Return and Volatility Transmission in Emerging and Developed Stock Markets

L YAROVAYA

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LARISA YAROVAYA

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ABSTRACT

This dissertation provides empirical evidence on the patterns of intra- and inter-regional transmission of information across 10 developed and 11 emerging markets in Asia, the Americas, Europe and Africa using both stock indices and stock index futures. First, the main channels of contagion are examined in the period from 2005 to 2014 through the analysis of return and volatility spillovers around the most recent crises based on the generalized vector autoregressive framework. The findings demonstrate that markets are more susceptible to domestic and region-specific volatility shocks than to inter-regional contagion. Second, the inter-regional spillovers across markets with non-overlapping trading hours are investigated using asymmetric causality test. The results demonstrate that the signal receiving markets are sensitive to both negative and positive volatility shocks, which reveals the asymmetric nature of volatility transmission channels. Third, this study explores the ability of foreign information to forecast returns on domestic market. The results have implications for international portfolio diversification. The spillovers between emerging and developed markets are weaker than between developed markets, consequently the benefits of international portfolio diversification are best achievable by investing in emerging markets in different geographical zones. The burst in spillovers during crisis episodes is verified, which is important for investors as during periods of turmoil diversification benefits are limited. A novel results reported in the study is a difference in patterns of international transmission between models employing indices and futures data. The study shows that futures data provide more efficient channels of information transmission, because the magnitude of return and volatility spillovers across futures is larger than across indices. The results presented in this dissertation suggest that the analysis of spillovers across stock index futures has important practical implications for the development of trading strategies. The findings are relevant to practitioners and policy makers to enhance their understanding of financial markets interconnectedness.

Content

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List of Acronyms

ADF test - The Augmented Dickey-Fuller Test

ANN - Artificial Neural Networks

ARDL Model – the Autoregressive Distributed Lag Model

ARCH - Autoregressive Conditional Heteroskedasticity

ASEAN - The Association of Southeast Asian Nations

BA – Bootstrap Aggregating (bagging)

BEKK model – acronym from Baba, Engle, Kraft and Kroner

BRIC - Brazil, Russia, India, China

BRICS - Brazil, Russia, India, China and South Africa

BRIICKS - Brazil, Russia, India, Indonesia, China, South Korea and South Africa

BRA - Brazil

CAN - Canada

CAPM - the Capital Asset Pricing Model

CB- Combination Forecast

CHN – China

DCC – Dynamic Conditional Correlation

DJIA – the Dow Jones Industrial Average index

DST – Daylight Saving Time

EDC – European Debt Crisis

EFSF – the European Financial Stability Facility

EFSM - the European Financial Stabilization Mechanism

EMH - Efficient Market Hypothesis

ESP - Spain

ETF- Equity Traded Funds

FIT – Foreign Information Transmission

FRA – France

GARCH - Generalized Autoregressive Conditional Heteroskedasticity

GBR – Great Britain

GER - Germany

GFC – Global Financial Crisis

GIPSI - Greece, Ireland, Portugal, Spain and Italy

GMT – Greenwich Mean Time

HAR Model - Heterogeneous Autoregressive Model

HKG – Hong Kong

HUN - Hungary

ICAPM - the International Capital Asset Pricing Model

I-CAPM - the Intertemporal Capital Asset Pricing Model

ICSS – the Iterated Cumulative Sum of Squares

IND - India

IPD – International Portfolio Diversification

JPN- Japan

KOR - Korea

KPPS – acronym from Kwiatkowski, Phillips, Schmidt, and Shin

MA- Moving Average

MEX - Mexico

MPT - Modern Portfolio Theory

MSCI – Morgan Stanley Capital International

MSFE – Mean Squared Forecast Error

MST - Minimum Spanning Tree

MFV – Multifractal Volatility

MYS – Malaysia

NDC - Next-day correlation

OLS – Ordinary Least Squares

PC - Principal Component Combination Forecasts

P-P - Phillips-Perron unit root tests

RUS – Russia

SDC - Same-day correlation

SGP – Singapore

SHCI - the Shanghai Stock Exchange Composite Index

SIC - Schwarz Information Criterion

SUI - Switzerland

SZCI - Shenzhen Stock Exchange Component Index

TGARCG- Threshold Generalized Autoregressive Conditional Heteroskedasticity

TUR - Turkey

TWN – Taiwan

UEDCC - Unrestricted Extended Dynamic Conditional Correlation

USA – United States of America

VAR – Vector Autoregressive

WLS – Weighted Least Squares

WTC – Wavelet Coherence

ZAF – South Africa

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Declaration

I declare that the work contained in this thesis has not been submitted for any other award and it is entirely my own work. I also confirm that this work fully acknowledges opinions, ideas and contributions from the work of others. Any ethical clearance for the research presented in this thesis has been approved.

Approval has been sought and granted by the Faculty Ethics Committee on 28/01/2014

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Name: Larisa Yarovaya

Signature:

Date: 25.01.2016

Chapter 1 Introduction to the thesis

1.1 Introduction

The issues of return and volatility spillovers across international financial markets have become critically important due to the increased integration of emerging markets in the world economy. Although much has been written about the economic and financial linkages between stock markets, the globalization and liberalization processes keep altering the geography of financial interconnectedness, suggesting that this topic is still relevant today and requires further consideration. Hence, this thesis investigates the dynamic of return and volatility spillovers between stock markets contributing to the contagion, international portfolio diversification (IPD), and predictability literature. Furthermore, the analysis of information transmission mechanisms has important practical implications, which makes this research particularity relevant to practitioners and policy makers.

This chapter is organized as follows:

Section 1.2 discusses the main sources of motivation to conduct the research on international return and volatility transmission. It also provides the research background of the thesis, discussing the most influential journal articles in this area.

Section 1.3 demonstrates the relevance of the research topic and presents the aims and objectives of this thesis.

Section 1.4 discusses to what extent this thesis is different from previous studies and how current research contributes to existing knowledge.

Section 1.5 outlines the thesis structure.

1.2 Research background and motivation

The background literature is vast. However, the drive to further augment the existing empirical evidence on information transmission mechanism is motivated by a few specific, but influential, papers that investigated the issue of cross-market information conveyance. This section focuses on these articles.

The first primary source of motivation for this research is the paper by Engle, Ito and Lin (1990), that introduced the 'heat wave' and 'meteor shower' hypotheses which were then further analysed by Baillie and Bollerslev (1990), Melvin and Hogan (1994) and Melvin and Peiers Melvin (2003), among others. The effect of meteor shower manifests itself in a situation when a volatile day on one market is followed by a volatile day on the other market. While heat wave effect suggests that a volatile day on one market is likely to be followed by a volatile day on the same market (Ibrahim & Brzeszczynski, 2009). Particularly, the meteor shower effect has been hypothesized and tested by many authors in order to extract signals transmitted from foreign markets that can be used in forecasting future returns on the domestic markets (e.g., Henriksson & Merton, 1981; King & Wadhwani, 1990; Hamao et al., 1990; Ito, Engle & Lin, 1992; Melvin & Melvin, 2003; Ibrahim & Brzeszczynski, 2009, 2012; Ye, 2014; Strohsal & Weber, 2015). However, Ibrahim and Brzeszczynski (2009) claimed that there is a lack of evidence in this topic area on the relative strength, direction and stability of the heat-wave-like and meteor-shower-like region-specific or inter-regional transmission of returns. Furthermore, Chapter 2 of this thesis identifies the fact that there is a lack of research investigated information transmission mechanisms employing alternative data to that of equity indices. This thesis aims to fill this gap in knowledge and to provide evidence from both stock indices and stock index futures.

The next sources of motivation are the papers by Koutmos and Booth (1995), Segal, Shaliastovich and Yaron (2015), Strohsal and Weber (2015), Baruník, Kočenda, and Vácha (2015), Kundu and Sarkar (2016), all of which inspired the analysis of the conveyance of both positive and negative return and volatility shocks which forms the main content of this thesis. This analysis provides the evidence on asymmetry in spillover effects that have not been widely discussed in this topic area to date, in contrast to the concept of asymmetric volatility (e.g., Nelson, 1991; Bekaert & Wu, 2000). The opportunity to augment existing knowledge by providing evidence on asymmetry in return and volatility spillovers by utilizing both emerging and developed stock index futures was appealing due to the lack of similar relevant research in this topic area.

New methodological developments in analysis of return and volatility transmission have also proved to be one of the sources of motivation for this thesis. The paper by Rapach and Strauss (2010) was particularly inspirational in this regard in that it led to the employment of the bootstrap aggregating and combination forecasts methods to further test the relevance of foreign information transmission between markets by assessing the predictive power of stock index futures returns. In previous literature, the Rapach and Strauss (2010) methodology, which is discussed in detail in Chapter 7, has been applied to the large number of macroeconomic predictors but has not been tested in the context of the international return and volatility transmission across stock index futures as yet.

This thesis is also justified by the need to provide global evidence on information transmission mechanisms that are being accessible to a wide variety of practitioners. Therefore, the methodology employed had to generate the results and be presented in a clear way to allow the reader to interpret and understand the main channels of transmission and to employ the results in practice. The Spillover Tables suggested by Diebold and Yilmaz (2009, 2012) provide useful tools to summarize the evidence for a large group of markets and display both intra- and inter-regional spillovers clearly. Furthermore, the DY framework employed in this thesis plots the dynamic of spillover, over the estimation period, and allows the linkage of the Total Spillover trend to key economic events. Consequently, the findings of this thesis can be easily understood, not only by econometricians and experts in international finance, but also by academics from other fields (which suggests the potential to employ the results in multidisciplinary studies), students at different levels and practitioners from diverse backgrounds.

1.3 Aims and objectives of the research

The primary goal of this thesis is to enhance the understanding of return and volatility transmission mechanisms across emerging and developed financial markets. More specifically, the aims and objectives of this study are specified below:

1. To analyse the differences in patterns of return and volatility spillovers across emerging and developed stock market indices and across stock index futures:

- to investigate the return and volatility spillovers between emerging and developed stock markets, employing the stock indices data of 21 emerging and developed markets, for the full-sample period from 03 October, 2005 to 03 October, 2014;
- to investigate the return and volatility spillovers between emerging and developed stock markets, employing the stock indices data of 21 emerging and developed markets, over the subsample period from 04 October, 2010 to 03 October, 2014;
- to compare the intensity and dynamic of spillovers for both the return and volatility across stock indices and stock index futures over the subsample period from 04 October, 2010 to 03 October, 2014;
- to analyse and discuss the differences obtained for returns and volatilities;
- to plot the Total Spillover index for both futures and spot markets and link the dynamic of spillovers with key economic events;
- to plot the Total Spillover index for each region to provide a regional perspective of cyclical movements of total return and volatility spillovers;
- to analyse and discuss the results in relation to previous studies.

2. To investigate the asymmetry in return and volatility spillovers across futures markets with non-overlapping stock exchange trading hours:

- to identify the market pairs with non-overlapping trading hours;
- to employ an asymmetric causality test for stock index futures returns of market pairs with non-overlapping trading hours;
- to employ an asymmetric causality test for stock index futures volatilities of market pairs with non-overlapping trading hours;

- to evaluate the number of cases suggesting asymmetry in spillovers for all market pairs from each region;
- to summarize the evidence on asymmetry in spillover effects;
- to discuss the results in relation to previous studies.

3. To evaluate the ability of foreign information contained in stock index futures returns to forecast returns on the domestic market:

- to generate an individual out-of-sample forecast for all combinations of the markets, i.e. with and without overlap in trading hours;
- to compare the accuracy of individual out-of-sample forecasts with the autoregressive (AR) benchmark model forecasts using the reduction in mean squared forecast error (MSFE) as a criterion;
- to conclude which foreign markets are better predictors for returns for each market in the sample;
- to employ bootstrap aggregating (BA) methodology to generate out-of-sample forecasts of futures markets (taking the period from 04 October, 2014 to 02 October, 2015 as the out-of-sample estimation period);
- to compare the accuracy of the BA forecasts with the AR benchmark model forecasts using the reduction in MSFE as a criterion;
- to employ various combination forecasts (CB) to generate an out-of-sample forecast for each market in the sample;
- to compare the accuracy of the CB forecasts with AR benchmark model forecasts using the reduction in MSFE as a criterion;
- to compare the relative forecasting performance of the BA model over various other combination forecasts methods employed;
- to conduct forecast encompassing tests to compare the influential power of information contained in BA and CB forecasts;
- to analyse, discuss and summarize the empirical results.

