1.9582	-18.0677	-12.662	-6.1869		-1405.200

Panel C: DE

Contagion tests (i=j)	Contagion model	Method (DR)	**Individual Tests**										**Joint Tests for all**
			UK	FRA	GER	BEL	NET	POR	ITL	IRL	SPA	US	
Correlation	Exogenously determined date (CFH)	P	1	1	1	1	1	1	1	1	1		1
Correlation	Endogenously determined date	P	1	1	1	1	1	1	1	1	1		1
Coskewness	Exogenously determined date (CFH)	BF	-14.6978	-57.1641	-76.6795	-72.5509	-8.9033	-1.2381	-9.0002	1.1945	-12.0863		-1331.000
Coskewness	Endogenously determined date	BF	-9.4688	-34.8086	-43.9603	-76.8237	-9.8624	-2.5772	-5.8494	0.9093	-10.6026		-975.121
Correlation & coskewness	Exogenously determined date (CFH)	BF	-117.653	-157.3676	-176.5072	-208.7548	-151.7906	-502.1482	-182.8199	-100.9056	-107.206		-5183.000
Correlation & coskewness	Endogenously determined date	BF	-163.056	-195.086	-147.4942	-239.6388	-131.5898	-659.4279	-228.1659	-195.1463	-178.3153		-6280.400

4.5.4. Sensitivity Tests of Contagion Model

In this sub-section, the chapter explores the sensitivity of our benchmark model to alternative specification with respect to the crisis date. It will examine the sensitivity of our benchmark results to two different start dates for the GFC. These dates were arbitrarily chosen based on own judgement. It examines the sensitivity of our results to dates that occur (1) one month before the endogenously determined date, and (2) one month after the endogenously determined date. These two dates are not too far from the endogenously determined dates analysed in the earlier. It will, thus, change start dates in the benchmark model for each region to these new dates and re-estimate the model. Running these sensitivity tests will allow us to check whether the magnitude of estimates is sensitive to changes in the dates. In addition, it will allow us to check whether the researcher's use of judgement in selecting the date can affect the magnitude of estimates.

In Table 4.7, the chapter reports the results of the sensitivity test to changes in the crisis dates for markets in the different regions. To evaluate these results, it contrasts them against the benchmark results. As in the previous sub-section, similar results are again obtained, but using a different set of crises dates. An important finding presented in Table 4.7 is that estimation errors in correlations remain negligible. This finding is in line with our benchmark results presented in the earlier. The probability of correlation is reasonably close to the benchmark results, there are just some slight differences in the values of probability. For instance, when it considers ELA region, the result shows that the alternative model slightly underestimates the value of the probability of correlation when the date occurs one month before or after the endogenously determined date. For example, the probability of correlation is underestimated for Chile, Colombia, and Mexico when the date occurs a month before. It is, however, underestimated for only Chile when the date occurs a month after. In the case of PEA, the result shows that the probability of correlation appears overestimated for Hong Kong and Korea when the date occurs one month before. In contrast, probabilities are underestimated for China and Singapore, but when the date occurs one month after, probabilities are overestimated for Hong Kong, Korea, Malaysia. Finally, for the DE the result shows that when the date occurs one month before and after, the probability of correlation is the same as that of the benchmark

Table 4.5: Sensitivity Test: Contagion through Correlation and Coskewness

Panel A: LA									
Contagion tests (i=j)	Contagion model	Method (DR)	**Individual Tests**						**Joint Tests**
			BRA	CHL	COL	MEX	PER	US	**for all**
Correlation	Benchmark model	P	1	1	0.9999	1	1		1
Correlation	1 month before	P	1	0.9947	0.9998	0.9999	1		1
Correlation	1 month after	P	1	0.9972	0.9999	1	1		1
Coskewness	Benchmark model	BF	1.0608	-6.3063	0.7919	1.0816	-1.771		-456.5517
Coskewness	1 month before	BF	-3.1684	-117.3651	0.8619	1.1117	1.7028		-718.9337
Coskewness	1 month after	BF	-0.7507	2.1897	0.8826	0.3228	-4.3373		-335.0372
Correlation & coskewness	Benchmark model	BF	-15.6014	-150.2359	-6.4793	-81.8931	-34.0022		-677.6638
Correlation & coskewness	1 month before	BF	-18.7227	-172.4814	-47.0637	-83.5215	-40.7874		-947.0036
Correlation & coskewness	1 month after	BF	-13.7594	-19.5768	-4.5635	-37.2769	-162.2721		-548.6066

Panel B: PEA

Contagion tests (i=j)	Contagion model	Method (DR)	Individual Tests										Joint Tests
			CHN	JPN	HKG	IND	KOR	MAL	PHI	SGN	THL	US	for all
Correlation	Benchmark model	P	1	1	0.9999	1	0.8822	0.9992	1	1	1		1
Correlation	1 month before	P	1	1	1	1	0.8966	0.9992	1	1	1		1
Correlation	1 month after	P	0.9999	1	1	1	0.9779	1	1	0.9999	1		1
Coskewness	Benchmark model	BF	0.3927	-1.4778	1.2264	1.1364	1.4456	1.453	-5.3315	1.7622	1.675		1359.500
Coskewness	1 month before	BF	-0.5914	1.4063	-0.7172	-1.1269	1.5486	1.5335	1.4589	-4.2997	1.7643		1393.800
Coskewness	1 month after	BF	-2.9421	0.9596	-0.2785	-1.1983	1.4037	-0.2166	-1.5514	1.832	1.4392		1437.300
Correlation & coskewness	Benchmark model	BF	-33.2178	-25.9437	-16.1456	-16.1112	-47.2826	1.9582	-18.0677	-12.6618	-6.1869		1405.300
Correlation & coskewness	1 month before	BF	-13.1074	-1.9375	-8.7431	-29.2813	-4.2209	1.6001	-2.4173	-47.5127	-4.5376		1460.300
Correlation & coskewness	1 month after	BF	-17.5263	-5.9724	-11.5783	-49.208	-9.0285	0.2677	-46.5993	-60.4719	-5.2379		1527.000

Panel C: DE													Joint Tests for all
Contagion tests (i=j)	Contagion model	Method (DR)	Individual Tests										
			UK	FRA	GER	BEL	NET	POR	ITL	IRL	SPA	US	
Correlation	Benchmark model	P	1	1	1	1	1	1	1	1	1		1
Correlation	1 month before	P	1	1	1	1	1	1	1	1	1		1
Correlation	1 month after	P	1	1	1	1	1	1	1	1	1		1
Coskewness	Benchmark model	BF	-9.4688	-34.8086	-43.9603	-76.8237	-9.8624	-2.5772	-5.8494	0.9093	-10.6026		-975.121
Coskewness	1 month before	BF	-0.455	-17.9014	-1.2937	2.3055	1.7308	-0.2125	-48.7362	2.0512	-135.0413		1164.500
Coskewness	1 month after	BF	-0.3711	-8.8746	-1.4351	2.2918	1.6908	-0.2552	-30.7194	2.0716	-120.5469		1230.300
Correlation & coskewness	Benchmark model	BF	-163.0558	-195.086	-147.4942	-239.6388	-131.5898	-659.4279	-228.1659	-195.1463	-178.3153		-6280.400
Correlation & coskewness	1 month before	BF	-265.4792	-245.9674	-172.4138	-185.1403	-251.003	-406.8745	-295.9606	-274.4528	-341.5386		-6868.600
Correlation & coskewness	1 month after	BF	292.7933	-253.6647	-189.7594	-255.9804	-190.5836	-383.0902	-257.2561	-306.523	-311.2089		-7487.700

model. In a nutshell, the value of the probability of correlation is either slightly understated or overstated depending on the date used for markets in ELA and PEA except for those in the DE. A second finding shown in Table 4.7 is that estimation errors in coskewness remains enormous. When the chapter considers the ELA region, the log of the Bayes factor is underestimated for Colombia, Mexico, and Peru while it is overestimated for Brazil and Chile when the date occurs one month before. In sharp contrast, it is underestimated for Chile and Colombia while overestimated for Brazil, Mexico, and Peru when the date occurs one month after. In the case of PEA, the result shows that the log of the Bayes factor is overestimated for China, Hong Kong, Indonesia, and Singapore while it is underestimated for Japan, Korea, Malaysia, Philippines, and Thailand when the date occurs one month before. In contrast, it appears overestimated for China, Hong Kong, Indonesia, Korea, Malaysia, and Thailand, while it is underestimated for Japan, Philippines, and Singapore when the date occurs one month after. Lastly, for the DE the result shows when the date occurs one month before, the log of the Bayes factor appears underestimated for the UK, France, Germany, Belgium, The Netherlands, Portugal, and Ireland whereas it is overestimated for Italy and Spain. In contrast, it is underestimated for the UK, France, Germany, Belgium, The Netherlands, Portugal, and Ireland while it is overestimated for Italy and Spain when the date occurs one month after.

Thus far, the chapter has analysed the results for correlation and coskewness. It now analyses the results for the joint occurrence of contagion through correlation and coskewness. The results reveal that there are noticeable differences between results of the benchmark model and the models with dates occurring one month before or after. For example, the result shows that the log of Bayes factor is overestimated for all markets in ELA when the date occurs one month before. In contrast, it is underestimated for Brazil, Chile, Colombia, and Mexico, but overestimated for Peru when the date occurs one month after. For markets in PEA, the result shows that the log of Bayes factor appear overestimated for Indonesia, Malaysia, and Singapore, while it is underestimated for China, Japan, Hong Kong, Korea, Philippines, and Thailand when the date occurs one month before. In contrast, the log of Bayes factor is overestimated for Indonesia, Malaysia, Philippines, and Singapore, while it is underestimated for China, Japan, Hong Kong, Korea, and Thailand when the date occurs one month after. Finally, for the DE the result shows that the log of Bayes factor is underestimated for Belgium and Portugal whereas it is overestimated for the UK, France, Germany, The Netherlands, Italy, Ireland, and Spain when the date occurs one month before. Conversely, when it adjusts the date to one month after, it finds that it is underestimated for the UK and Portugal, but overestimated for France, Germany, Belgium, The Netherlands, Italy, Ireland, and Spain.