1.4 Research contribution and implications

There are various fields of literature to which the analysis of international information transmission is related, for example the literature on international portfolio diversification (IPD), financial contagion, stock market integration, and predictability. The analyses of the meteor shower hypothesis (Engle et al, 1990) have implications to the predictability of equity returns (see, e.g., Ibrahim & Brzeszczynski, 2009; 2012), which may challenge the efficient market hypothesis (EMH). Indeed, although the spillover effect and increased correlation between markets limits the benefits of IPD, the conveyance of information between markets can generate buying and selling signals. These can then be used in practice for the creation of a trading strategy able to outperform the market. Therefore, information transmission mechanisms provide the opportunity to forecast the behaviour of return and volatility of the markets which are susceptible to foreign shocks. The analysis of the dynamic, intensity and direction of return and volatility spillovers should be extended to analysis of the transmission of positive and negative shocks across markets and, moreover, to the assessment of the predictive power of foreign information.

This thesis augments the existing literature in several important areas. First, this thesis provides evidence of the patterns, asymmetry and predictive power of spillover effects across stock index futures, which distinguishes this research from the majority of the previous studies that utilized only equity indices data. The employment of futures data in analysis of information transmission has more realistic practical implications, since the futures contracts are actually tradable instruments and attractive for investors due to the relatively lower costs of trading on financial futures than managing a portfolio of constituent stocks. This thesis is original and differs from previous studies in that it provides international evidence on the issues of information transmission mechanisms (i.e., contagion, asymmetry, predictability etc.) using alternative data to that derived from equity indices.

Second, this thesis adds to existing knowledge by comparing the patterns of intra- and inter-regional spillovers across stock index futures with the patterns of spillovers across equity indices, something which has not been explained before. The study utilized data from 21 emerging and developed markets from four geographical regions: Asia, the Americas, Europe and Africa. While the existing literature on the meteor shower hypothesis is restricted to analysis of the largest developed markets of the USA, Japan and Europe, and omits the emerging stock markets, this research contributes to the literature by investigating the spillovers effect in a sample which is not restricted to developed markets (see, e.g., Worthington & Higgs; 2004; Syriopoulos, 2007; Diebold & Yilmaz, 2009, 2012; Singh, Kumar & Pandey, 2010; Beirne et al, 2013; Beirne & Fratzscher, 2013; Cho, Hyde & Nguyen, 2014). Consequently, the study provides implications for international portfolio diversification and provides evidence of return and volatility transmission between emerging and developed financial markets.

According to Modern Portfolio Theory (MPT), introduced by Markowitz (1952), minimization of the volatility of a portfolio can be achieved by combining negative correlating assets. The observed historically low correlation between emerging and developed stock markets revealed the opportunities for improving the risk-return position of a portfolio by including emerging stocks in it (Levy & Sarnat, 1970). However, it has been established that correlation between emerging and developed stock markets increased dramatically in the last decades, diminishing the opportunities of IPD for investors (e.g., Erb, Harvey & Viskanta, 1994; Longin & Solnik, 1995, 2001). This thesis has utilized the most recent data available to date and provides the most recent evidence on the new geography of financial market interconnectedness which is highly significant for portfolio management. It also takes into account the constantly changing correlation structure among markets. Due to the fact that this thesis employed alternative data from equity indices which, in practice, are not easily investable assets, the results have significant practical implications, especially for investors that have diversification as a goal.

Third, this thesis analyses the intensity and dynamic of spillovers across the most recent crisis episodes, i.e. the Global Financial Crisis (GFC) and the European Debt Crisis (EDC), and so contributes to contagion literature. The intensification of spillovers across markets during crisis periods can limit the opportunities for global diversification, and may also destabilize the markets in other regions, threatening global financial stability. Therefore, the results of this research are important for policy makers and financial regulators. Furthermore, the thesis goes beyond the investigation of the intensity of spillovers during periods of turmoil and tranquillity and also analyses the transmission of negative and positive returns and volatility shocks across markets with non-overlapping trading hours, providing the evidence from stock index futures data. In addition, this thesis contributes to the literature by providing an empirical investigation of the relatively unexplored concept of asymmetry in return and volatility spillovers across markets, providing new evidence on stabilizing and destabilizing spillover effects.

Finally, since the analysis of the meteor shower effect has implications on return predictability (Ibrahim & Brzeszczynski, 2009), this thesis demonstrates that the international return spillovers can be used as predictors of domestic stock market returns. The present research compares the forecasting performance of the individual autoregressive distributed lag (ARDL), bootstrap aggregating (BA) and combination (CB) models over the autoregressive (AR) benchmark providing the evidence for a large number of markets and predictors. Furthermore, it employs a forecast encompassing test to evaluate the usefulness of the information contained in both BA and CB models for the prediction of futures returns. The returns of stock index futures of 21 markets is also utilized, providing international evidence as to the predictive power of futures returns that, so far, does not have the analogues in the literature.

1.5 Structure of the thesis

While Chapter 1 highlights the aims and objectives, relevance, motivation and contribution of the research, the remainder of the thesis is organized as follows:

Chapter 2 presents a review of the core literature on return and volatility transmission and describes the most commonly used econometric methods that have been employed by researchers investigating stock market linkages and information transmission mechanisms.

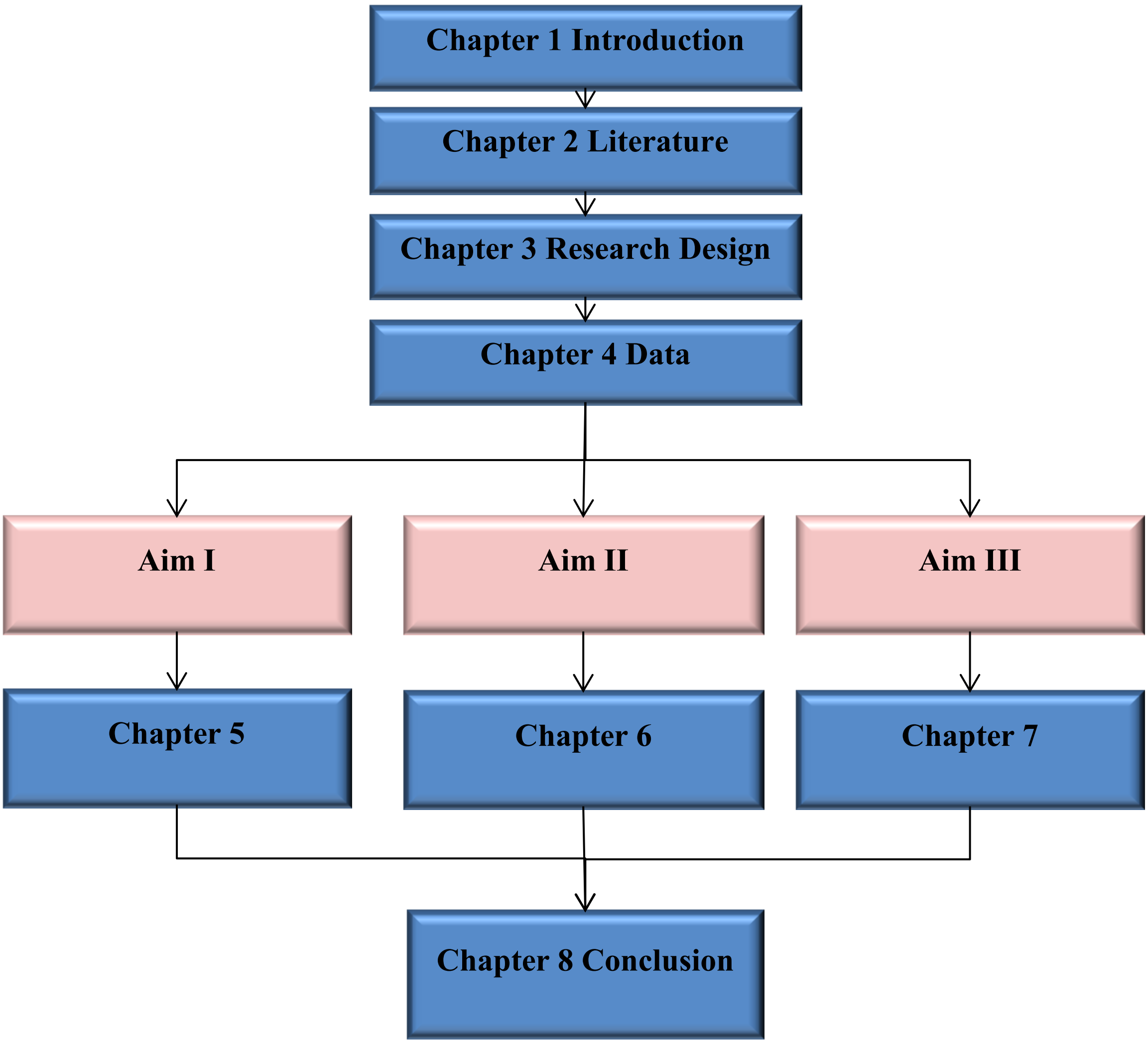
Chapter 3 presents a discussion of research philosophy and research design employed in this thesis and highlights the research questions and research hypotheses which have been tested. It also presents the research design of this study, and explains the process of new knowledge creation.

Chapter 4 describes data and presents the results of the preliminary data analysis, i.e. tests on the stationarity of data and cross-market correlation. It also discusses data collection issues.

Chapter 5, 6 and 7 are three empirical chapters structured in accordance with the articulated aims and objectives.

Figure 1.1 illustrates the logical linkages between the empirical analysis carried out and the aims of this research.

Figure 1.1 Thesis structure in relation to research aims.



Chapter 5 investigates the differences in patterns of return and volatility spillovers across 21 emerging and developed stock market indices and across stock index futures utilizing the Diebold and Yilmaz (2009, 2012) methodology. It compares the intensity and dynamic of spillovers for both the return and volatility across stock indices and stock index futures over a subsample estimation period from 04 October, 2010 to 03 October, 2014. Chapter 5 also plots the Total Spillover index for both futures and spot markets, linking the dynamic of spillovers to key economic events. This provides evidence on intra- and inter-regional information transmission across financial markets, taking into account structural breaks in variances.

Chapter 6 explores asymmetry in return and volatility spillovers across futures markets with non-overlapping stock exchange trading hours. The chapter identifies market pairs with non-overlapping trading hours and employs an asymmetric causality test by Hatemi-J (2012) for stock index futures returns and volatilities separately, and explores stabilizing and destabilizing volatility spillover effects.

Chapter 7 analyses the ability of foreign information, contained in stock index futures returns, to forecast returns on the domestic market. The performance of individual out-of-sample forecasts for all combinations of markets, i.e. with and without overlap in trading hours, is compared with the AR benchmark using reduction an MSFE ratio as criterion. The chapter follows the Rapach and Strauss (2010) paper which employs a similar methodological framework in the context of the predictive power of international stock index futures returns. There is also an evaluation of the relative forecasting performance of the BA-model over various combination forecast methods employed using the MSFE criterion. Furthermore, Chapter 7 conducts the forecast encompassing test to compare the influential power of information contained in BA and CB forecasts.

Chapter 8 summarizes the findings of the empirical chapters to address the research questions and tests the hypotheses put forward It also highlights the contribution and implications of the empirical results for existing knowledge. Finally, Chapter 8 discusses the limitations of this thesis and provides direction and suggestions for further research.