Overall, our results are highly sensitive to changes in the crisis start dates. Even when the dates are not too far from the endogenously determined one, the results are quite different. In addition, the chapter finds that there are wide differences in the magnitude of estimates, especially for the coskewness. This suggests that the use of researcher's judgement in selecting the date appear to affect the magnitude of estimates in contagion models. All the analyses in this sub-section have been conducted using high frequency data. Consequently, endogenously determining the date is important, but it is even more important for high frequency analysis using daily data. This is because it might be extremely difficult to use one's judgement or even event-based markers to pick out the true date that a crisis started from daily frequency data.

4.6. Conclusion

This chapter demonstrated that determining the start date of a crisis endogenously matters for magnitude of contagion model estimates. The chapter employed the QA and a variety of BP test procedures based on least-squares estimation. These tests were used to select the location of break points in the regional index of stock returns (vis-à-vis US stock returns) for stock markets in DE, PEA and ELA. It has also estimated dates for these break points and have identified the start dates for the GFC across markets in these different regions. The econometric tests were performed to allow us to identify the start dates of the crisis period accurately. Moreover, these tests have also been conducted to avoid potential sample selection bias prior to testing for contagion. This bias could arise when the full sample is not correctly split into non-crisis and crisis periods. Individual and joint tests for contagion through correlation and coskewness in regime switching models, where it assumed stock returns follow a skew normal distribution, have also been performed. In regime switching models, the endogenously determined start dates for the GFC were used to demarcate the non-crisis from crisis periods. The tests for contagion were all carried out using the Bayesian approach to inference. All our analyses were conducted using data from 04 January 2005 to 17 October 2018.

Many models for testing contagion in much of the previous research have used crisis start dates that were exogenously determined to partition the sample into non-crisis and crisis periods. Using this approach to partition the sample could result in a sample selection bias because the researcher forces a split of the full sample at an observation, which is not the true crisis start date, and as such, sub-samples may not be representative of the non-crisis and crisis periods. Clearly, sample selectivity might be present when the dates are exogenously determined. Even though the use of exogenously determined crisis start date is convenient, as the date can be easily be determined from event-based markers. Researchers run the risk of mis-specifying contagion models, which may confound results and the validity of inferences. The chapter proceeded to also test for contagion using models with exogenously determined dates. It compared the magnitude of estimates from contagion models with endogenously determined dates against models with exogenously determined dates. This comparison allowed us to evaluate whether there are differences between the estimates of contagion models based on these two approaches to crisis date identification. It also allowed us to ascertain whether estimation errors could arise from the choice of the crisis start date. Finally, this chapter explored the sensitivity of our benchmark results to different crisis start dates for robustness.

Based on our analysis, the chapter documents some important findings. First, it finds break dates associated with the global crisis. These dates are different for the three regions in our analysis. Our results thus justify the use of test procedures for structural breaks to identify crisis dates for contagion analysis, rather than determining these dates exogenously. Second, it finds evidence in favour of contagion occurring through correlation and this evidence is strongest for markets in DE than their counterparts in other regions. This suggests that markets in DE may be more closely linked to the US. Within the context of coskewness, interestingly it finds decisive evidence in favour of contagion for more markets in DE than in ELA and PEA. This finding suggests that there may be asymmetries in the dependence between US stock returns and returns of other regional markets. It also finds that contagion occurs mostly through correlation, rather than through coskewness. So, although coskewness does not account for most of the change in returns during crisis, it partly accounts for the change in returns. Third, it finds that the results of tests for contagion can substantially differ depending on how the start date of the crisis period is identified. This is because our result for the benchmark model that uses endogenously determined crisis date cannot be reconciled with the alternative model of contagion that uses exogenously determined crisis date. The result shows that changing the approach for date selection has a significant impact on the estimated results.

It is harder to find evidence of contagion through correlation using the benchmark model; however, it is easier to find evidence of contagion through coskewness using the alternative model. Although the chapter sometimes find that the alternative model attenuates the values of correlation and coskewness, it finds that it exaggerates these values and hence favours the existence of contagion where there is none. Our finding of overestimation and underestimation of the values of correlation and coskewness indicates a problem of sample selection bias with the use of exogenously determined dates in contagion models, which often tend to result in estimation errors. This finding shows that previous works of contagion through correlation and coskewness may likely suffer from estimation errors due to sample selection bias, especially when the start dates of the crisis period are not identified correctly. In general, it finds that the estimation error in correlation is trivial while it is enormous for coskewness. Thus, forthcoming studies on contagion based on higher-order comoment must determine crisis start dates using econometric tests prior to testing for contagion; otherwise researchers might run the risk of biasing results of contagion models.

In all, our findings suggest that the choice of the crisis start date can affect the magnitude of change in correlation and coskewness. Hence, it can make an enormous difference whether an exogenously or endogenously determined crisis start date is adopted. Identifying the crisis start date endogenously is crucial when the analysis is based on high frequency stock returns since it can be quite difficult to select the true start date of a crisis from such a frequency.

Our empirical work argues clearly against the use of exogenously determined crisis start dates in contagion models. A crisis start date that is endogenously determined might provide researchers with more accurate estimates due to correct sample split for the non-crisis and crisis periods. Finally, for robustness, our sensitivity analysis findings further indicate that contagion models are sensitive to the choice of the crisis start date. This suggests that the determination of the crisis start date for contagion analysis across stock markets is an important issue. The general conclusion that this chapter draws from our results is that the determination of the crisis start date might be such an important means through which the magnitude of correlation and coskewness are affected and neglecting the correct identification of the crisis start dates might lead one to either overstate or understate the magnitude of correlation and coskewness.

Our findings underline the importance of identifying crisis dates using empirical procedures, because any other approach to identification such as sequence of events may otherwise generate contagion estimates that are biased. The measurement of contagion can be improved by determining the crisis start date accurately using endogenously determined crisis start dates. By endogenously determining the crisis start dates, one will have a correctly specified contagion model and the estimated values of correlation and coskewness will become accurate. It is important to determine the crisis dates endogenously because when one does so, it allows the data on stock returns to speak for itself and this would not bias our findings on contagion. Thus, instead of exogenously determining the crisis start date, one could perhaps use structural break tests to locate the break points in the data on stock returns and estimate the break dates, this would help to overcome sample selection bias and model misspecification caused by the use of the wrong start date for the crisis period. Identifying the crisis start date accurately is not only useful in avoiding sample selection bias; it is also useful in eliminating estimation errors in contagion models. Applying our test procedures is the one of the most acceptable way of improving the accuracy of tests for contagion because one is able to avoid sample selection bias and this may guarantee that unbiased estimates are obtained, allowing one to make reliable inferences. Modelling contagion more accurately by correctly identifying the start date of a crisis should be an important consideration in contagion studies and should not be ignored.

It would be interesting if future research could consider applying our approach in other applications, for example, for studies on other financial market. Our study says nothing about other possible measures of contagion such as, co-kurtosis and co-volatility. Our empirical strategies may be useful for research in these contexts since it can easily be applied to most model specifications of contagion. While our focus has been on the crisis date, one could extend this analysis to examine other potential sources of estimation error in contagion models, but this is beyond the scope of our analysis in this present chapter. So, future research could investigate other unexplored but potential sources of estimation error. An interesting area would be to determine whether some other bias exists beside sample selection bias, and to explore how these biases would affect contagion estimates. Finally, another study could replicate our own study to investigate contagion from other crisis. This chapter does not pursue these extensions. The empirical strategies used are rather general and could be applied to any other study on crisis date identification.

Chapter 5: Conclusion

This thesis has presented a quantitative approach to the analysis of bubbles and financial contagion in stock markets of DEEs. Specifically, the analysis has focused on the stock markets in three different regions – developed Europe, Pacific and emerging Asia, and emerging Latin America. It has investigated some of the macroeconomic factors which contributed to the duration of stock bubbles and examined the existence of contagion in the presence of distinct breaks. Finally, it investigated how the choice of the crisis start date affects the magnitude of changes in coskewness. The investigation was based on multivariate clog-log and multivariate VAR, and the regime switching models.

The thesis showed empirically that the duration of bubbles has been primarily influenced by some macroeconomic factors. It has shown the significance and effect of factors on duration of stock bubbles. It has also showed that stock markets in DEE were affected by the recent financial crisis that originated from the US, and that the transmission of shocks has resulted in contagion, rather than interdependence during the GFC. If contagion has occurred between markets, then it is going to have significant implications for the international diversification of portfolios.

This chapter contains two sections. Section 1 provides a summary of the research undertaken in this thesis. Section 2 discusses some of the potential implications the empirical findings of the thesis might have for stock market dynamics in DEEs. In addition, this section concludes with some potential directions for future research. It places emphasis on the need to complement the analysis conducted in this thesis with research into other potential measurement issues and how these issues would affect the accuracy of contagion estimates and an investigation of business cycles effects on bubbles and its duration could be explored.

5.1. Summary of Research

This thesis was divided into 5 chapters. Chapter 1 presented a succinct summary of the motivation, key contributions, and layout of the thesis.