Chapter 2 Review of the literature and methodology

2.1 Introduction

The question of stock market interlinkages has already been considered in many studies in the finance area. The structuring of the literature review presented in this thesis is informed by the main literature surveys in this topic area (e.g., Gagnon & Karolyi, 2006). The review starts with the earliest pioneering studies which formed the theoretical basis of the research and continues to cover the most recent studies which provided empirical evidence on information transmission mechanisms. The aims and objectives of the research indicate the need to evaluate different strands in the literature to demonstrate the place of this specific research within existing knowledge. Since the contemporary theoretical and empirical evidence of each literature field covering the issues of return and volatility transmission is very rich, this chapter cannot be a fully comprehensive review of every article published on the topic. Therefore, the main purpose of this chapter is to provide an overview of the core and key literature on information transmission mechanisms across international financial markets. The chapter focuses on the seminal papers, which are the most influential in the topic area and significant for the present research, based on the fact that these papers provided contextualisation of the main theoretical concepts, and proposed the key methodologies, actively employed by researchers

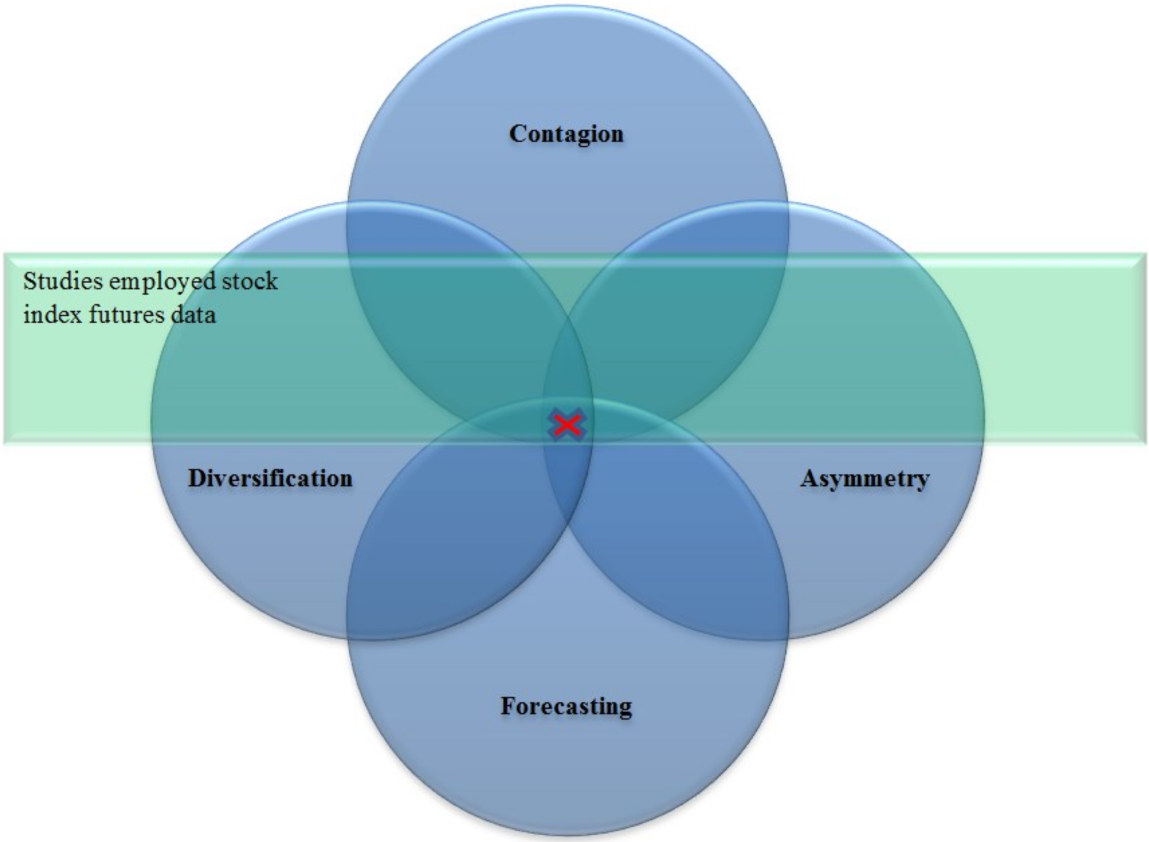
Besides the papers framing the intellectual basis of this research, the chapter also discusses the empirical evidence provided by recent studies on return and volatility transmission. Preference was given to those papers that included analysis based on similar aims and objectives, utilised the same or a similar selection of countries (i.e. evidence for Asia, Europe, Africa and the Americas markets are of interest), and a similar time period examined in this thesis. More specifically, the chapter particularly focuses on the data employed by existing empirical studies; firstly, whether developed or emerging markets are considered (or a combination of both, which is the most desirable); secondly, whether stock index data or stock index futures data are used (or a combination of both); and thirdly, whether the estimation period covers the most recent crisis episodes, i.e. The Global Financial Crisis and the European Debt Crisis.

The review of the background literature provides an explanation for the existing gaps in knowledge and supports the need for, and relevance, of this research. The literature review highlights the importance of the research questions and explains the terminology used in the specification of the research hypotheses discussed in Chapter 3. Furthermore, this chapter discusses the main methodologies and econometric techniques employed by researches within this topic area, explaining the choice of methods used in the empirical analysis conducted in this thesis.

Although, as mentioned earlier, this literature review was informed by seminal literature surveys in the topic area, Figure 2.1 shows that this chapter forms an original, and customized, literature survey based on logical reasoning and philosophical beliefs of the author of this thesis. For instance, Andersen and Bolleslev (1997, p.117) divided existing literature into three categories. The first group of studies analysed the interrelation between returns in geographically separated financial markets that trade sequentially, while the second group of studies is concerned with the lead-lag relations between two or more markets that trade simultaneously. A third group of studies investigates the role of information flow and other microstructure variables as determinants of intraday return volatility. Another classification is provided in the notable literature review by Gagnon and Karolyi (2006). First, they divided early papers on international portfolio diversification into the three categories: i) studies motivated by the mean-variance introduced by Markowitz (1952), which investigate the potential benefits of international diversification; ii) studies analysing the structural patterns in international financial market co-movements; iii) studies focusing on the lead-lag relationships between international markets. Gagnon and Karolyi (2006) further split the third category, i.e. studies on lead-lag relationships across markets, according to data sample and data frequency employed in the analyses. This chapter structures the background literature differently in order to match the aims and objectives of the research and provides an overview of diversification, contagion, asymmetry, and forecasting literature fields focusing on the data utilised in existing papers.

Figure 2.1 illustrates the literature fields covered in literature survey in the formation of the theoretical background to the present research:

Figure 2.1 Literature and methodology review.



The remainder of the chapter is organised as follows:

Section 2.2 discusses the pioneer studies on international portfolio diversification and global stock market interconnectedness which form the theoretical basis for this thesis. These studies employed the most commonly used methods and techniques to investigate correlation, co-integration and causal linkages across global financial markets. This section focuses on the integration of developed and emerging markets to explore the diversification opportunities, and challenges, of investing in emerging stock markets.

Section 2.3 presents studies investigating the behaviour of stock market interconnectedness around periods of economic turbulence. This section also defines the terms contagion and spillover effect used in this thesis. Furthermore, this section includes both contagion papers and papers investigating the intensity of return and volatility spillovers around crisis episodes.

Section 2.4 discusses literature that analysed the asymmetry in causal linkages across markets, providing an overview of the most popular methodologies used in this field. This section also defines the term asymmetry in spillover effect used in this thesis.

Section 2.5 discusses literature on intra- and inter-region return and volatility spillovers to capture the global perspective on the investigated phenomena. This section explains the Meteor Shower and Heat Waves hypotheses by Engle et al (1990) and other studies that investigated return and volatility transmission across markets with non-overlapping trading times.

Section 2.6 investigates the predictability literature and sheds light on the practical significance of foreign information transmission mechanisms. It also discusses how investigation of return and volatility transmissions across emerging and developed stock markets can contribute to studies on stock market efficiency.

Section 2.7 provides an overview of studies using data alternative from stock market indices in the analysis of global return and volatility transmission, i.e. stock index futures.

Section 2.8 highlights the literature gap, based on a discussion of relevant studies and methods, to justify the necessity of this research.

Section 2.9 provides a conclusion based on the reviews.

2.2 Global stock market integration and opportunities for international portfolio diversification

2.2.1 Early proponents of international portfolio diversification

One of the main issues faced by individual investors and financial institutions is how to allocate their wealth among assets available in the market. The complexity of this problem increases if investors aim to diversify their portfolios globally. Modern Portfolio Theory (MPT) introduced by Markowitz (1952, 1959) aims to find an optimal portfolio in a situation where the investor is informed about return distribution over a specific time period. Markowitz (1952) formulated the portfolio problem as a choice of the mean and variance of a portfolio of assets. In the context of the Markowitz portfolio theory, investors should optimise the weighting of assets in a portfolio with regard to the expected rate of return and volatility. Tobin (1958) contributed to Portfolio Theory by the introduction of Efficient Frontier. The process of investment choice involves two parts: "first, the choice of a unique optimum combination of risky assets; and second, a separate choice concerning the allocation of funds between such a combination and a single riskless asset" (Sharpe, 1963, p.426). Based on individual risk-return preferences investors can choose the combination of assets in their portfolio from market efficient frontier. The important message of portfolio theory is that investors could not consider the individual characteristics of a single security without understanding how this asset will be co-moved with other securities (Elton & Gruber, 1997). These co-movements of assets entail the possibility of constructing the portfolio with a desirable rate of return and lower variance rather than any individual security, which justifies the necessity of diversification. Elton and Gruber (1997) claimed that Modern Portfolio Theory (MPT) is the cornerstone in this topic area, despite all alternatives developed later, for two main reasons. First, the proponents argued that there is no evidence that adding additional data requirements to mean variance theory could improve the desirability of the portfolio selected. Second, MPT is well developed and implemented in practice, and mean variance theory is widely known and has a huge impact on academics and practitioners.

The measures of diversification benefits found natural implications in asset pricing, due to the fact that the consideration of diversification and dependence between assets should affect the price of risk in international markets (e.g., Chollete, de la Pena & Lu, 2012). The Capital Asset Pricing Model (CAPM) is built on the portfolio choice model by

Markowitz (1959). The CAPM introduced by Sharpe (1964) and Lintner (1965) signals the birth of asset pricing theory along with- parallel studies on CAPM presented, for example, by Mossin (1966) and Black (1972). The CAPM is widely used in measuring equity risk premium, estimating a firm's cost of equity, evaluating the performance of diversified portfolios, and consequently has implications for stock market integration. Providing mathematical equations describing the relation between expected return and risk of asset, the CAPM model has become a basic theoretical model widely discussed in all finance textbooks as a fundamental model of portfolio theory. The Sharpe-Linter CAPM equitation can be described as follow:

$$E(R_i) = R_f + \left[E(R_m) - R_f\right]\beta_{iM}, \tag{2.2.1}$$

where $E(R_i)$ is the expected return from an asset i $(i = 1, \dots, N)$; R_f is the risk free interest rate, $E(R_m)$ is the expected market return and β_{iM} is the asset's market beta.

The CAPM assumes first, that the investor agrees to the joint distribution of asset returns from *t-1* to *t* period of time. The second assumption is that borrowing and lending is at a fixed risk-free rate and is available in the market for all investors, for any amount of funds involved in investment transactions (Fama & French, 2004). However, the list of simplifying assumptions of CAPM is not limited to these two, hence such assumptions as the normal distribution of returns, and the single-period problems of mean-variance theory, also entail further empirical problems (Fama, 1970). The notable paper by Fama and French (2004) provided a critical review of CAPM empirical records and tests of the model. Authors concluded that the problems with the model are serious enough to invalidate most applications of the CAPM. For example, Black, Jensen, and Scholes (1972), as well as Friend and Blume (1970), indicated failure of CAPM in the estimation of the cost of capital: for high beta securities the model's forecasts are too high compared with historical averages; for low beta securities they are too low. Many financial economists, during the more than forty years of its existence, tried to improve the CAPM. For example, one of the logical extensions of CAPM is the intertemporal capital asset pricing model (I-CAPM) developed by Merton (1973). The main idea of Merton's model was to capture dynamic effect while maintaining CAPM's simplicity. In reality, the list of I-CAPM assumptions is not inferior in size to Sharpe-Lintner's model, including such standard assumptions of the perfect market where investors could rebalance its assets continuously in time, ignoring transaction costs, taxes and further restrictions.