Chapter 2 investigated empirically whether macroeconomic factors affect the duration of bubbles in stock markets of DEEs. Emphasis was placed on the role of growth in GDP per capita, inflation, real oil prices, real gold prices, volatility in GDP per capita, inflation volatility, volatility in oil prices, volatility in gold prices and portfolio inflows, real interest rate gap and yield spreads in DEE. It also examined these roles across group of countries with different levels of income and financial development. The chapter argued that examining the roles of factors using the duration of bubbles, rather than the dynamics of bubbles, is also crucial because duration is also an important characteristic of bubbles. It further argued that exogenous factors matter, rather than just domestic factors. The chapter, first, examined the existence of bubbles in stock markets of DEE and extracted the durations of the bubbles for further analysis. It identified three important biases, which could pose problems and affect estimates: firstly, it argued that stock markets are heterogeneous and that there are factors that could affect the pricing of stocks that are not directly observable. Largely, this may be true for DEEs given their different local environments and different managerial quality in the international stock market. Thus, heterogeneity among markets and the problem of unobserved random effects needs to be addressed. Secondly, the chapter argued that estimates could be weakened due to the presence of endogeneity caused by the correlations of macroeconomic variables with the error terms, which violates the assumptions of independence and strict exogeneity. Thirdly, it argued that the omission of other possible explanatory variables in estimation model, which can be relevant for the analysis of the duration of bubbles in stock markets, could result in an omitted variable bias. The chapter addressed all these important sources of bias and adopted a multivariate clog-log regression model that could account for heterogeneity among stock markets and analyse the role of macroeconomic factors on the duration of bubbles. The chapter presented the baseline results and documented that two macroeconomic factors contemporaneously determined the duration of bubbles across all markets: firstly, the important role of inflation for the duration of bubble in stock markets of DEEs; and secondly, the role of portfolio inflows for bubble duration. The chapter concluded that both of these contemporaneous macroeconomic factors increased the duration of bubbles and reduced the probability that bubbles would end. Results also showed that some lagged macroeconomic factors determined the duration of bubbles across all markets. These factors, which consisted of past inflation, past portfolio inflows, past yield spreads, and past volatility in gold prices, decreased the probability of bubble duration. The results also showed that unobserved random effects influenced the duration of bubbles in DEE’s stock markets. It thus highlighted that it is crucially important to control for heterogeneity in stock markets to obtain accurate estimates. Finally, the chapter recognized that there are important differences between countries and so separated countries based on their level of income and financial development. The results based on countries' levels of income and financial development showed that macroeconomic factors had weaker effects on the duration of bubbles in financially developed stock markets situated in developed economies.

Chapter 3 empirically examined and tested whether there are changes and breaks in conditional correlation of returns during the GFC to assess contagion in stock markets of DEE. It argued that contagion occurred when cross-market dependence increased significantly following a shock to a particular country or set of countries. It further argued that it is only when such increased dependence is large enough to cause breaks in the process that generates returns that it can be implied that contagion has occurred. It further argued that common shocks were transmitted during the crisis. In addition, this chapter also argued that contagion occurred when return volatility spilled over from the crisis country to other countries. It relied on the assumption of distinct breaks for testing the existence of contagion through changes and breaks in conditional correlation of returns, and spillovers of return volatilities across stock markets of DEE. The chapter thus relied on this assumption to examine contagion as changes and breaks in conditional correlation of returns. While maintaining this assumption, it also examined contagion through spillovers of volatilities, which represented an empirical investigation into the behaviour, and evolution of spillovers of volatilities across stock markets. The chapter used a multivariate VAR model and a novel sequential procedure, to examine and test whether there are changes and breaks in conditional correlation of returns. It used the same model to obtain generalized forecast variance decompositions and used the variance decompositions to compute spillover indices. The indices were then used to examine the behaviour and evolution of volatility spillovers. Results showed that conditional correlations of returns changed significantly during the GFC and that transmission of shocks during this period caused breaks in the conditional correlation of returns, which were associated with the period of the GFC. Still in terms of changes in conditional correlation of returns, the result showed that the degree to which it changed varied across stock markets. Importantly, these changes were not interpreted as interdependence, but as evidence in support of the view that these correlations significantly increased during the GFC and caused contagion across stock markets of DEEs. The result showed that the evidence in favour of contagion was true for more markets in the

DE than markets in other regions. This reflected, in part, DE's high level of market integration in global financial markets. Finally, the result further showed that spillovers of volatilities exhibited time-variation because the model used for estimation relied on the assumption of distinct breaks. It thus established that the assumption of distinct breaks was important for detection of time variation in spillovers of volatilities.

Chapter 4 examined whether the approach used to determine the start date of the GFC crisis matters for estimates of contagion through coskewness for markets in DEE. It argued that, although the start date has been determined exogenously and endogenously for the analysis of contagion through coskewness, the magnitude of the change in coskewness could be affected by the choice of the date. Thus, the estimation accuracy could be affected by the choice of the crisis start date. In relation to the crisis start date, the chapter highlighted that it is crucial for demarcating the sample into non-crisis and crisis sub-samples prior to the analysis of contagion. It highlighted that two approaches could be used to determine the date: (i) exogenous, and (ii) endogenous. It, however, pointed out that the demarcation using dates based on the chronology of crisis events, i.e., exogenously determined dates, could result in a sample selection bias, and may result in biased estimates. It argued that if the underlying stochastic process for stock returns exists, then the start date of a crisis period could be determined quite precisely in models by applying test procedures that are inherently designed to detect the exact date, i.e., endogenously determined. It further argued that the magnitude of changes in higher-order comoments like coskewness could be affected by the approach used to determine the date. The chapter is thus an investigation of how the choice of this date affects the magnitude of changes in the coskewness of returns. The chapter presented the methodologies on structural break tests at unknown dates in linear regression based on least squares estimators for endogenously determining the start date of the GFC for markets in DEE. It also presented a detailed discussion of a regime switching model with skew normal distributional assumptions. The model, which was estimated using Bayesian approach based on the MCMC Gibbs sampling technique, was used for the analysis of contagion through changes in correlation and coskewness. Result showed different endogenously determined start dates of the GFC for the three regions under investigation. It further showed increased correlation and coskewness of returns in the stock markets of DEE during the GFC and that contagion occurred through both channels. The increased coskewness was interpreted as evidence of contagion, which suggested that there might be comovements in extreme returns during the GFC and strong dependence between the US market and other markets. In addition, contagion transmitted through the channel of correlation dominated, rather than coskewness. It confirmed that contagion through both channels was much stronger for markets situated in the DE than markets in other regions. This stronger contagion was interpreted as close links between markets in the DE and the crisis country. Importantly, the chapter showed that estimates of contagion models using endogenously determined crisis dates could not be reconciled with models that exogenously determined these dates. It thus highlighted the importance of endogenously determining the start date of a crisis particularly for higher-order comoment like coskewness. Overall, this chapter highlighted that the magnitude of contagion estimates could substantially differ depending on how the start date of the crisis period is determined.

It conducted this investigation by assessing the magnitude of changes in the coskewness of returns from models with endogenously and exogenously determined dates.

5.2. Implications for Policy

In the case of bubbles, this thesis has shown empirically its existence in stock markets of DEE. Stock prices can change dramatically, and markets can boom. When the sharp run-up in stock prices is caused by a bubble it usually boosts economic activity. However, sustained periods of rising stock prices will also generate inflation (Mishkin, 2008). This will raise policy concerns about the most appropriate and effective monetary policy measures to formulate to combat the inflation. The intervention of the monetary authority will be required and ultimately, the attempt by them to fight inflation or reduce inflationary pressure, however, through tighter monetary policy stance, could eventually destabilize the economy. This is because the monetary authority would maintain interest rates at high level and this contraction in policy could intensify liquidity constraints for firms, particularly small firms. Indeed, in this thesis, there was evidence that past inflation and the fluctuation of these rates - which reflect uncertainty and rise in persistence, were the driving forces behind the duration of stock bubbles. Prescription of improved inflation stabilization policies is necessary while ensuring liquidity constraints are addressed.

Against the background of increased financial integration in DEE's, it was earlier highlighted in this thesis that contagion is an important aspect of this integration. The stock markets of DEE experienced sharp falls in returns and increased volatility during the GFC. The plummeted returns and enormous volatility experienced by markets was caused primarily by the transmission of shocks that arose from the crisis. In the context of volatilities, a higher fluctuation in stock returns prompted investors to withdraw money from markets, particularly markets in emerging economies, which triggered large underperformance in these markets (Niklewski and Rodgers, 2013).

The behaviour of stock markets in DEE becomes severely affected in the case of increased cross-market dependence, measured by either correlation or coskewness, particularly if this pronounced increases in cross-market dependence is caused by a crisis event. During the GFC, the stock markets of DEEs were characterised by significantly increased cross-market dependence and sudden breaks in extreme comovements. Indeed, the crisis in fact caused structural changes across stock markets of DEE, i.e., crisis-induced changes in the structure of stock markets. As mentioned earlier, the dynamics observed in the stock markets of DEE's during the GFC bring, yet again, the question of international portfolio diversification to the centre of discussion. It is argued that the diversification of investors' portfolios would help to eliminate non-compensated risk (Goetzmann and Kumar, 2008), but following the recent financial crisis, many investors were unable to hold a diversified portfolio of stocks.

This thesis has support for the theory of contagion across stock markets of DEE during the GFC. Indeed, the policy measures that would insure against adverse shock transmission and increase resilience in the stock markets are advocated. It is thus paramount that countries reduce their vulnerability to such shocks. To prevent the build-up of vulnerabilities, according to Forbes and Rigobon (2000), the channel through which shocks are transmitted matters. For instance, if they are transmitted mainly through transitory channels — which are channels that exist just after a crisis has occurred —, then capital controls, which is a type of short-run isolation strategy, could be extremely effective in reducing the effect of shocks transmitted from a crisis to other parts of the world. Thus, this strategy could be crucially important in times of crisis to prevent large and sudden breaks in the transmission mechanisms between markets. However, this strategy would not always be appropriate particularly if shocks are transmitted largely through permanent channels — which are channels that exist in all states of the world, i.e., when there is no contagion. This is because the use of capital controls will cause a delay in the country's adjustment to shocks. Thus, in Forbes and Rigobons' (2000), view, capital controls could be useful in temporarily delaying the transmission of a crisis from one country to the other; however, this strategy cannot inhibit the necessary fundamental adjustment through long-term linkages such as trade. Obviously, this strategy is not sufficient to insure against shock transmission to stock markets of DEEs. Complementary strategies are important.