In order to predict the effectiveness of complex internationally diversified portfolios, the logic of CAPM had been transferred to a global perspective. The existing need to capture more factors that have an effect on expected returns of portfolio led to the appearance of the International Capital Asset Pricing Model (ICAPM), initially proposed by Solnik (1974), Merton (1980), Sercu (1980), Adler and Dumas (1983) and others. According to Bartram and Dufey (2001), ICAPM can be formally stated as:

$$E(R_i) - R_f = \beta_i^w RP^w + \sum_{k=1}^{K} \gamma_{ik} RP_k, \tag{2.2.2}$$

where RP^w and RP_k are the risk premia on the world market portfolio and the relevant currencies, respectively, R_f is the risk-free interest rate.

The ICAPM has, generally, been tested in terms of performance of a simulated trading strategy based on Markowitz's mean-variance framework. The fact that a mean variance framework could not be assumed automatically without close monitoring of the stock markets limits the advantage provided by the simplicity of this framework. In an international context, a portfolio constructed according to the market capitalization of the individual markets is not mean-variance efficient (Bartram & Dufey, 2001). Lagoarde-Segot and Lucey claim that under financial integration, the domestic equity market becomes part of the global equity market (2006). They make the point that "therefore domestic assets are rewarded in function of their covariance with the world portfolio, as the risk premium on any asset is proportional to its world beta" (2006, p.19), thus highlighting the implications of ICAPM model to the measurement of financial market integration.

It was Grubel (1968) who first suggested that one country's specific risk could be diversified through investing in different countries' financial markets. The results also indicated that the allocation of assets across different countries would boost the performance of a US investor portfolio by increasing the annual rate of return from 7.5% to 12.6%. Solnik (1974) successfully demonstrated that investing in foreign securities can provide greater risk reduction than domestic diversification. These studies were based on the concept of constructing a diversified portfolio by including stock from international markets with a low or negative correlation with domestic markets. Therefore, the increased attention to emerging markets was a natural extension of the literature in this area. Correlation between emerging and developed markets was lower than among developed markets, providing benefits for international portfolio diversification. Levy and Sarnat (1970) considered 28 developed and emerging markets over the period 1951–1967 and found that the inclusion of emerging stock in American investor's portfolios improved the risk-return position. However, Brumelle (1974, p.473) argues that negative correlation is sufficient only if variables have "bivariate normal distribution or the investors have a quadratic utility function". This author proves that negative correlation is neither necessary nor sufficient for diversification, while the form of dependence, involving the entire distribution of assets returns, is sufficient for diversification. A study by Brumelle (1974) is in line with earlier work by Samuelson (1967) which also discusses the need for restriction on joint distribution, in order to achieve diversification.

There are two main problems widely discussed in literature with assets joint distribution: heavy tails and tail dependence, where the former refers to marginal asset distributions, while the latter refers to the connection between asset distributions at extreme quantiles (Chollete et al., 2012). Both heavy tails and tail dependence can significantly affect the diversification features of the portfolio (e.g., Samuelson, 1967; Brumelle, 1974; Ibragimov & Walden, 2007; Chollete et al., 2012). For example, Ibragimov, Jaffee and Walden (2011, p.334) claim that "the higher the correlation and the heavier the tails of the risk distribution, the less beneficial risk-sharing is".

The studies by Markowitz (1952, 1959), Tobin (1958), Samuelson (1967), Grubel (1968), Solnik (1974), and other early period scholars, inspired extensive research that investigated the interconnectedness of stock markets across the globe. However, while early papers indicated a stability of correlation between markets (e.g., Panton, Lessig, & Joy, 1976; Watson, 1980), further papers reported that correlation changes with time (e.g., Longin & Solnik, 1995; Bekaert & Harvey, 1995; Cappiello, Engle & Sheppard, 2006). The correlation between financial markets was found to be increasing over time, which was explained by Campbell and Hamao (1992), Roll (1992), Bracker and Koch (1999), to name but a few, and was identified as a cause of increases in real economic linkages between markets. The instability of correlation structure and, consequently, the time-varying benefits of international portfolio diversification, were actively discussed in studies that considered equity market integration.

2.2.2 Integration of financial markets

Increasing financial market interconnectedness has been found to be consistent with increasing equity market integration (e.g., Erb, Harvey & Viskanta, 1996; Forbes & Rigobon, 2002; Hardouvelis, Malliaropulos & Priestley, 2006; Kearney & Poti, 2006), and is seen to be driven by markets forces (e.g., increasing international trade, increasing business cycle synchronization, low and convergent inflation and interest rates etc.) but constrained by regulatory barriers (Aggarwal, Lucey & Muckley, 2010). Similar to the correlation between financial markets, international equity market integration varies over time and among markets. It is a dynamic process which is often considered in literature within the context of increasing financial liberalization, globalization and economic development. According to the generic definition, as stated in Lagoarde-Segot and Lucey, (2006, p.17), the integration of financial markets means that "all potential market participants with the same characteristics (i) face a single set of rules when they decide to deal with financial instruments, (ii) have equal access to these financial instruments, and (iii) are treated equally when they are active in the market (Baele et.al, 2004)". More specifically, increased financial market integration manifests itself in the absence of arbitrage opportunities among markets situated in different geographical regions. Therefore, integration of financial markets leads to an intensification of equity market interconnectedness at both intra-regional, and inter-regional, levels.

As the integration of the financial markets is not a uniform process that significantly progressed in time, many studies analyse integration utilizing various estimation periods and varying country selections, providing evidence from different methodologies. Due to the fact that integration is a dynamic process it is challenging to measure it. The study by Kearney and Lucey (2004) discussed different approaches to the investigation of integration. There are two main categories of measures that can be used to evaluate the integration of financial markets: direct measures and indirect measures. The first approach, i.e. direct measures, suggests evaluating the extent to which the rate of returns of financial assets, with the same maturity and risk characteristics, are equalized across financial markets. The direct measures approach is based on the so-called law of one price, following the logic that the lessening of regulatory barriers between markets will cause the distribution of capital flows to the most attractive asset classes across the globe, consequently equalising the returns on the assets with the same risk characteristics. However, the main challenge of this approach to measuring integration is to identify assets that are sufficiently homogenous in terms of their risk profiles to make an adequate comparison of the equalisation of financial markets (Kearney & Lucey, 2004, p. 573). Examples of studies that employed the first approach includes, but is not limited to, Lewis (1999), Ayuso and Blanco (1999), and Coelho et al. (2007). The second approach, i.e. indirect measures, can also be divided into two categories. The former examines whether asset returns are a function of domestic or international factors, relying on the concept of international capital market completeness. The latter assumes equity market integration can be assessed through investigation, whether domestic investment is financed from world savings or from domestic savings. Examples of studies that used indirect measures include Portes and Rey (2000) and Bekaert, Harvey, and Lumsdaine (2003). A more detailed literature review of the measures of integration can be found in Kearney and Lucey (2004), Bekaert et al. (2003), and Goetzmann and Rouwenhorst (2005). However, both approaches to measuring integration are based on a similar idea, that is, the existence of unrestricted capital flow between markets, which naturally links to unrestricted information flow and the minimising of asymmetry of information.

The investigation of the information transmission mechanisms, including responses to the common macroeconomic shocks of the financial markets, as well as transmission of shocks occurring on one of the markets compared to other markets, are used as direct measures of integration as well. Generally, as it was claimed by Coelho et al. (2007, p.456) the direct approach is considered to be preferable among researchers, despite the complexity in finding reliable data and a method to prove the existence of integration. One of the methods used, for example, by Coelho et al (2007) is a rolling and recursive minimum spanning tree (MST) to assess the evolution of integration among 53 equity markets for the period from 1997 to 2006.

The MST is a graph of interconnected *N* nodes, where each of the nodes is a variable that represents the return of equity indices from the selected data set. The MST methodology starts with minimising the sum of the distances between nodes that are measured by a correlation matrix of returns. First, the correlation coefficient is computed for all pairs of returns (i, j) using the following equation:

$$\rho_{ij} = \frac{\langle R_i R_j \rangle - \langle R_i \rangle \langle R_j \rangle}{\sqrt{(\langle R_i^2 \rangle - \langle R_i \rangle^2)(\langle R_j^2 \rangle - \langle R_j \rangle^2)}}, \quad (2.2.3)$$

where R_i and R_j are the vectors of the time series of log-returns.

Second, each correlation coefficient is converted to a metric, i.e. the distance between pairs of returns:

$$d_{ij} = \sqrt{2(1 - \rho_{ij})}, \tag{2.2.4}$$

where $d_{ij} \in [0; 2]$, corresponding to correlation values $\rho_{ij} \in [-1; 1]$, i.e. smaller values of d_{ij} imply high correlation. Third, these distances form the $N \times N$ distance matrix D, which is used to construct the MST.

The MST methodology provides useful visualisation of the interconnectedness between large set of markets, that can be also applied dynamically to capture the evolution in patterns of stock market linkages over time. The results obtained by Coelho et al. (2007) show that the developed European countries have consistently constituted the most tightly linked markets among the countries in the sample. Further, the results have implications for international portfolio diversification indicating diminishing diversification benefits with time. However, due to the fact, that the correlation structure between markets is less likely to stay stable during the average holding period of portfolio investment, it makes sense to rebalance the assets in a portfolio to maximise the benefits of the diversification available in a specific time period (Coelho et al., 2007).

The fact the empirical results of integration tests suggests that there are implications for international portfolio diversification is not surprising, due to the meaning of integration assumed by the majority of studies. The increase in integration between financial markets will cause a reduction in diversification benefits. Besides, Aggarwal et al. (2010, p. 643) shows that increased integration can also have the following implications: i) the more complete the world's capital markets are, the more robust the economies of individual states will be; ii) household savings rates will consequently change over time. While the former will have a generally positive impact on the economic growth of a country, variability of household savings has a more uncertain impact. First, the increased attractiveness of domestic stock investment may lead to restructuring of household expenditure, replacing the consumption on domestic stock market investment. Second, lessening regulatory barriers will encourage a search for more profitable investments on foreign markets, ultimately resulting in a higher mobilization of savings (Oshikoya & Ogbu, 2003; Lagoarde-Segot & Lucey, 2006).

Kearney and Lucey (2004, p. 574) further divided the literature on financial integration into three categories, testing: i) the segmentation of equity markets via the international CAPM (e.g., Bekaert & Hodrick, 1992; Campbell & Hamao, 1992; Errunza, Losq, & Padmanabhan, 1992); ii) the extent, and determinants, of changes in the correlation or co-integration structure of markets (e.g., Bernard, 1991; Gilmore & McManus, 2002); and iii) time-varying measures of integration (e.g., Bekaert & Harvey,1995; Longin & Solnik, 1995; Forbes & Rigobon, 2002; Barari, 2004; Birg & Lucey, 2006; Aggarwal, Lucey, & Muckley, 2003, 2010). While the first two categories demonstrated limited attempts to measure the time-varying nature of integration, the third category of papers used more sophisticated methodologies to capture the dynamic linkages between markets.

For example, Birg and Lucey (2006) employed methodology proposed by Akdogan (1996, 1997) and its further extension by Barari (2004), to measure global equity market integration based on the international risk decomposition model, where "integration scores are calculated as a fraction of systematic risk in total country risk vis-à-vis the global benchmark. This measures the contribution of a country's market to global risk. Integration scores' calculation involves the use of a country's beta against the global benchmark portfolio" (Birg & Lucey, 2006, p.4). The findings demonstrate that developing European markets (i.e. Estonia, Hungary, the Czech Republic, Lithuania, and Poland) have become more integrated with both regional and global equity markets. The comparative examination of regional and world integration measures suggested by this methodology is highly important. Although a market can become less integrated with the world, its significance in a region may increase, consequently increasing the degree of regional integration, especially in the light of the formation of regional economic and political alliances (Birg & Lucey, 2006). However, recent evidence provided by Claus and Lucey (2012) shows that membership of a formal economic organization, such as ASEAN, does not seem to increase stock market integration, thus "financial market liberalization is a necessary, but not sufficient, condition for stock market integration" (p.149). While liberalisation tends to decrease some restrictions and barriers to capital, there are certain institutional barriers, for example taxes, that can restrict international capital flows and may cause stock market segmentation.

Another method proposed by Flood and Rose (2005a, b) suggests that markets are integrated if, at one point in time, the expected discount rates in different markets are equal:

$$p_t^j = E_t\left[d_{t+1} x_{t+1}^j\right], \tag{2.2.5}$$

where p_t^j is the price at time t of asset j and $E_t[]$ is the expectations operator conditional on information available at time t; d_{t+1} is the market discount rate for income accruing in period $t+1$, or the marginal rate of intertemporal substitution; x_{t+1}^j is the income received at $t+1$ by owners of asset j at time t. Notation used as in Claus and Lucey (2012). Flood and Rose (2005a, b) show that this methodology is consistent with intertemporal models of asset pricing, discussed in previous subsection.

The equation (2.2.5) can be rewritten as follows:

$$\frac{x_{t+1}^j}{p_{t-1}^j} = \delta_t\left(\left(\frac{p_t^j}{p_{t-1}^j}\right) + \beta_j^0 + \sum_{i=1}^m \beta^i f_t^i\right) + \varepsilon_{t+1}^j, \tag{2.2.6}$$

where $\delta_t \equiv 1/(E_t[d_{t+1}])$, $\varepsilon_{t+1}^j \equiv x_{t+1}^j - E_t[x_{t+1}^j]$, that is a predictor error, and a factor model with $\{\beta_j\} = \{\beta_j^0, \beta^i\}$, $i=1,\ldots,m$; ε_{t+1}^j is white noise. The model also has the following restriction:

$$Cov[d_{t+1}x_{t+1}^j] = \beta_j^0 + \sum_{i=1}^m \beta^i f_t^i, \tag{2.2.7}$$

where β_j^0 is an asset specific intercept, β^i is a set of m market-specific factor coefficients, and f_t^i is a vector of m time varying factors.

This methodology has been employed by Claus and Lucey (2012) in their analysis of stock market integration across 10 emerging and developed markets in the Asia Pacific region over the period April to May, 2006. The findings for Asian markets, i.e. Japan, Hong Kong, Singapore, South Korea, Taiwan and Malaysia show higher degrees of integration in the developed markets of Japan and Hong Kong, and lower in those of Singapore and the emerging markets of Taiwan and Malaysia. The results also show that emerging markets from the Asian region have a relatively lower degree of financial integration than those of developed markets.

Finally, since co-integration has an intuitive appeal to researchers of integration, a significant number of studies have used cointegration measures to assess integration between markets (Kearney & Lucey, 2004, p. 576). Due to the fact that this literature is extensive it has been considered separately in the next subsection.

2.2.3 Tests on co-integration

The literature testing co-integration includes numerous papers that analysed long- and short-term relationships between financial markets (including Alagidede & Panagiotidis, 2009; Cajueiro, Gogas, & Tabak, 2009; Singh et al., 2010;). The conventional analysis of equity markets co-integration is based on the idea that returns of co-integrated markets have a unit root. One of the most popular conventional approaches to testing markets on co-integration is to test series for one unit root by utilizing the augmented Dickey-Fuller (ADF) test suggested by Engle and Granger (1987). The Engle-Granger methodology for testing the co-integration hypothesis was employed by early studies (e.g., Bernard, 1991; Arshanapalli & Doukas, 1993; and Gallagher, 1995.).

The Augmented Dickey-Fuller (ADF) test constructs a parametric correction for higher-order correlation by assuming that the Y series follows an AR(p) process and adding *p* lagged difference terms of the dependent variable Y to the right-hand side of the test regression:

$$\Delta y_t = \alpha y_{t-1} + x'_t\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \cdots + \beta_p \Delta y_{p-2} + v_t \qquad (2.2.8)$$

where *t* is a time trend and v_t is a white noise

The Null and alternative hypotheses may be written as:

$$H_0: \alpha = 0 \qquad (2.2.9)$$

$$H_1: \alpha < 0$$

A levels-regression is performed to generate residuals which may be thought of as equilibrium pricing errors, where the residuals are then subjected to tests for co-integration (Chen, Firth & Rui, 2002, p.1125).

It is worth mentioning, that the majority of studies that employed the Engle-Granger methodology only indicated low levels of integration among markets, providing surprisingly consistent evidence for countries from different regions. Later, the ADF test for co-integration was often employed together with the more sophisticated multivariate co-integration technique based on the trace statistics and eigenvalues introduced by Johansen (1988), which has a starting point in the VAR mode:

$$X_t = \mu + A_1 X_{t-1} + A_2 X_{t-2} + \cdots + A_k X_{t-k} + \varepsilon_t, \qquad (2.2.10)$$

where X_t is an $n \times 1$ vector of variables; ε_t is an $n \times 1$ vector of innovations; A_k is an $n \times n$ coefficient matrix. The notation used is as in Hjalmarsson and Österholm (2007).

The equation (2.2.10) can be re-written as:

$$\Delta y_t = \mu + \Pi y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t, \quad (2.2.11)$$

where

$$\Pi = \sum_{i=1}^{k} A_i - I \text{ and } \Gamma_i = -\sum_{j=i+1}^{k} A_j, \quad (2.2.12)$$

If the coefficient matrix Π has reduced rank $r < n$, then there exist $n \times r$ matrices $\propto$ and β each with rank *r* such that $\Pi = \propto \beta'$ and $\beta' y_t$ is stationary, where r is the number of co-integrating relationships; $\propto$ denotes the adjustment parameter in the vector error correction model; β is a cointegrating vector.

The Johansen Cointegration test analyses the presence of co-integrating vectors in a set of non-stationary data. The trace test assesses the Null Hypothesis of *r* cointegration vectors against the alternative hypothesis of *n* co-integrating vectors. The maximum eigenvalue test assesses the Null Hypothesis of *r* co-integrating vector against the alternative hypothesis of *r+1* co-integrating vectors (Hjalmarsson & Österholm, 2007). The trace statistics and maximum eigenvalues tests can be described as follow:

$$J_{trace} = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i), \quad (2.2.13)$$

$$J_{max} = -T \ln(1 - \hat{\lambda}_{r+1}), \quad (2.2.14)$$

where *T* is the sample size and $\hat{\lambda}_i$ is the *i*th largest canonical correlation.

The Johansen co-integration test has been notably employed by Gilmore and McManus (2002) and Manning (2002). While a combination of the ADF and Johansen co-integration test is employed by Chen et al. (2002) to test co-integration hypothesis among six emerging stock markets from Latin America. Authors found that there were limited diversification benefits in investing in various stock markets from Latin America, up until 1999, due to the commonalities of the business cycle and economic policies. However, the accuracy of the standard co-integration tests deteriorated once significant time-varying relationships and structural breaks were evident in the data generating process, resulting in the failure to reject the null hypothesis of no co-integration (e.g., Campose et al., 1996; Gregory & Hansen, 1996). The Johansen co-integration test has been employed as it takes into account regime-switch for regime switching in co-integrating relationships (e.g., Lucey & Voronkova, 2008; Kenourgios & Samitas, 2011; Kenourgios & Padhi, 2012), Chelley-Steeley (2004) utilized the nonlinear smooth transition logistic trend model of Granger and Terasvirta (1993), which allows testing co-integration among markets by identifying the deterministic structural changes in data. One of the important findings reported by Chelley-Steeley (2004) was the low degree of both global and regional integration of the Taiwan market.

Furthermore, Gregory and Hansen (1996) suggest that the standard co-integration tests may spuriously fail to reject the null hypothesis of no co-integration with the presence of structural changes. Their Monte Carlo simulation exercise further verifies that standard co-integration test loses validity and provides false conclusions when shifts in parameters take place. Gregory and Hansen (1996) discussed three alternative models to capture the changes in the co-integration vector. The first is the level shift model (or C model) that represents the change in the intercept at the time of the shift. The second model is level shift with trend (or C/T model) which allows the slope vector to shift as well. The last model allows for changes both in the intercept and in the slope of the co-integration vector (or C/S model). The co-integration test proposed by Gregory and Hansen (1996) allows one regime switch which is determined by the data. This methodology has been employed by Voronkova (2004) to test co-integration among developed European markets and the emerging Central European markets over a period from September, 1993 to April, 2002. The empirical results suggests that the increased integration between the emerging markets, i.e. the Czech Republic, Hungary, and Poland, and the developed markets, i.e. the UK, France, Germany, and the US, indicate diminution of the diversification benefits available in emerging markets in this region.

Finally, based on the framework of Gregory and Hansen (1996), a model that takes into account two structural shifts is developed by Hatemi-J (2008). His model considers the impact of two structural breaks on both the intercept and slopes (two regime shifts). With a bivariate case of two markets, the method used in Hatemi-J (2008) could be specified as:

$$y_{1t} = \mu_1 + \mu_2 D_{1t} + \mu_3 D_{2t} + \lambda_1^T y_{2t} + \lambda_2^T y_{2t} D_{1t} + \lambda_3^T y_{2t} D_{2t} + \varepsilon_t \qquad (2.2.15)$$

where $\mathrm{D}_{1\mathrm{t}}$ and $\mathrm{D}_{1\mathrm{t}}$ are dummy variables defined by Eqs. (2.2.16) and (2.2.17):

$$D_{1t} = \begin{cases} 0, & if\ t \leq [n\tau_1], \\ 1, & if\ t > [n\tau_1], \end{cases} \qquad (2.2.16)$$

$$D_{2t} = \begin{cases} 0, & if\ t \leq [n\tau_2], \\ 1, & if\ t > [n\tau_2], \end{cases} \qquad (2.2.17)$$

The date of pairwise breaks is estimated with the unknown parameters $\tau_1 \in (0,1)$ and $\tau_2 \in (0,1)$. The null hypothesis of no cointegration between markets is tested by the Zt statistics of Phillips (1987). The Zt statistics is estimated as $Z_t^* = inf_{(\tau_1 \tau_2) \in T} Z_{t((\tau_1 \tau_2),}$ where $T = (0.15n, 0.85n)$.

The existence of structural breaks is a classical statistical problem which affects volatility and long-range dependence in stock returns (Andreou & Chysels, 2002). Besides cointegration literature, the test on structural breaks has been actively used in analyses of volatility spillovers, more specifically for investigation of the contagion phenomenon and for identification of the length of the financial crisis (e.g., Karanasos et al., 2014; Dimitriou, Kenourgios & Simos, 2013). A structural break, which can naturally be associated with the crisis shock, may change the stock market interdependencies during the crisis. Consequently, this limits the international portfolio diversification benefits available during turmoil periods, when they are needed the most (Longin & Solnik, 2001). The issue of contagion is another important field in literature underpinned this thesis and will be considered in detail in the next section.

2.3 Return and volatility spillovers during crisis episodes

2.3.1 Defining contagion and the spillover effect

One of the central issues of international portfolio diversification is the increasing interdependencies of the financial markets during crisis periods. There are numerous studies that investigate this phenomenon, considering various crises such as the October Crush in 1987 (e.g., Roll,1988, 1989; Eun & Shim,1989; Von Furstenberg & Jeon,1989; King & Wadhwani,1990), the Mexican Currency Crisis in 1994-1995 (e.g., Calvo & Reinhart, 1996; Caramazza, Ricci & Salgado, 2004; Haile & Pozo, 2008), the Asian Crisis in 1997 (e.g., Sheng & Tu, 2000; Masih & Masih, 2001; Climent & Meneu, 2003; Khalid & Kawai, 2003; Caporale, Pittis & Spagnolo, 2006; Engle, Gallo & Velucchi, 2012), the Russian Default in 1998 (e.g., Chen et al., 2002; Yang, Hsiao & Wang, 2006), as well as other crises. The most recent literature to date has analysed contagion during the Global Financial Crisis in 2008-2009 (e.g., Zhang, Li & Yu, 2013; Bekiros, 2014; Luchtenberg & Vu, 2015) and the European Debt Crisis in 2010-2011 (e.g., Petmezas & Santamaria, 2014; Albulescu, Goyeau & Tiwari, 2015), or both crisis episodes. The analysis of contagion has become critically important because in a globalised world no one market can fully insulate itself from foreign shocks. The analysis of the contagion phenomenon provides insight into international transmission mechanisms, i.e. return and volatility transmissions.