Following the general discussion about insuring against adverse shock transmission presented above, more specific policy implications that directly stem from our results will be discussed hereafter. The finding of this thesis provides important insights for policy makers in DEEs and for researchers. The results suggest that the magnitude of changes in coskewness are considerably affected by how the crisis start dates are chosen. Researchers need to ensure that these dates are always endogenously determined, as this is important for avoiding sample selection bias and unbiased contagion effects. Second, the results show evidence of breaks in conditional correlation of returns during crisis and contagion. Policy makers need to consider strategies that could be used to insure against adverse shock transmission and increase resilience in the markets. Finally, the results show that macroeconomic factors are important for the duration of bubbles, especially inflation. To this end, effective policy tools must be continuously used by policy makers to stabilize general prices.

This thesis has opened up three interesting directions for future research on contagion and bubbles based on the results and their implications discussed earlier. First, the findings of this thesis have revealed that the choice of the crisis start date is a source of bias in estimates of contagion models. Other unexplored but potential sources of measurement issues can be explored to determine how these issues would affect contagion estimates. Second, an extensive investigation into the breaks in conditional correlations using contagion models the rely on the assumption of distinct breaks is necessary, if possible using data on the different economic sectors in the stock market would provide a deeper insight into the specific sectors affected by the transmission of shocks. Finally, an investigation of whether business cycles effects are important for the duration of stock bubbles is an area that could be considered in future research. Investigation into all these areas will be rewarding and will produce important policy implications.

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Appendices

Appendix 1: List of Countries Grouped by Income and Financial Development Levels

Countries	Grouping by income level	Grouping by level of financial development
Australia	High	High
Belgium	High	High
Brazil	Middle	High
China	Middle	Intermediate
Colombia	Middle	Intermediate
Germany	High	High
Hong Kong	High	High
Indonesia	Middle	Intermediate
Ireland	High	High
Italy	High	High
Japan	High	High
Korea	High	High
Malaysia	Middle	High
Mexico	Middle	Intermediate
Netherlands	High	High
New Zealand	High	Intermediate
Portugal	High	High
Singapore	High	High
Spain	High	High
Thailand	Middle	High
US	High	High

Notes: Countries were classified into high- and intermediate- levels of financial development using the IMF's country ranking for level of financial development. Countries with highly developed financial sectors have a score between 0.951 and 0.635 on the ranking scale while countries at the intermediate level of financial development have a score ranging between 0.634 and 0.318.

Appendix 2: Variables, Variable Description and Sources

Variables	Description	Sources
Stock returns	Changes in the log of stock prices	MSCI and own computations
duration of bubbles	The total time period that a stock market is at risk of bubbles	own computations based on GSADF test estimates
Bubbles	Dummy variable that equals one if a stock bubble survives, and zero otherwise	own computations based on GSADF test estimates
Growth in GDP per capita	The growth in GDP per capita deflated by the Purchasing Power Parity (measured in US$)	World Bank
Real oil prices	Brent crude oil prices deflated by the CPI (measured in US$)	IMF
Real gold prices	Gold prices deflated by the CPI (measured in US$)	IMF
Growth in consumption	Growth in consumption is measured as the change in real consumption. Real consumption is the nominal final consumption expenditure deflated using the CPI and divided by GDP (measured in US$)	World Bank
Growth in investment	Growth in investment is measured as the change in real gross capital formation. Real gross capital formation is the nominal gross capital formation deflated by the CPI divided by GDP (measured in US$)	World Bank
Inflation	Rate of change in CPI multiplied by 100	World Bank
Portfolio inflows	Portfolio investment liabilities divided by GDP in percentages	World Bank

Variables	Description	Sources
Interest rate gap	Interest rate gap is the difference between the short-term real interest rate and the Wicksell's natural rate of interest	IMF, OECD and own computations
Yield spreads	Yield spreads is computed as the difference between the 10-year sovereign bond yields and the treasury bills rates	IMF, Thomson Reuters DataStream and Eikon
volatility in GDP per capita	Volatility in GDP per capita is the standard deviation of the log difference of real GDP per capita	World Bank, own computations
Inflation volatility	Inflation volatility is computed as one plus the standard deviations of three-year rolling window of the CPI inflation rate in logarithms	World Bank, own computations
Volatility in oil prices	Volatility in oil prices is the standard deviation of the log difference of real crude oil prices	IMF, own computations
Volatility in gold prices	Volatility in gold prices is the standard deviation of the log difference of real gold prices	IMF, own computations
GDP deflator	Inflation as measured by the rate of price change of the GDP implicit deflator	World Bank
Inflation volatility, GDP deflator	Inflation volatility is computed as one plus the standard deviations of three-year rolling window of the GDP deflated inflation rate in logarithms	World Bank, own computations

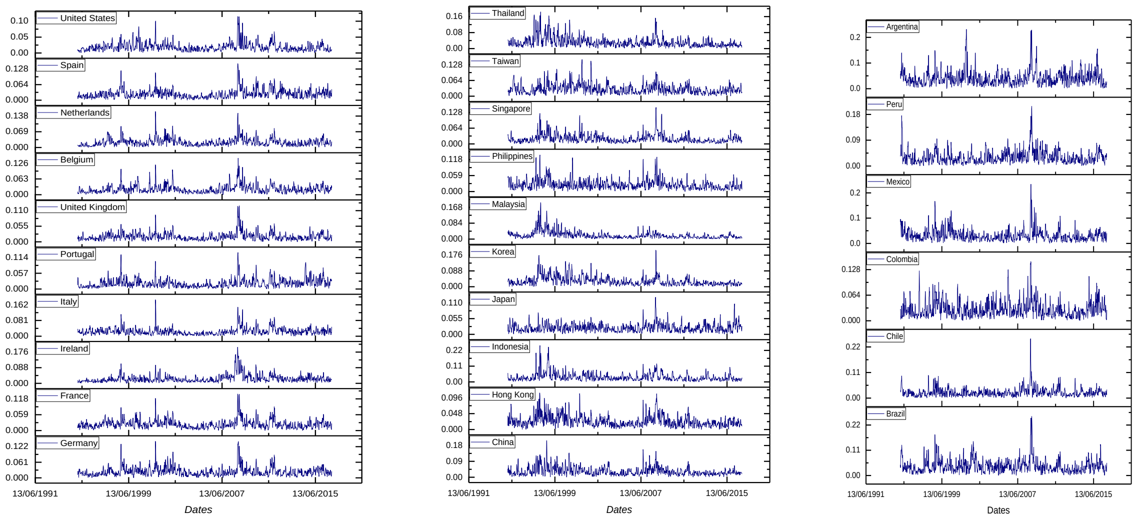
Appendix 3: Summary Statistics for Returns Volatility

	Mean volatility of returns	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Panel A: DE markets						
UK	0.0192	0.1268	0.0003	0.0144	2.6980	15.9420
France	0.0247	0.1359	0.0004	0.0166	2.1029	11.2885
Germany	0.0253	0.1428	0.0004	0.0188	2.3133	11.5896
Belgium	0.0230	0.1461	0.0001	0.0169	2.1746	10.8129
The Netherlands	0.0237	0.1579	0.0004	0.0172	2.3885	13.9890
Portugal	0.0217	0.1320	0.0002	0.0166	2.0528	9.9266
Italy	0.0256	0.1877	0.0008	0.0189	2.6515	15.9779
Ireland	0.0274	0.2034	0.0001	0.0227	2.9399	16.3819
Spain	0.0265	0.1501	0.0004	0.0186	2.0436	10.3613
Panel B: PEA markets						
China	0.0356	0.2077	0.0010	0.0259	1.8490	8.2879
Hong Kong	0.0262	0.1106	0.0001	0.0177	1.5779	6.2185
Indonesia	0.0348	0.2542	0.0006	0.0305	2.7908	14.9752
Japan	0.0240	0.1297	0.0012	0.0154	1.7357	9.1597
Korea	0.0325	0.2038	0.0007	0.0262	2.0542	9.2673
Malaysia	0.0209	0.1929	0.0002	0.0206	3.2148	18.8190
Philippines	0.0267	0.1347	0.0004	0.0189	2.0322	9.6671
Singapore	0.0223	0.1481	0.0001	0.0183	2.3684	11.6765
Taiwan	0.0299	0.1491	0.0008	0.0204	1.6024	7.0785
Thailand	0.0334	0.1835	0.0007	0.0270	2.1726	9.1893
Panel C: ELA markets						
Brazil	0.0430	0.2579	0.0005	0.0311	2.3000	12.4360
Chile	0.0254	0.2553	0.0001	0.0205	3.9311	34.8829
Colombia	0.0302	0.1480	0.0006	0.0216	1.6834	7.1830
Mexico	0.0334	0.2342	0.0004	0.0252	2.5987	14.6728
Peru	0.0318	0.2082	0.0003	0.0239	2.3435	13.0762
Argentina	0.0429	0.0310	0.0001	0.2311	2.2620	11.2853
Panel D: Crisis source market						
U.S.	0.0196	0.1150	0.0004	0.0146	2.4370	12.5565