The term "contagion" is consistently used within this literature. However, its definition varies between studies. The respected paper by Forbes and Rigobon (2002) provides a narrow definition of contagion describing contagion effect as the increased spillovers between different markets after a crisis shock has occurred in one of the markets. In other words, volatility shock on one market can cause the contagion effect and spillover of volatility in another market, while the change in correlation between markets is defined as interconnectedness. Alternatively, Bekaert, Harvey and Ng (2005), who used an asset pricing approach to model the shock and correlation structure around crisis periods, defined contagion as the correlation among residuals of a two-factor asset pricing model. They claim that an increase in correlation between returns during the crisis can be the consequence of their exposure to a common factor.

The investigation of contagion has been defined as "*the significant increase in cross-market linkages after a shock*" (Forbes & Rigobon, 2002, p.2224) forms an important part of this thesis. Forbes and Rigobon (2001) use the alternative term "shift-contagion", which clarifies that contagion arises from a shift in cross-market linkages and gives a straightforward framework for assessing contagion effect. However, Morales and Andreosso-O'Callaghan (2014) argue that any definition of contagion should not be so restrictive and should take into account not only financial but also macroeconomic fundamentals. Morales and Andreosso-O'Callaghan raised challenging questions:

> Is it possible to talk about contagion effects that are derived solely from one particular market or variable? Would real contagion take place anyway when many of the financial and economic fundamentals of a country are affected and transmitted to the rest of the world economies? (2014, p.113)

They claim that the impact of the GFC on cross-markets interdependencies across various regions could be defined as "spillover effect" rather than "contagion", clarifying the difference between these two terms. This view on contagion is supported in an early paper by Eichengreen, Rose and Wyplosz (1996) who claim that contagion exists if the probability of a crisis in one country increases conditional on the occurrence of a crisis elsewhere, after allowing for the standard set of macroeconomic fundamentals. Furthermore, a similar definition of contagion has been used by Edwards (1998) and Eichengreen and Rose (1999). An alternative viewpoint was provided in studies by Wolf (1999), Masson (1999, 2004), and Pretorious (2002) who claimed that the term 'contagion' can be used to describe only those transmissions of crises that cannot be identified with observed changes in macroeconomic fundamentals. For example, financial contagion according to Masson (1999; 2004) involves changes in investors' expectations and, consequently, market behaviours that are not related to changes in a country's macroeconomic fundamentals.

Another explanation of contagion phenomenon is provided by Jokipii and Lucey (2006, p.9) who associated the term contagion with "a structural break producing an intensification of relationships during a period of turmoil". Contributing to the debate about differences in the terms "contagion" and "interdependence", authors considered contagion as a dynamic process, i.e. changes in the degree of co-movements during a period of turbulence, while interdependence is assumed to be "a divergent phenomenon whereby stability persists, and no change in the relationships between markets is evident" (Jokipii & Lucey, 2006, p.8). Authors provided two ways as to how the contagion phenomenon can be explained: the fundamental causes and investor behaviour theories. The fundamental reasons why contagion may occur include: i) a common shock, which can result in large capital outflows from the emerging markets affecting the degree of co-movements. “For example, a major economic shift in industrial countries, a change in commodity prices or a reduction in global growth” (p.9); ii) changes in trade linkages during the crisis due to the reduction in demand affecting the trade balance and other fundamentals; iii) strong intra-regional financial linkages causing the spread of crisis shock from one country to another within the same region through trade credit reductions, direct foreign investment and other capital flows (Jokipii & Lucey, 2006, p.9).

Alternatively, the contagion can be explained using investors’ behaviour theories. For example, a crisis occurring on the domestic market may cause a liquidity problem for a large group of investors and cause them to sell the foreign assets from their portfolio, causing, in turn, a fall in the price of securities in the foreign market. Similarly, this investor behaviour can be understood by risk aversion bias. Evaluation of the risk of the portfolio against the same benchmark may force investors to sell their holdings in emerging markets simultaneously during the crisis, which can destabilise the market of the other country without any fundamental reasons. Finally, Jokipii and Lucey (2006) claimed that information asymmetries and imperfect information may affect an investor’s behaviour due to a belief that a crisis can simply spread to neighbouring markets, forcing numerous investors to leave the market without proper investigation of the macroeconomic fundamentals of that market.

A similar explanation of contagion presented in a study by Haile and Pozo (2008, p.574), contained a review of various definitions of contagion and a variety of economic models explaining how a crisis that occurred in one country can spread to other countries. The authors also provided two major categories of models explaining contagion. The first category is named “fundamentals-based contagion”, including models that assume that crises spread through changes in macroeconomic fundamentals caused by shocks from the country where a crisis originally occurred. Alternatively, the second category includes models explaining contagion through changes in the behaviour of investors. In this case, crises spreads from one country to another following the information flows transmitted across borders through various channels affecting the behaviour of financial agents rather than the macroeconomic fundamentals of the specific country.

Although this thesis does not investigate the causes of contagion, neither fundamental nor behavioural, these explanations are very useful for defining contagion. This research focuses on information transmission mechanisms across markets and does not consider the changes in macroeconomic fundamentals. Following the definition provided by Forbes and Rigobon (2002), this thesis provides a narrow definition of contagion effect, and defines contagion as:

A phenomenon of the increased magnitude of return and volatility spillovers across markets after a crisis shock has occurred in one of the markets.

This type of contagion has been called "pure contagion" (e.g., Kumar & Persaud, 2002; Kenourgios & Dimitriou, 2015), because it ignores the transmission of shocks through macroeconomic fundamentals.

The term "spillover effect" in this thesis is used in regard to transmission of information contained in both returns and volatilities of assets. Therefore two definitions are used:

Return spillover effect is a situation when changes in return in one market affect changes in return in another market.

Volatility spillover effect is a situation when changes in volatility in one market affect the volatility of another market.

In other words, this thesis assumes that spillover effect can appear across both returns (returns spillovers) and volatility (volatility spillovers), and the intensity of the spillover effect changes over time. The increased magnitude of return and volatility spillovers, i.e. "bursts in spillovers", after a crisis shock is assumed to be a contagion.

This supports the position adopted by Forbes and Rigobon (2002), who critiqued studies that employed cross-market correlation coefficients to test contagion, due to the fact that a conditional correlation coefficient can increase after a crisis episode. This is mainly due to the increase in market volatility, rather than any unconditional correlation across markets. Thus, the increase in cross-market correlation coefficient is a biased measure and it is not possible to prove either contagion or spillover effect across markets. The terms "stock market interconnectedness", "stock market interdependencies" and "stock market interlinkages" are used in this thesis as synonymous descriptive linkages across stock markets that can be measured by conditional correlation coefficients. "Contagion" and "spillover effect" are more specific terms than those defined above, and require the application of more sophisticated techniques than cross-market correlation, for example, due to the heteroskedasticity problem of financial time-series.

2.3.2 The ARCH-family models

The presence of autoregressive conditional heteroskedasticity (ARCH effect) can impact on linear test statistics, thus the Nobel Prize winning paper by Engle (1982) that introduced ARCH class of models causing the development of new procedures for modelling and forecasting time-varying financial market volatility (Bollerslev, 2008). The ARCH model by Engle (1982), and its generalisation by Bollerslev (1986), has been extended by many researchers and employed in analysis of stock market dependency. The most influential early papers on ARCH class of models were presented in Engle (1995). The ARCH family models have a dominant position in the analysis of international return and volatility transmissions across markets (e.g., Hamao et al., 1990). The reason for the popularity of these models was their ability to capture the autoregressive conditional heteroskedasticity, which could not be captured by other famous methodologies, for example, the VAR methodology employed by Eun and Shim (1989), Von Furstenberg and Joen (1989), Huang, Yang and Hu (2000), Sheng and Tu (2000), Masih and Masih (2001), and Climent and Meneu (2003).

The simple ARCH (p) model by Engle (1982) provides parameterization to capture the tendency for large (small) variance to be followed by other large (small) variance. Let R_t denote stationary time series, and then R_t can be described as follow:

$$R_t = \mu + \varepsilon_t, \tag{2.3.1}$$

where μ is the mean of R_t, and ε_t is error term. To allow conditional heteroskedasticity, assume that error term ε_t has the time varying conditional variance h_t :

$$var_{t-1}[h_t] = \varepsilon_t^2, \tag{2.3.2}$$

Where var_{t-1} is the variance conditional on information at time $t-1$, and can be expressed as:

$$\varepsilon_t^2 = \omega + b_1 h_{t-1}^2 + \cdots + b_p h_{t-p}^2, \tag{2.3.4}$$

h_t is a positive linear function of the squared error terms in the past p periods that are defined:

$$var_{t-1}[h_t] = E[h_{t-1}^2] = \varepsilon_t^2, \text{ since} \tag{2.3.5}$$

$$E[h_t] = 0 \tag{2.3.6}$$

Therefore the simple ARCH (p) model can be written as follow:

$$h_t = \omega + \sum_{i=1}^{p} b_i \varepsilon_{t-i}^2, \tag{2.3.7}$$

where ω is positive and parameters b_i are non-negative, to ensure strictly positive variance. The equation explains that the large past squared shocks caused a large conditional variance h_t at time *t*.

Later, Bollerslev (1986) improved the ARCH (*p*) model by adding q autoregressive in the conditional variance equation, which means that conditional variance depends on the squares residuals in the previous p periods, and the conditional variance in the previous q periods:

$$h_t = \omega + \sum_{i=1}^{p} b_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} c_i h_{t-j}^2, \tag{2.3.8}$$

where ω is positive and the coefficients b_i and c_i are non-negative to ensure that the conditional variance h_t is always positive.

The model described by equation (2.3.8) is known as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and its specification GARCH (p, q) has become one of the most commonly used models of the ARCH family. The GARCH (p, q) model is more suitable to the capture of the dynamics of a time series' conditional variance. The model also includes four phases: data preparation, model identification, parameter estimation and diagnostic checking (Tan, Zhang, Wang & Xu, 2010). When $q = 0$ the GARCH model reduces to the ARCH model. A GARCH (p,q) model is stationary if the sum of its coefficients is smaller than one:

$$\sum_{i=1}^{p} b_i + \sum_{j=1}^{q} c_i < 1, \tag{2.3.9}$$

There are a number of techniques that could be employed to estimate the parameters of the GARCH model, for example, maximum likelihood approach. The maximum likelihood estimator is a nonlinear estimator and more efficient than the OLS estimator.

There are several multivariate extensions of the univariate GARCH model, such as MGARCH, VEC and BEKK. Bollerslev, Engle and Wooldridge (1988) propose the general VEC (1, 1) model which is defined:

$$h_t = c + A\eta_{t-1} + Gh_{t-1} \tag{2.3.10}$$

where

$$h_t = vech(H_t) \quad (2.3.11)$$

$$\eta_t = vech(\varepsilon_t \varepsilon_t') \quad (2.3.12)$$

where is $vech\ (.)$ is the operator that stacks the lower triangular portion of a $N \times N$ matrix as $N(N+1)/2 \times 1$vector. A and G are square parameter matrices of order $(N+1)N/2$ and c is a $(N+1)N/2 \times 1$ parameter vector (Bauwens, Laurent & Rombouts, 2006, p.82). The number of parameters can be calculated as $N(N+1)(N(N+1)+1)/2$ depending on the value of N which makes this model very complex to use in practice, and convenient only for bivariate cases.

Another parameterisation of H_t called the BEKK model was proposed by Engle and Kroner (1995). The acronym came from the work on multivariate models by Baba, Engle, Kraft and Kroner (1991). Bauwens et al. (2006) define the BEKK (1, 1, K) model as follows:

$$H_t = C^{*\prime}C^* + \sum_{k=1}^{K} A_k^{*\prime}\, \varepsilon_{t-1}\varepsilon_{t-1}' A_k^* + \sum_{k=1}^{K} G_k^{*\prime} H_{t-1} G_k^* \quad (2.3.13)$$

where $\mathrm{C}^*, \mathrm{A}_\mathrm{k}^*$ and G_k^* are $\mathrm{N} \times \mathrm{N}$ matrices, C^* is upper triangular.