Source: Author’s compilation

Appendix 4: Evolution of Returns Volatility

Figure A4.1: Plots of the Evolution of Returns Volatility



Appendix 5: Conditional Means and Variances using Returns Volatility

Table A5.1: Results of Changes and Breaks in Conditional Means and Variances using Returns Volatility

max LR test	T.S [739.35]	C.V [364.60]	p-value [0.00]
Estimated break dates	15-Oct-99	19-Mar-04	15-Aug-08
95% confidence intervals	[20-Aug-99, 05-Nov-99]	[27-Feb-04, 02-Apr-04]	[01-Aug-08, 24-Oct-08]
Coefficients changes for DE	Regime 1 to 2	Regime 2 to 3	Regime 3 to 4
Constant	1.862	-4.118	4.896
GER_{t-1}	-4.279	1.984	-1.629
FRA_{t-1}	1.766	-3.733	-0.748
IRL_{t-1}	4.452	0.531	6.455
ITL_{t-1}	2.344	3.330	1.865
POR_{t-1}	4.907	-4.131	1.326
UK_{t-1}	-0.260	0.192	-0.117
BEL_{t-1}	5.490	-2.537	5.293
NET_{t-1}	-1.364	-5.472	4.535
SPA_{t-1}	-2.538	2.551	-2.791
USA_{t-1}	-0.415	0.242	-0.169
max LR test	T.S [845.99]	C.V [420.66]	p-value [0.00]
Estimated break dates	10-Mar-00	08-Jun-07	28-Oct-11
95% confidence intervals	[20-Aug-99, 25-Aug-00]	[02-Sep-05, 15-Jun-07]	[21-Oct-11, 06-Apr-12]
Coefficients changes for PEA	Regime 1 to 2	Regime 2 to 3	Regime 3 to 4
Constant	-53.201	112.515	-30.300
CHN_{t-1}	49.949	-81.058	39.894
HKG_{t-1}	-0.226	0.221	-0.249
IND_{t-1}	-0.017	0.423	-0.186
JPN_{t-1}	-0.392	2.809	-0.929
KOR_{t-1}	-3.178	4.769	-5.198
MAL_{t-1}	-2.704	2.730	-1.277
PHI_{t-1}	0.617	-0.488	2.551
SIN_{t-1}	0.536	0.442	-2.438
TAI_{t-1}	1.754	-8.215	6.878
THA_{t-1}	2.847	-1.174	-1.546
USA_{t-1}	-0.442	-1.152	1.823
max LR test	T.S [450.74]	C.V [193.84]	p-value [0.00]
Estimated break dates	14-Apr-00	16-Dec-05	21-May-10
95% confidence intervals	[25-Jun-99, 22-Dec-00]	[21-Oct-06, 06-Jan-06]	[30-Apr-10, 27-Aug-10]
Coefficient change for ELA	Regime 1 to 2	Regime 2 to 3	Regime 3 to 4
Constant	21.374	71.010	-1.108
BRA_{t-1}	-0.763	0.028	0.040
CHI_{t-1}	-0.567	2.650	-1.728
COL_{t-1}	2.187	-0.527	-0.898
MEX_{t-1}	-0.160	0.116	-0.073
PER_{t-1}	1.135	-0.853	0.971
ARG_{t-1}	0.471	-0.240	-0.124
USA_{t-1}	-1.273	-0.219	2.066

Panel B: Conditional variance			
max LR test	T.S [1156.96]	C.V [387.02]	p-value [0.00]
Estimated break dates	11-Oct-02	06-Apr-07	19-Aug-11
95% confidence intervals	[18-Feb-00, 22-Nov-02]	[23-Feb-07, 06-Apr-07]	[19-Aug-11, 04-May-12]
Change in standard deviation for DE	Regime1 to 2	Regime 2 to 3	Regime 3 to 4
GER	-0.425	0.420	0.040
FRA	-0.408	0.556	-0.217
IRL	-0.278	0.265	-0.529
ITL	-0.500	0.320	-0.285
POR	-0.515	0.369	-0.255
UK	-5.010	8.454	-2.881
BEL	-0.232	0.144	0.015
NET	-0.476	0.389	-0.025
SPA	-0.246	1.015	-0.412
USA	-4.242	5.085	0.518
max LR test	T.S [2488.23]	C.V [281.24]	p-value [0.00]
Estimated break dates	02-Feb-01	22-Dec-06	06-Jan-12
95% confidence intervals	[22-Dec-00, 06-Jul-01]	[14-Jul-06, 13-Jul-07]	[20-May-11, 25-May-12]
Change in standard deviation for PEA	Regime 1 to 2	Regime 2 to 3	Regime 3 to 4
CHN	-0.931	0.792	-0.569
HKG	-51.436	71.526	-35.219
IND	-2.824	38.644	8.837
JPN	-2.329	2.078	0.393
KOR	0.244	3.183	-2.166
MAL	-2.573	2.043	-1.185
PHI	-4.771	4.529	1.307
SIN	-4.195	9.141	-9.144
TAI	-1.363	0.224	-0.708
THA	-2.650	2.012	0.063
USA	-1.754	3.647	-0.940
max LR test	T.S [3906.73]	C.V [270.48]	p-value [0.00]
Estimated break dates	04-Jun-99	21-Oct-03	18-Apr-08
95% confidence intervals	[28-May-99, 09-Jul-99]	[17-Oct-03, 05-Dec-03]	[04-Apr-08, 03-Apr-09]
Change in standard deviation for ELA	Regime 1 to 2	Regime 2 to 3	Regime 3 to 4
BRA	-5.333	25.875	5.701
CHI	-3.478	7.460	11.526
COL	-1.232	5.788	4.710
MEX	7.339	24.556	22.497
PER	-1.242	10.190	5.505
ARG	-2.269	9.559	16.077
USA	5.979	-5.668	4.771

Figure A5.1: Changes in Coefficients of Conditional Means and Variances for the DE

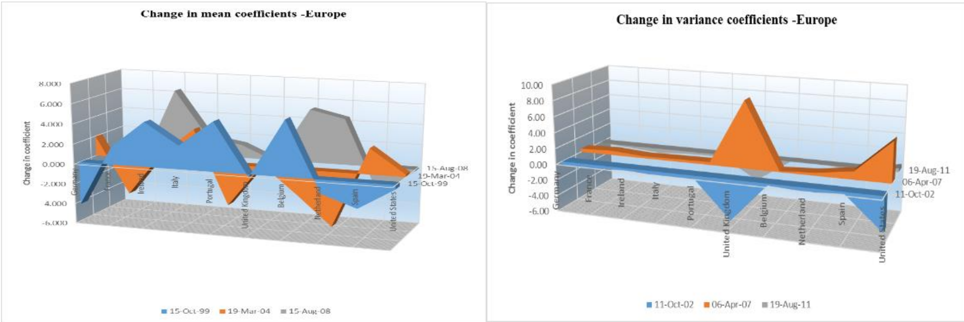


Figure A5.2: Changes in Coefficients of Conditional Means and Variances for PEA

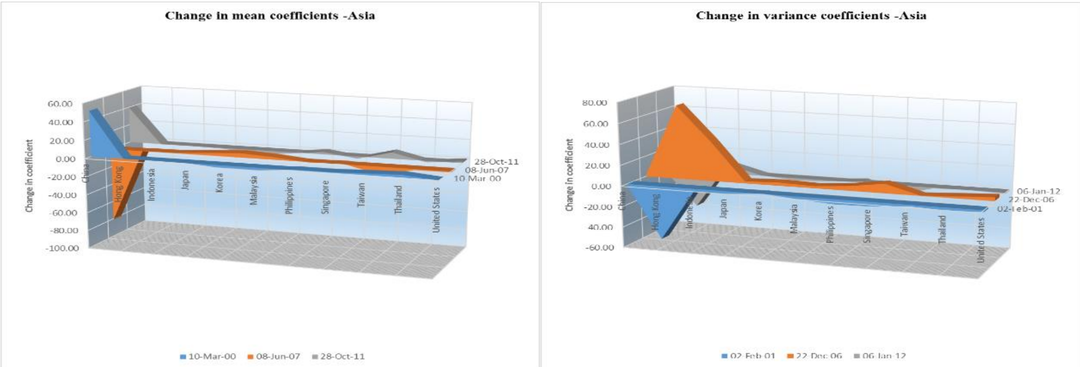
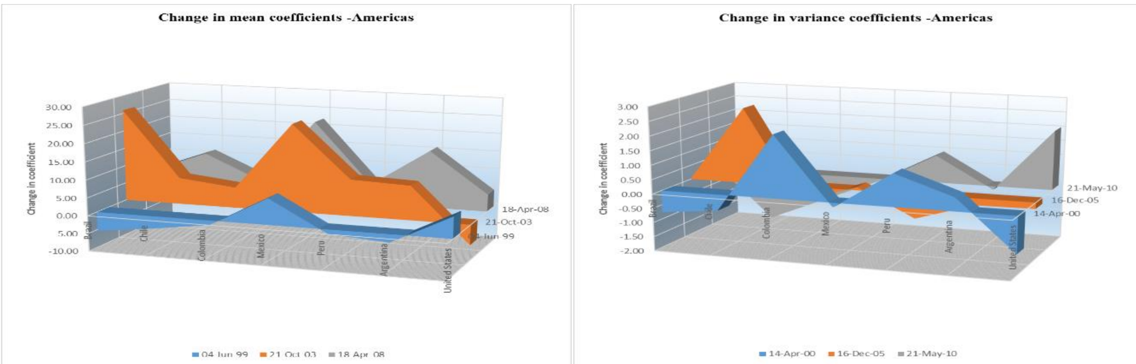


Figure A5.3: Changes in Coefficients of Conditional Means and Variances for ELA



Appendix 6: Bayesian Inference Methods via Gibbs Sampling MCMC Technique

Here, the empirical strategy for estimating the regime switching model and the implementation steps is briefly presented. Approximation techniques, specifically MCMC technique, are commonly applied when performing standard Bayesian inferences. To generate useful posterior distribution approximations and to arrive at accurate probabilistic inferences of model parameters, it applies Bayesian inference methods by Gibbs sampling MCMC approximation technique due to the presence of hidden factors. This chapter adopts this technique because it readily accommodates data with high dimensionality, it is efficient at sampling high dimensional vector of variables, and it provides a satisfactory performance because it does not suffer from the problem of non-convergence.

The MCMC procedure utilizes the posterior distributions during estimation to provide efficient estimates, which makes it particularly suitable and convenient for the joint estimation of the model's conditional parameters. The posterior distributions are generated by updating the prior belief of our model parameters through Bayesian iterative procedure with likelihood functions. The updating process that this chapter uses is via Gibbs-type posteriors based on Kim *et al*., (1998), Kim and Nelson, (1999), Koop and Korobilis, (2010) and Del Negro and Primiceri (2015). Thus, the regime switching model can be estimated with greater flexibility. Moreover, the procedure allows for the possibility of modelling parameter uncertainty. It is important to model uncertainty in model parameter because there might be considerable prior uncertainty in the parameters of the specified model, which can be crucial for understanding the behaviour of stock returns. The Bayesian procedure can handle higher-order moments in the probability density function.

Consider the likelihood function given by

$$f\ (y|Z,\Theta,\mathrm{s}) = (2\pi)^{-\frac{mT}{2}} \prod_{t=1}^{T} \left|\Sigma_{s_t}\right|^{-\frac{1}{2}} exp\left\{-\frac{1}{2}\sum_{t=1}^{T}\left[y_t - X_t\beta_{s_t}\right]'\Sigma_{s_t}^{-1}\left[y_t - X_t\beta_{s_t}\right]\right\}, \qquad (1)$$

where $\Theta = (\beta_0, \beta_1, \Sigma_0, \Sigma_1)$ and $s_t \in \{0, 1\}$, Π denotes the underlying distribution.

The Prior specification

To implement the joint estimation of returns for the different measures of contagion, for each measure, this thesis uses the following prior parameters given by

$$\beta_{s_t} \sim N\left(\underline{\beta}, \underline{V_\beta}\right), \tag{2}$$

$$\Sigma_{s_t} \sim IW\left(\underline{S_\Sigma}, \underline{\tau_\Sigma}\right), \tag{3}$$

$$p_{it} = \Pr\left(s_t = 1|s_t = i\right), \qquad 1 - p_{it} = \Pr\left(s_t = 0|s_t = i\right), \tag{4}$$

where $IW\left(\underline{S_\Sigma}, \underline{\tau_\Sigma}\right)$ denotes the normal inverted Wishart distributions used as the conjugate prior having a positive definite scale matrix, $\underline{S_\Sigma}$ with degree of freedom, $\underline{\tau_\Sigma}$. In our empirical analysis, the prior mean, $\underline{\beta}$ and prior covariance matrix, $\underline{V_\beta}$ are set to $\underline{\beta} = \left(\underline{\mu'}, \underline{\omega'}\right)'$ and $\underline{V_\beta} = \begin{bmatrix} \phi_\mu I_m & 0 \\ 0 & \phi_\omega I_k \end{bmatrix}$, respectively, where $k = m^2$. A fraction p_{it} of the measures of contagion have its parameters obtained from the normal inverted Wishart distributions when $s_t = 1$while a fraction $1 - p_{it}$ of the measures have truncated normal distributions.

The Posterior specification

From Bayesian inference, it follows that the joint posterior distribution depends on the joint prior distribution, $\pi\ (\Theta, Z, s|y)$ and the likelihood function for all data, $f\ (y|Z, \Theta, \mathrm{s})\ f\ (Z)\ f\ (\mathrm{s}|\Theta)$ which is defined as

$$\underbrace{\pi\ (\Theta)}_{\text{joint posterior distribution}} = \underbrace{\pi\ (\Theta, Z, s|y)}_{\text{joint prior distribution}} \quad \underbrace{f\ (y|Z, \Theta, \mathrm{s})\ f\ (Z)\ f\ (\mathrm{s}|\Theta)}_{\text{likelihood function for all data}}, \tag{5}$$

where π denotes probability density functions (p.d.f.) for the prior and posterior. Equation (5) shows that the joint posterior distribution, on the left-hand side of the equation, consists of two terms. The first term on the right-hand side of this expression, is the joint prior distribution, which is the distribution based on relevant and available prior information. The second term is the likelihood function for all data, which is the sample information.

If this thesis assumes that the independence assumption holds between β and Σ, then the joint prior density of Eq. (5) is

$$\pi\,(\Theta) = \pi\,(\beta_0)\pi\,(\beta_1)\pi(\,\Sigma_0)\pi\,(\Sigma_1). \qquad (6)$$

The sampling procedure, which requires drawing random samples via the Gibbs sampler from the true joint posterior distributions, $\pi(\cdot)$ proceeds in several steps:

Step 1. Specify initial values for all parameters in the set $\Theta^{(0)} = \left(\beta_0^{(0)}, \beta_1^{(0)}, \Sigma_0^{(0)}, \Sigma_1^{(0)}\right)$ and $Z^{(0)}$ where $\beta_l^{(0)}\left(\mu_l^{(0)'}, \omega_l^{(0')}\right)'$. Restrict the interval of the elements for all parameters over the range zero to one, $l = 0, 1$. Then initialize counter for 1 to nth iterative loop.

Step 2. Sample $s^{(loop)}$ from $\pi\left(s|y, z^{(loop-1)}, \Theta^{(loop-1)}\right)$ where $\Theta^{(loop)} = \left(\beta^{(loop)}, \Sigma^{(loop)}\right)$.

Step 3. Sample $\beta_l^{(loop)}$ from $\pi\left(\beta_l|y, z^{(loop-1)}, \Sigma^{(loop-1)}, s^{(loop)}\right)$.

Step 4. Sample $\Sigma_l^{(loop)}$ from $\pi\left(\Sigma_l|y, z^{(loop-1)}, \beta_l^{(loop-1)}, s^{(loop)}\right)$.

Step 5. Sample $z^{(loop)}$ from $\pi\left(Z|y, \Theta^{(loop-1)}, s^{(loop)}\right)$.

Step 6. Return to step 2 and repeat up to nth loop

As with any standard Bayesian inference method, our MCMC technique for approximating the skew-normal sampling distributions involves repeatedly generating realizations for each parameter through simulations.

The posterior distribution of the parameter, $\beta_l = l = 0, 1$ which is conditional on $(y, Z, \Sigma_0, \Sigma_1)$ and s has a q-variate normal distribution with $q = m + k$ is

$$(\beta_l|y, Z, \Sigma_l, \mathrm{s}) \sim N_q\left(\hat{\beta}_l, \mathrm{D}_{\beta_l}\right), \;\; l = 0, 1, \qquad (7)$$

where $\mathrm{D}_{\beta_l} = \left(\underline{V}_\beta^{-1} + \sum_{t=1}^{T} 1(s_t = l)X_t' \Sigma_{s_t}^{-1} X_t\right)^{-1}$ and $\hat{\beta}_l = \mathrm{D}_{\beta_l}\left[\underline{V}_\beta^{-1}\underline{\beta} + \sum_{t=1}^{T} 1(s_t = l)X_t' \Sigma_{s_t}^{-1} y_t\right]$.

The posterior distribution of the parameter, $\Sigma_l = l = 0,1$ which is conditional (y, Z, β_0, β_1) on s is a normal inverted Wishart distribution given by

$$(\Sigma_l | y, Z, \beta_l, \mathrm{s}) \sim IW\left(\underline{S_\Sigma, \tau_\Sigma}\right), \tag{8}$$

where $\underline{S_\Sigma} = \underline{S_\Sigma} + \sum_{t=1}^{T} 1(s_t = l)\left(y_t - X_t\beta_{s_t}\right)\left(y_t - X_t\beta_{s_t}\right)'$ and $\underline{\tau_\Sigma} = \underline{\tau_\Sigma} + \sum_{t=1}^{T} 1(s_t = l)$. The hidden variables $Z_1, \dots, Z_T$ are conditionally independent on $y, \beta_0, \beta_1, \Sigma_0, \Sigma_1$ and s. Each Z_t has an independent m-variate truncated normal.

$$(Z_t | y, \Theta, \mathrm{s}) \sim i.i.d\ N\left(\hat{Z}_t, \mathrm{D}_{z_t}\right) 1\left(Z_{jt} > c, j = 1, \dots, m\right), \tag{9}$$

where $\mathrm{D}_{z_t} = \left(I_m + \delta_{s_t}' \sum_{s_t}^{-1} \delta_{s_t}\right)^{-1}$ and $\hat{Z}_t = \mathrm{D}_{z_t}\left(cI_m + \delta_{s_t}' \sum_{s_t}^{-1}\left(y_t - \mu_{s_t}\right)\right)$.

Testing for Contagion and Hypothesis Evaluation Methods for Contagion Tests

The details of the procedure for testing contagion are set out in this sub-section. This thesis is interested in performing tests for contagion individually and jointly. It will discuss the restrictions on the parameters of the regime switching model that are required to perform these tests for contagion. It will also lay out the methods applied in evaluating the hypothesis.

Appendix 7: Hypothesis Evaluation for Contagion Tests

Table A7.1: Summary of the restrictions on the parameters of the model and the methods for hypothesis evaluation for contagion tests

Tests	Method (decision rules)	Restrictions	
Contagion tests ($i \neq j$)		market i	$\forall i$
Correlation	p	$p_{ij,0} < p_{ij,1}$	$\gamma_0 < \gamma_1$
Coskewness	BF	$\omega_{ij,0} = \omega_{ij,1}$	$\Omega_0 = \Omega_1$
Corr. & coskew.	BF	$p_{ij,0} = p_{ij,1}, \omega_{ij,0} = \omega_{ij,1}$	$\gamma_0 = \gamma_1, \Omega_0 = \Omega_1$
Joint contagion ($i \neq j$)			
All	BF	$p_{ij,0} = p_{ij,1}, \omega_{ij,0} = \omega_{ij,1}$	$\gamma_0 = \gamma_1, \Omega_0 = \Omega_1$

Notes: The tests are for comparing change in model parameters during the crisis period $s_t = 1$ as against a non-crisis period $s_t = 0$. The hypothesis evaluation method (decision rules) for the different tests is shown in the table. p and BF denote decisions based on probability and the log of the Bayes factor.

The unrestricted model (M_u) which is the regime switching model has two sets of regime-specific parameters, i.e., it has mean vectors μ_0 and μ_1 (each of dimension $m\ x\ 1$), covariance matrices Σ_0 and Σ_1 (each of dimension $m\ x\ m$) and coskewness matrices Ω_0 and Ω_1 (each of dimension $m\ x\ m$). Recollect that $\mu_{i,l}$, $\Sigma_{ij,l}$ and $\Omega_{ij,l}$ denote the ith elements of μ_l, Σ_l and Ω_l, respectively. The correlation coefficient $p_{ij,l}$ is the covariance $\left(\Sigma_{ij,l}\right)$ divided by the product of the square root of the variances $\Sigma_{ii,l}$ and $\Sigma_{jj,l}$. γ_l denotes the sum of the individual correlation coefficients $\gamma_l = \sum_{i=1}^{m} \sum_{j \neq i}^{m} \rho_{ij,l}$ used in the joint test for contagion through correlation.