In the BEKK (1, 1, 1) models, the number of parameters is $(5N+1)/2$, causing the problem of application to the big matrices. There are several restrictions proposed in literature to minimise the number of parameters in both VEC and BEKK models. However, these models are very rarely applied to the cases where the number of series is more than 3 or 4.

For example, Li and Giles (2014) employed an asymmetric BEKK model to investigate volatility spillovers across the USA, Japan and the emerging stock markets of China, India, Indonesia, Malaysia, the Philippines and Thailand over the period 1 January, 1993 to 31 December, 2012. The results show that the US stock market has unidirectional shock spillovers to both the Japanese and the emerging stock markets, and these channels of information conveyance are robust in both the long and short term. Furthermore, the paper reports the volatility spillovers from Japan to the Asian emerging markets in both the long and short term. It is noteworthy that the linkages between the Japanese market and the emerging markets in the Asian region have become stronger during the past 5 years.

2.3.3 The Dynamic Conditional Correlation

Engle (2002) introduced the dynamic conditional correlation (DCC) estimator which has several advantages over multivariate GARCH models. The first advantage is that it can be applied to large correlation matrices, which was inconvenient under the multivariate GARCH models because of the large number of parameters to be estimated. The number of parameters in the DCC method is not dependent on the number of the correlated series. Therefore, the DCC estimators keep the simplicity and flexibility of the univariate GARCH model. The DCC method can be ascertained using the original paper by Engle (2002). Cappiello et al. (2006), who proposed the asymmetric generalized dynamic conditional correlation (AG-DCC) model, developed it based on the seminal work of the DCC-GARCH model (Engle, 2002). The model takes into account conditional asymmetries in both volatilities and dynamic correlations, and it allows the modelling of time varying correlation during periods of negative shocks in a multivariate setting.

The estimation process involves a two-step procedure. The first step estimates univariate volatility using a GARCH (1, 1) model as detailed in Bollerslev (1986). The second step adopts the standardized residuals for each time series in step 1 to estimate the correlation parameters. Where the standardized residuals can be denoted as $\varepsilon_{i,t} = r_{i,t}/\sqrt{h_{i,t}}$, we use the same notations as in Kenourgios and Padhi (2012), where the data generating process as given in Engle (2002) is:

$$Q_t = (1 - a - b)\bar{P} + a\varepsilon_{t-1}\varepsilon_{t-1}' + bQ_{t-1} \tag{2.3.14}$$

$$P_t = Q_t^{*-1}Q_tQ_t^{*-1} \tag{2.3.15}$$

where $\bar{P} = E[\varepsilon_t\varepsilon_t']$ and a and b are scalars $(a + b < 1)$. $Q_t^* = [q_{iit}^*] = [\sqrt{q_{iit}}]$ is a diagonal matrix with the square root of the ith diagonal element of Q_t on its ith diagonal position. When $Q_t > 0,\ Q_t^*$ is a matrix which guarantees $P_t = Q_t^{*-1}Q_tQ_t^{*-1}$ is a correlation matrix with ones on the diagonal and every other element ≤ 1 in absolute value.

However, the model described by equations (2.3.15) and (2.3.16) does not capture the conditional asymmetries in volatilities and dynamic correlation. Therefore, Cappiello et al (2006) suggested the model:

$$Q_t = (\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G) + A'^{\varepsilon_{t-1}\varepsilon_{t-1}'}A +$$

$$+G'n_{t-1}n_{t-1}'G + B'Q_{t-1}B), \tag{2.3.16}$$

where A, B and G are $k \times k$ parameter matrices, $n_t = I[\varepsilon_t < 0]°\varepsilon_t$ ($I[\cdot] is\ a\ k \times 1$ indicator function which takes on value 1 if the argument is true and 0 otherwise, while "°" indicates the Hadamard product) and $\bar{N} = E[n_t n_t']$. Eq. (13) is the AG-DCC model, where Q_t is positive definite for all possible realizations if the intercept $\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G$ is positive semi-definite and the initial covariance matrix Q_0 is positive definite.

2.3.4 Empirical evidence of contagion

The Global Financial Crisis in 2007-2010 was the strongest global shock after the Great Depression and facilitated the new stream of academic literature investigating return and volatility spillovers around these crisis episodes (e.g., Luchtenberg & Vu, 2015). The recent Eurozone debt crisis in 2010 is also well presented in the contemporary literature on contagion (e.g., Petmezas & Santamaria, 2014). This strand of literature is very important in this thesis because contagion across markets during periods of turmoil changes the benefits of international portfolio diversification available for investors. These crisis episodes are also significant in accordance to the analysed estimation period. Zhang et al. (2013) claim that after the world financial crisis, diminishing diversification benefits had become a long-running and world-wide phenomenon. However, according to the definition of contagion utilized by this thesis, the increased magnitude of return and volatility transmissions across international financial markets can offer further opportunities to forecast domestic market returns by using foreign information transmissions.

There is great diversity of methodologies, country selection, and data frequency and length of estimation periods employed within the literature. A study by Jung and Maderitsch (2014) investigates volatility spillovers across the US, Europe and Hong Kong using intra-daily data and confirms findings provided by Forbes and Rigoborn (2002). The authors claim that there is no contagion across target markets. However, there is sound evidence of interdependence. Ahmad, Sehgal and Bhanumurthy (2013) employed the DCC-GARCH model to investigate contagion effects between daily returns on developed markets of GIPSI (Greece, Ireland, Portugal, Spain and Italy), the USA, the UK and Japanese markets, and daily returns on BRIICKS (Brazil, Russia, India, Indonesia, China, South Korea and South Africa) emerging stock markets for the period from 19 October, 2009 to 31 January, 2012. The empirical results show strong contagion shock caused by the Eurozone debt crisis affected the markets of Brazil, Russia, India, China and South

Africa (BRICS), while Indonesia and South Korea demonstrate interconnectedness rather than contagion.

The paper by Bekiros (2014) analyses the volatility spillovers between the US, the EU and the BRIC markets using the daily returns for the period from 5 January, 1999 to 28 February, 2011. The results demonstrate the intensification of linkages between BRIC and developed markets after the Global Financial Crisis. Similar results provided by Kenourgios, Samitas and Paltalidis (2011) used both a multivariate regime-switching Gaussian copula model and the asymmetric generalized dynamic conditional correlation (AG-DCC) approach to investigate non-linear correlation dynamics across the US, the UK and the BRIC stock markets during the period 1995–2006 which includes five crisis episodes. These findings are consistent with a recent paper by Syriopoulos, Makram and Boubaker (2015) which confirms strong spillovers from the US to BRICS stock markets providing evidence from the VAR (1) – GARCH (1, 1) framework. The empirical findings support a strong contagion effect from the crisis country to all others. Besides the contagion effect, Bekiros (2014) analysed the so-called "decoupling" phenomenon, which manifests itself in a growing influence of the emerging markets on developed markets, based on the assumption that the emerging markets become the major drivers of world economic growth as opposed to the US economy. However, the paper failed to provide evidence on the decoupling hypothesis.

The study by Dimitriou et al. (2013) employed a multivariate Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) dynamic conditional correlation (DCC) framework to investigate the contagion effect of the Global Financial Crisis, analysing the US and BRICS stock markets. A study suggests that there is no evidence of "a pattern of contagion for all BRICS' markets that could be attributed to their common trade and financial characteristics" (Dimitriou, Kenourgios & Simos, 2013, p.55). The researchers employed the DCC of Tse and Tsui (2002) instead of Engle (2002) to the daily returns from 1997-2012, covering the various phases of the Global Financial Crisis. One of the recent studies by Karanasos, Yfanti and Karoglou (2014) employed the vector AR-DCC-FIAPARCH model with DCC specification by Engle (2002) to the daily returns on eight developed stock market indices (the US, Canada, the UK, Germany, France, Hong Kong, Japan, and Singapore). The paper demonstrated sound contagion effect for both Global Financial Crisis and Asian crisis, due to financial liberalization and integration of the markets. Karanasos, Paraskevopoulos, Ali, Karoglou and Yfanti (2014) employed the bivariate unrestricted extended dynamic conditional correlation (UEDCC) AGARCH (1, 1) to the daily data from 1988 to 2010 to analyse the volatility spillovers from the stock market of the UK to Germany and from Japan to Hong Kong. The findings support the existence of the contagion effect during crisis periods. Choudhry and Jayasekera (2014) employed the GARCH-GJR framework to evaluate the spillovers effect during the Global Financial Crisis across developed stock markets, i.e. Germany, the UK and the US, and the smaller affected developed markets, i.e. Italy, Ireland, Greece, Spain and Portugal. The empirical results also indicated an increased spillover effect during the crisis.

Several recent studies have provided a regional perspective on return and volatility spillovers around crisis episodes. The study by Morales and Andreosso-O'Callaghan (2014) analyses contagion effect, derived from the US stock market, on a set of 58 countries taken from four geographical regions: America, Europe, Asia and Africa. The full estimation period is from January, 2003 to May, 2009, where the Global Financial Crisis is identified from October, 2007 to May, 2009. The authors claim that there is no evidence of contagion effect from the US shock to the markets from other regions. This supports the findings by Bekaert, Ehrmann, Fratzscher and Mehl (2011) that also show weak evidence of contagion from the U.S. market to global equity markets during the crisis. These findings are different from the mainstream results.

However, the root of this difference again goes to the actual definition of contagion effect. Morales and Andreosso-O’Callaghan (2014) separate the term “contagion” from the “spillover effect” and discusses the difference between these two terms. The paper provides evidence of the strong spillover effect from the US economy to other markets from various regions across the globe. A study by Beirne, Caporale, Schulze-Ghattas and Spagnolo (2013) analysed information transmissions from mature markets to 41 emerging markets from four geographical regions. The paper employs the trivariate GARCH–BEKK to the period from June, 1993 to March, 2008 providing the evidence of spillovers from developed to emerging stock markets. These papers can also be contributed to another major strand in the literature, which analysed international information transmissions across various regions, and is presented in the next section.

2.4 Intra- and inter-regional return and volatility spillovers

2.4.1 Regional perspective

The spillover effect has been analysed by many scholars with regard to their origins and the intensity of information transmission across markets from the both the same, and different, geographical regions. This branch of literature is particularly relevant to this research because the return and volatility spillovers across 21 markets, from 4 geographical regions, are analysed in this thesis. The regional perspective of contagion and spillover effect is critically important for portfolio managers and for policy makers due to the existence of various regional economic agreements (EU, ASEAN, BRICS, etc.). One of the central issues in this literature field is the existing channels of international information transmissions across the globe. The question why some countries are more susceptible to external shocks than others, and what the underlying reasons for this difference are, have become crucial to an understanding of the mechanisms of information transmission.

Kenourgios and Dimitriou (2015) investigated regional perspectives of financial contagion during the GFC by using aggregate stock indices and sector stock indices, rather than considering individual equity indices. The authors examined ten sectors in six developed and emerging regions using the multivariate AR (1)–FIAPARCH–DCC to test various channels of information transmission by: "(i) contagion of regional aggregate stock markets, (ii) contagion of the financial sector across regions, (iii) contagion of the real economy sectors across regions, and (iv) contagion of the real economy sectors within a region" (Kenourgios & Dimitriou, 2015, p.283). Similar channels of contagion have been utilized by Baur (2012). The important findings provided by Kenourgios and Dimitriou (2015) show that Developed Pacific regions were less affected by the GFC, therefore these markets could, potentially, offer diversification benefits to investors. They also highlighted that the intensity of co-movements may vary among sectors within a country or region. The role of the particular sector in a country's economy will influence the interconnectedness of this country with the rest of the world, depending on how prone this sector is to contagion. For example, Aloui, Aissa and Nguyen (2011) analysed cross-market linkages between the US and BRIC and found that countries with higher sensitivity to commodity-price changes tend to co-move closely with the US in both bullish and bearish markets. Brazil and Russia, which are commodity-exporting countries, were found to be more susceptible to US shock than China and India, whose exports are oriented towards finished goods. Alternatively, as was mentioned earlier, Dimitriou et al. (2013, p.55) report that there is “no evidence of a pattern of contagion for all BRICS' markets that could be attributed to their common trade and financial characteristics”.