This thesis uses two decision rules for evaluating the contagion hypotheses subject to the form that the hypothesis takes. The hypotheses can either have inequality or equality restrictions. For hypotheses with inequality restrictions, the probability of contagion is calculated using the proportion that the hypothesis is true in the MCMC draws and this is denoted by p. On the other hand, for hypotheses testing with equality restrictions the Bayesian model comparison method using the natural logarithm of the Bayes factor are conducted and this is denoted by BF.

The Bayesian model comparison method is a unified approach for comparing non-nested models. This method is an alternative to the classical hypothesis test. Consider comparing two models, M_r and M_u, evidence in support of the restricted model M_r can be measured using a Bayes factor (BF_{ru}), which is the ratio of the marginal likelihoods of the two models, is defined as

$$BF_{ru} = \frac{p(y|M_r)}{p(y|M_u)} \qquad (10)$$

where $p(y|M_r)$ and $p(y|M_u)$ are the marginal likelihoods of the data under models M_r and M_u. More explicitly, $p(y|M_r)$ is the marginal distribution of y under model M_r and it is evaluated using the data. Clearly, if the data are improbable under the M_r model, then the marginal likelihood will be small and vice versa. Thus, the Bayes factor is used to show the model that the data are better predicted under.

Consider model i, the marginal likelihood of the data under this model can be defined as

$$p(y|M_i) = \frac{f(y|\Theta)\pi(\Theta)}{\pi(\Theta|y)}, \qquad i = r, u, \qquad (11)$$

where Θ is a parameter set in the model, $f\ (y|\Theta)$ and $\pi(\Theta|y)$ are the likelihood function and posterior density. The prior density can be evaluated without difficulty; however, MCMC methods would be required to evaluate the likelihood and the posterior density. The marginal likelihoods can be computed using the Chib's method (Chib, 1995; Chib and Jeliazkov, 2001).

Appendix 8: Decision Rules

Table A8.1: Scale of Evidence for Bayesian model selection

Value of the log of the Bayes factor $ln(BF_{ru})$	Evidence categories for Bayesian model selection
$(0, \infty)$	Evidence in favour of model M_r
$(-1.15, 0)$	Very slight evidence in favour of model M_u
$(-2.30, -1.15)$	Slight evidence in favour of model M_u
$(-4.60, -2.30)$	Strong evidence in favour of model M_u
$(-\infty, -4.60)$	Decisive evidence in favour of model M_u

Notes: Following Jeffrey's rule (Jeffreys, 1998), the log of the Bayes factor used for model selection is $ln(BF_{ru}) = ln(p(y|M_r)) - ln(p(y|M_u))$.

The posterior odds ratio for model M_r relative to model M_u is given by

$$PO_{ru} = \frac{\pi(M_r)}{\pi(M_u)} BF_{ru}, \qquad (12)$$

where $\pi(M_r)$ and $\pi(M_u)$ are the prior probabilities of models M_r and M_u, respectively. Apparently, if the posterior odds ratio for the two models under comparison are equally likely prior to observing the data, then in principle the posterior odds ratio of both models is also the Bayes factor. Assuming the two models are nested, the Bayes factor can be easily computed using a generalization of the Savage-Dickey density ratio (Verdinelli and Wasserman, 1995). This density ratio can be used for the computation of the Bayes factor because hypothesis testing can be applied as though one is comparing nested models. If the Bayes factor in favour of model M_r is sufficiently large, then model M_r will be selected instead of model M_u. The scale of evidence for Bayesian model selection proposed Jeffreys (1998) upon which this decision is based is shown in Table A8.1 above.

The contagion tests are based on changes in correlation and coskewness. To test for the presence of contagion between asset markets i and j based on increases in the correlation coefficient in regime $s_t = 1$ relative to $s_t = 0$ the contagion test is a test of the restriction:

$$\rho_{ij,s_t=1} > \rho_{ij,s_t=0}, \quad i \neq j. \qquad (13)$$

The prior is that the correlation coefficients are likely to increase as asset markets comove even more closely during a crisis. The relevant representation of the test for changes in correlation between asset markets i and j is $\rho_{ij,1} - \rho_{ij,0} > 0$. Probability of contagion through correlation between markets i and j that can be estimated directly from MCMC draws is

$$\Pr\left(\rho_{ij,1} - \rho_{ij,0} > 0 | y, M_u\right) \qquad (14)$$

Testing for the presence of contagion through joint correlation between $m-1$ pairs of asset returns with market j is also possible. Accordingly, the test is based on the relevant representation of this restriction:

$$\gamma_0 \leq \gamma_1, \qquad (15)$$

where γ_l is the sum of the individual correlation coefficients $\gamma_l = \sum_{i=1}^{m} \sum_{j \neq i}^{m} \rho_{ij,l}$.

The joint probability of contagion through correlation across the $m-1$ markets with market j can also be estimated from the MCMC draws.

To test for the presence of contagion based on changes in the asymmetric dependence (coskewness) of returns i and j in $s_t = 1$ relative to $s_t = 0$ the contagion test is a test of the restriction:

$$\omega_{ij,s_t=0} \neq \omega_{ij,s_t=1}, \quad i \neq j. \qquad (16)$$

The restricted model for contagion test based on changes in coskewness is $\omega_{ij,0} = \omega_{ij,1}, \ i \neq j$.

Along similar lines, the joint test for contagion through coskewness across all m asset markets is similar to the bivariate statistic by Fry et al. (2010). The restriction on the model

$\sum_{i=1}^{m}\sum_{j\neq i}^{m}\omega_{ij,0} = \omega_{ij,1}$ can also be expressed as $\omega_0 = \omega_1$. Marginal likelihoods are used to compute the relevant Bayes factors.

Appendix 9: QA and BP Tests using Country-Level Data on Stock Returns

Table A9.1: Results of the QA and BP Tests using Country-Level Data on Stock Returns

Structural break tests	**BEL**	**BRA**	**CHL**	**CHN**	**COL**	**FRA**
Panel A: QA test						
Sup LR Statistic	25.6758***	36.5126***	13.2929***	6.6834**	14.1906***	41.7534***
p-value	(0.000)	(0.000)	(0.000)	(0.023)	(0.000)	(0.000)
Break dates	25/3/2009	13/11/2008	27/10/2008	11/6/2009	12/8/2014	27/3/2009
Exp LR Statistic	8.7075***	11.1639***	1.6451**	1.5585*	5.0835***	16.5060**
p-value	(0.000)	(0.000)	(0.045)	(0.054)	(0.000)	(0.001)
Ave LR Statistic	6.7284***	7.9415***	2.2530*	2.0806*	7.4887***	9.7360***
p-value	(0.000)	(0.000)	(0.054)	(0.071)	(0.000)	(0.000)
Panel B: BP test						
$SupF_T\ (m)$ *statistic*						
Sequential F-statistic determined breaks	5	5	4	5	5	5
Break: 1 **	25.6758	36.5126	13.2929	6.6834	14.1906	41.7534
Break: 2 **	18.2052	19.3367	13.3287	8.0139	14.7975	29.0483
Break: 3 **	14.0109	14.3178	10.4018	6.3570	12.5184	20.0000
Break: 4 **	10.9034	11.4431	8.3158	4.9591	10.2706	15.7221
Break: 5 **	8.4155	5.7383		3.4418	8.1785	12.9841
Double maximum statistics						
UDmax Statistic[a]	51.3516**	73.0253**	26.6574**	16.0279**	29.5950**	83.5069**
WDmax Statistic[b]	51.3516**	73.0253**	31.3601**	18.8554**	34.8159**	83.5069**
$SupF_T\ (\ell + 1/\ell)$ *statistic*						
Sequential F-statistic determined breaks	2	1	2	1	3	2
Break test: 0 vs. 1 **	25.6758	36.5126	13.2929	6.6834	14.1906	41.7534
Break test: 1 vs. 2 **	7.2400		13.2698		15.2867	15.8626
Break test: 1 vs. 3 **					7.8426	
Estimated break dates						
	27/2/2007	11/07/2007	27/10/2008	20/2/2007	13/3/2007	27/2/2007
	01/10/2008	13/11/2008	23/11/2010	16/10/2008	13/11/2008	27/3/2009
	25/3/2009	24/5/2010	21/12/2010	02/6/2009	15/4/2009	01/6/2009
	12/11/2010	09/9/2011	23/1/2013	11/6/2009	09/12/2010	02/9/2011
	29/12/2011	06/8/2012	13/3/2014	16/11/2010	09/6/2011	03/10/2013
	02/1/2013	17/12/2012	15/12/2015	28/9/2011	11/8/2014	24/8/2016
	19/3/2014	07/10/2013		14/12/2012	12/8/2014	
	06/9/2016	29/8/2014		13/8/2014	23/9/2016	
		28/1/2016		20/3/2015		
		29/1/2016		06/9/2016		
		23/9/2016		07/9/2016		

Structural break tests	GER	HKG	IND	IRL	ITL	JPN
Panel A: QA test						
Sup LR Statistic	30.4343***	9.0486**	3.9215	11.3775***	77.9070***	4.0383
p-value	(0.000)	(0.002)	(0.217)	(0.000)	(0.000)	(0.199)
Break dates	30/3/2009	19/9/2008	28/10/2008	09/10/2008	27/2/2009	22/6/2015
Exp LR Statistic	10.5818***	0.9005	0.5125	1.8606	32.8888	0.9433
p-value	(0.000)	(0.223)	(0.512)	(0.029)	(1.000)	(0.203)
Ave LR Statistic	7.7342***	0.8364	0.9045	2.3599**	22.6982	1.6006
p-value	(0.000)	(0.493)	(0.445)	(0.046)	(1.000)	(0.150)
Panel B: BP test						
$SupF_T\ (m)$ statistic						
Sequential F-statistic determined breaks	5	4	3	5	5	2
Break: 1 **	30.4343	9.0486	3.9215	11.3775	77.9070	5.4062
Break: 2 **	21.0589	6.3667	5.4107	10.7531	46.6137	4.4377
Break: 3 **	15.7263	4.8406	4.5119	8.4324	34.5385	
Break: 4 **	12.7950	3.7423		6.5981	26.4531	
Break: 5 **	10.5166			4.9846	21.3099	
Double maximum statistics						
UDmax Statistic[a]	60.8687**	18.0973**	10.8215**	22.7550**	155.8140**	10.8125**
WDmax Statistic[b]	60.8687**	18.0973**	12.7306**	25.3002**	155.8140**	12.7200**
$SupF_T\ (\ell+1/\ell)$ statistic						
Sequential F-statistic determined breaks	2	1	0	2	3	
Break test: 0 vs. 1 **	30.4343	9.0486		11.3775	77.9070	
Break test: 1 vs. 2 **	11.4981			10.0688	14.7010	
Break test: 1 vs.3 **					9.9058	
Estimated break dates						
	28/8/2007	19/9/2008	28/10/2008	21/6/2007	30/1/2007	05/11/2008
	10/10/2008	12/1/2011	19/8/2011	09/10/2008	27/2/2009	05/6/2012
	30/3/2009	16/6/2011	13/1/2016	16/7/2009	27/10/2011	25/6/2015
	10/8/2011	30/5/2013		12/11/2010	18/12/2013	
	18/8/2011	28/5/2015		28/9/2011	24/8/2016	
	17/9/2013	24/6/2015		13/5/2014		
	24/8/2016			12/9/2016		

Structural break tests	**KOR**	**MAL**	**MEX**	**NET**	**PER**	**PHI**
Panel A: QA test						
Sup LR Statistic	8.8273**	16.6906***	26.5027***	18.8397***	10.4892***	3.1910
p-value	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.363)
Break dates	10/10/2008	21/11/2008	22/10/2007	01/6/2009	19/9/2008	07/11/2008
Exp LR Statistic	0.7583	3.3915**	10.0605***	6.0706***	1.6150**	0.3928
p-value	(0.303)	(0.001)	(0.000)	(0.000)	(0.048)	0.655
Ave LR Statistic	0.9213	3.0562**	9.1384***	5.1417**	2.1730*	0.6996
p-value	(0.434)	(0.016)	(0.000)	(0.001)	(0.061)	0.600
Panel B: BP test						
$SupF_T\ (m)$ *statistic*						
Sequential F-statistic determined breaks	4	5	5	5	5	
Break: 1 **	8.8273	16.6906	26.5027	18.8397	10.4892	
Break: 2 **	6.6518	9.3355	17.5152	14.3792	12.1136	
Break: 3 **	4.9270	7.3420	12.2652	10.5846	9.2909	
Break: 4 **	3.8309	6.2123	10.0708	8.4674	7.1661	
Break: 5 **		3.9063	8.2974	6.8939	5.8340	
Double maximum statistics						
UDmax Statistic[a]	17.6546**	33.3813**	53.0054**	37.6795**	24.2273**	
WDmax Statistic[b]	17.6546**	33.3813**	53.0054**	37.6795**	28.5013**	
$SupF_T\ (\ell + 1/\ell)$ *statistic*						
Sequential F-statistic determined breaks	1	1	2	2	1	
Break test: 0 vs. 1 **	8.8273	16.6906	26.5027	18.8397	10.4892	
Break test: 1 vs. 2 **			8.4136	9.8223		
Estimated break dates						
	10/10/2008	08/4/2008	07/6/2007	23/4/2007	24/4/2007	
	23/9/2011	21/11/2008	22/10/2007	01/6/2009	19/9/2008	
	05/1/2011	24/5/2010	31/10/2007	27/10/2011	28/5/2009	
	30/1/2013	15/10/2012	12/8/2009	07/6/2012	21/6/2011	
	22/6/2015	13/1/2011	02/9/2011	11/8/2014	27/8/2014	
		27/7/2012	06/9/2011	06/9/2016	27/8/2015	
		20/2/2013	06/11/2013		23/9/2016	
		21/8/2014	12/9/2016			
		30/1/2015	23/9/2016			
		19/3/2015				
		23/6/2015				
		15/9/2016				

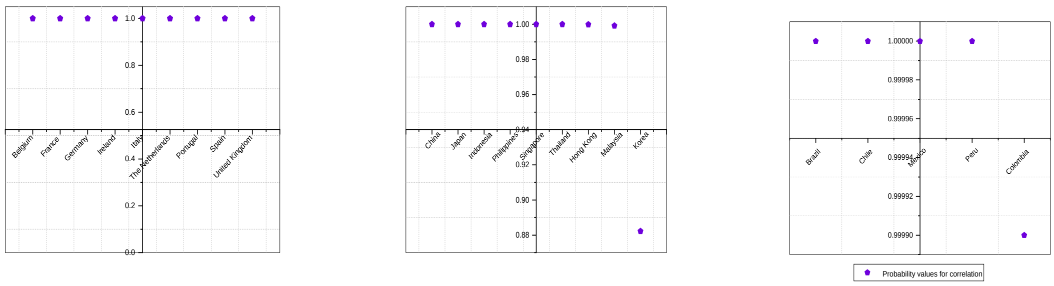
Structural break tests	POR	SNG	SPA	THL	UK
Panel A: QA test					
Sup LR Statistic	56.7553***	8.7191**	42.3882***	9.5215**	9.6309**
p-value	(0.000)	(0.003)	(0.000)	(0.001)	(0.001)
Break dates	02/10/2009	03/9/2008	01/6/2009	11/8/2008	30/3/2009
Exp LR Statistic	25.0503	1.4396*	17.5685**	1.1725	2.1959**
p-value	(1.000)	(0.070)	(0.008)	(0.124)	(0.014)
Ave LR Statistic	24.7238	1.6943	11.1012***	1.1148	2.2239*
p-value	(1.000)	(0.130)	(0.000)	(0.323)	(0.057)
Panel B: BP test					
$SupF_T\ (m)$ statistic					
Sequential F-statistic determined breaks	5	5	5	5	5
Break: 1 **	56.7553	8.7191	42.3882	9.5215	9.6309
Break: 2 **	32.4916	6.1691	28.8629	6.7506	11.8797
Break: 3 **	26.5149	4.5062	20.1552	5.1966	8.3239
Break: 4**	21.1043	3.8651	15.4685	4.4167	6.6476
Break: 5 **	17.2911	3.1351	12.5536	2.9963	5.5608
Double maximum statistics					
UDmax Statistic[a]	113.5108**	17.4383**	84.7765**	19.0430**	23.7594**
WDmax Statistic[b]	113.5108**	17.4383**	84.7765**	19.0430**	27.9508**
$SupF_T\ (\ell + 1/\ell)$ statistic					
Sequential F-statistic determined breaks	3	1	2	1	2
Break test: 0 vs. 1 **	56.7553	8.7191	42.3882	9.5215	9.6309
Break test: 1 vs. 2 **	7.9974		14.9136		13.7869
Break test: 1 vs. 3 **	14.0682				
Estimated break dates					
	21/2/2007	22/2/2007	12/2/2007	08/8/2007	27/2/2007
	23/7/2007	03/9/2008	01/6/2009	11/8/2008	30/3/2009
	05/6/2009	18/3/2009	17/6/2009	17/9/2008	01/6/2009
	17/8/2009	25/4/2011	19/6/2012	01/9/2009	07/6/2012
	02/10/2009	24/7/2012	31/7/2014	08/12/2010	11/8/2014
	02/8/2011	02/10/2013	24/8/2016	27/9/2011	06/9/2016
	07/7/2014	15/9/2016		23/7/2014	
	12/9/2016			25/7/2014	
				22/8/2016	
				12/9/2016	

Notes: Reported tests for testing structural breaks include the QA test and the BP test, respectively. These tests are based on a linear regression model for each region log of GDP-weighted stock return indices with the US stock index. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. The figures in the parentheses are the probability values (p-values). The p-values for the tests are calculated using the method in Hansen (1997). [a] 5% UDmax critical value is 11.70. [b] 5% WDmax critical value is 12.81. For the $SupF_T\ (m)$ test, the critical values for break 1, 2, 3, 4, and 5 are 11.47, 9.75, 8.36, 7.19 and 5.85, respectively. For the $SupF_T\ (\ell + 1/\ell)$ test, the critical value for break test: 0 vs. 1 is 11.47, the critical value for break test: 1 vs. 2 is 12.95 and the critical value for break test: 1 vs. 3 is 14.03.

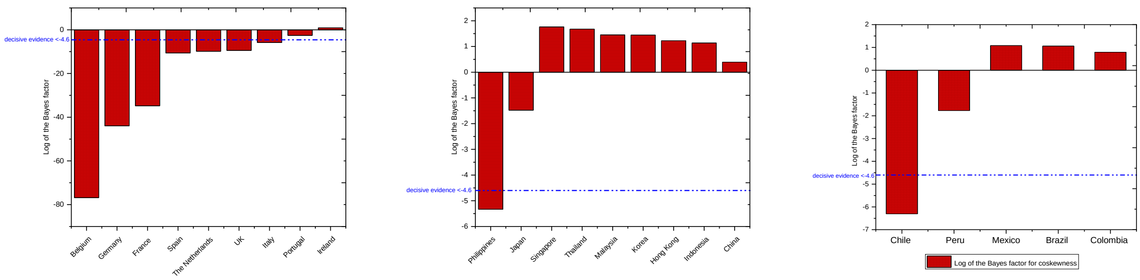
Appendix 10: Plots of Probability and Log of Bayes Factor

Figure A10.1: Plots of Benchmark Results

Panel A: Probability Values for Correlation



Panel B: Log of the Bayes Factor for Coskewness



Panel C: Log of the Bayes Factor for Correlation and Coskewness