Bekaert et al. (2011) examined six different categories of channels of international information transmission: (i) international banking sector links at the country level; (ii) country-specific policy responses to the crisis; (iii) trade and financial linkages; (iv) information asymmetries and informational flows; (v) domestic macroeconomic fundamentals; (vi) “investor contagion” caused by herding behaviour. The paper proposed an international three-factor model including the US factor, a global financial factor, and domestic factor $F_t' = [R_t^U, R_t^G, R_t^D]$, which can be specifies as follows:

$$R_{i,t} = E_{t-1}\left[R_{i,t}\right] + \beta_{i,t}{}'F_t + \mu_{i,t}CR_t + e_{i,t} \quad (2.4.1)$$

$$\beta_{i,t} = \beta_{i,0} + \beta_1' Z_{i,t-k} + \alpha_{i,t}CR_t \quad (2.4.2)$$

$$\alpha_{i,t} = \alpha_{i,0} + \alpha_1{}'Z_{i,t-k} \quad (2.4.3)$$

$$\mu_{i,t} = \mu_{i,o} + \mu_1{}'Z_{i,t-k} \quad (2.4.4)$$

where $R_{i,t}$ is the excess return of portfolio i during week t, $E_{t-1}\left[R_{i,t}\right]$ is the expected excess return, F_t is the vector of the three observable factors, CR_t is a crisis dummy, and $Z_{i,t}$ is a vector of control variables, designed to capture time and cross-sectional variation in factor exposures, $\mu, \alpha, \beta,$ are the parameters matrices. Coefficients μ in equation (2.4.1) captures non-fundamental contagion, unrelated to the observable factors Ft of the model; α in equation (2.4.2) measures contagion via the factors Ft, i.e. changes in interdependence during the crisis.

Bekaert et al. (2011) analysed information transmission across 55 equity markets, while 10 sectors provided evidence of contagion during the GFC. However, the dominant role of the US as the main source of contagion in global markets was not indicated. The strongest evidence contagion was from domestic equity markets to individual domestic equity portfolios, while more financially integrated countries experienced less contagion from the US market. This led to rejection of the ‘globalization hypothesis’ (i.e. countries that are highly integrated globally, through trade and financial linkages, are more susceptible to the crisis shock). Instead, Bekaert et al (2011) found that portfolios in countries with weak macroeconomic fundamentals, i.e. high political risk, large current account deficits, large unemployment and high government budget deficits, were much more affected by the GFC and, in particular, by shock transmitted from the US., supporting the 'wake-up call' hypothesis. The "wake-up call hypothesis states that a crisis initially restricted to one market segment or country provides new information that may prompt investors to reassess the vulnerability of other market segments or countries, which spreads the crisis across markets and borders" (Bekaert et al., 2011, pp. 2-3).

Furthermore, Bekaert et al. (2011) argue that asymmetries in information may reduce capital flows across the borders and cause another well-established phenomenon called home bias. The home bias hypothesis is also known as the 'home bias puzzle', where investors holding a small amount of foreign stocks omit the potential diversification benefits available on international markets is analysed by numerous researchers (Cooper & Kaplanis, 1994; Kang & Stulz, 1997). One of the causes of information asymmetries in the global markets can be the fact that stock exchanges are situated in different regions and time-zones. Therefore, the home bias hypothesis is often analysed with related trading-place-bias hypothesis. For example, Kao, Hob and Fung (2015) claim that the trading-place-bias hypothesis implies that the price is influenced mainly by information linked to the trading hours or the location, while the home bias hypothesis assumes that information flows originate primarily in the home market, due to the fact that investors are better informed about their domestic firms and prefer to invest in securities traded on the home market. Also, in behavioural finance, the home bias puzzle is explained by investor behavioural bias referred to as "ambiguity aversion", which describes irrational behaviour of investors' decision making caused by avoidance of everything unknown and new.

2.4.2 VAR framework

One of the popular methods that allows the analysis of the partial effect of the markets on each other is the VAR model introduced by Sims (1980). Although a substantial quantity of available literature has investigated intra- and inter-regional information transmission, the existing empirical evidence is focused predominantly on the largest developed stock markets, and omits the emerging markets. The VAR method has been employed by Eun and Shim (1989) to investigate international information transmission across the developed stock markets of the US, the UK, Canada, France, Germany, Switzerland, Australia, Japan and Hong Kong. The specification of the VAR model used by Eun and Shim (1989) is expressed as:

$$R_t = \Phi + \sum_{k=1}^{n} \Psi_k R_{t-k} + \varepsilon_t, \qquad (2.4.5)$$

where R_t is a 9×1 matrix of daily returns of the target stock markets; Φ and $\Psi_k$are 9×1 and 9×9 coefficient matrices respectively, n is the length of the lag, ε_t is a vectors of forecasting error of the best predictor of R_t using all the past R_k. Empirical results provide evidence of numerous interdependencies across markets for the period from December, 1979 to December, 1985.

Later, with the increased role of developing countries in the global economy, it becomes essential to include emerging markets in any analysis of information transmission mechanisms (e.g., Syriopoulos, 2007, Diebold & Yilmaz, 2009, 2012; Singh, Kumar & Pandey, 2010; Yilmaz, 2010; Kumar, 2013; Cho, Hyde & Nguyen, 2014). Diebold and Yilmaz (2009) analysed return and volatility spillovers across seven developed and twelve emerging equity indices using a generalized VAR framework. The generalized VAR is employed in Chapter 5 of this thesis, therefore methodology described in details in section 5.2. The writers found a significant burst in volatility spillovers across markets during the crisis episodes, where the overall length of the estimation period was taken from January, 1992 to November, 2007.

Singh et al. (2010) investigated return and volatility spillovers across 15 markets from three geographical regions, Europe, Asia and North America, using the AR/VAR model to incorporate same day effect. Same day effect manifests itself in transmission of information across markets with non-overlapping trading hours within the same day, for example, from the stock market of Tokyo to the stock market of New-York. The VAR model with exogenous variables for the markets that open simultaneously, as given by Singh et al. (2010), is specified bellow:

$$r_t = \delta + \sum_{i=1}^{p} \theta_i r_{t-i} + \sum_{1}^{k} \vartheta_{kt} r_{kt} + \sum_{1}^{l} \varphi_{lt} r_{lt-1} + \varepsilon_t, \qquad (2.4.6)$$

where, $r_t = (r_{1t}, r_{2t}, \dots, r_{nt})$ $n \in N$ are the indices that opened simultaneously and modelled endogenously, k is the number of indices that open/close before the *n* indices; l is the number of indices that open/close after the *n* indices.

The authors utilized daily close-to-close and open-to-open returns from January, 2000 to February, 2008 and found that the market that opens prior to the current market has a strong influence on it. These findings are particularly significant for this research because it supports meteor shower effect and related same day effects that are discussed in subsequent subsections.

2.4.3 The meteor shower and heat waves hypotheses of Engle, Ito and Lin (1990)

Ross (1989) showed that in absence of arbitrage, the volatility in asset returns depends upon the rate of information flow, which means that information transmitted from one market can generate an excess of volatility on another market. Engle et al. (1990) incorporated the ARCH approach to an analysis of transmission of information contained in the first and second moments of stock market returns and the impact of those returns in other markets. Engle et al. (1990) used the real astronomical analogy with a meteor shower to describe the process of information transmission across global markets. Alternatively, the analogy with heat waves phenomenon has been used by Engle et al. (1990) to postulate that financial market volatility depends only on its own past shocks.

The phenomenon of the meteor shower is widely discussed in astrophysics and astronomy literature and comes in the form of a parallel stream of meteoroids entering the Earth's atmosphere at high speed. It is called a "shower" because, from the observers from Earths' viewpoint, it can appear that this stream of meteoroids has been generated from one point in sky. The heat waves phenomenon is a situation of abnormal increase in temperature in one particular country from the standard temperature normal for this area and season, lasting from a few days up to several weeks. Using these analogies, Engle et al. (1990) introduced the meteor shower hypothesis which assumes positive volatility spillover effects across markets, and alternatively the heat wave hypothesis which assumes that volatility has only country-specific autocorrelation. In other words, the meteor shower hypothesis suggests that a volatile day on one market is likely to be followed by a volatile day on another related market, while the heat wave hypothesis suggests that a volatile day on one market is likely to be followed by a further volatile day on the same market (Ibrahim & Brzeszczynski, 2009). Engle et al. (1990, p.528) modified the GARCH model by letting $\varepsilon_{i,t}$ be the intra-daily exchange rate change divided by the square root of trading hours in market i on date t:

$$\varepsilon_{i,t}|\Psi_{i,t} \sim N\ (0, h_{i,t}) \qquad (2.4.7)$$

$$h_{i,t} = \alpha_i + \beta_{ii} h_{i,t-1} + \sum_{j=1}^{i-1} \gamma_{ij} \varepsilon_{j,t}^2 + \sum_{j=i}^{n} \gamma_{ij} \varepsilon_{j,t-1}^2, \qquad (2.4.8)$$

where $\Psi_{i,t}$ is the information set for market i*=1, 2,…,n,* on date t, i.e. which includes the past information on date $t-1$ and the current information from market 1 to marker $i-1$ on date t, i.e. $\Psi_{i,t} = \{\varepsilon_{i-1,t}, \varepsilon_{i-2,t}, \dots, \varepsilon_{1,t}\} \cup \Psi_{n,t-1}$, and $\Psi_{n,t-1}$ denotes the sequence of information sets generated by $\{\varepsilon_{1,k}, \dots, \varepsilon_{n,k}\}_{k=1}^{t-1}$. The model described by equations (2.4.7) and (2.4.8) relies on assumptions of non-zero mean of $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ distributions; absence of correlation between $\varepsilon_{i,t}$ and $\varepsilon_{i,t}$ for$i \neq j$. The model also assumes that $\varepsilon_{j,t-1}^2 = 0$ for$j = i+1, \dots, n$, or $\varepsilon_{j,t}^2 = 0$ for $j = 1, \dots, i-1$ if market j is closed because of a holiday on date t or $t-1$.

The heat wave hypothesis assumes that volatility is susceptible to past shock on the same market and independent from volatility of another market. It can be tested using null hypothesis $\gamma_{ij} = 0$ for $j \neq i$, while the meteor shower hypothesis is the alternative. Thus, Engle et al. (1990) provide the evidence for rejection of the heat wave hypothesis, which supports the notion of international information transmission. The execution of investment strategies based on international information transmission mechanisms is one of the most popular areas of financial research due to its high level of practical significance.

2.4.4 Same day effect

The meteor shower hypothesis is often tested in the context of so-called same day effect. The same day effect can be defined as spillover effect across geographically separated financial markets that trade sequentially (Andersen & Bollerslev, 1997). This effect has a central role in the analysis of inter-regional information transmission due to the fact that world stock exchanges operate in different time-zones and it is possible to investigate spillover across markets with non-overlapping trading hours. The main data, employed by researchers analysing same day effect, is open-to-close returns or a combination of open-to-close and close-to-open returns, representing daily and overnight returns (e.g., Hamao, Masulis & Ng, 1990; Singh et al, 2010). Another group of studies used high-frequency return data to ex-post estimate the volatility of low-frequency returns (e.g., Melvin & Melvin, 2003; Koopman et al., 2005; Andersen et al, 2006; Dimpfl & Jung, 2012), or intraday data various frequencies (e.g., Andersen & Bollerslev, 1997; Maderitsch, 2015).

A study by Hamao et al. (1990) employed an MA(1)-GARCH(1,1)-M model to open-to-close and close-to-open returns to the stock markets of Tokyo, London and New York from April, 1985 to March, 1988 and found significant spillover effect across markets that open and close. The MA (1)-GARCH (1, 1)-M model is specified as follows:

$$R_t = \alpha + \beta h_t + \gamma \varepsilon_{t-1} + \delta D_t + \varepsilon_t \quad (2.4.9)$$

$$h_t = \mu + \rho h_{t-1} + \sigma \varepsilon_{t-1}^2 + \tau D_t + f X_t^2, \quad (2.4.10)$$

where h is the conditional variance of the stock index return R, at time t. The dummy variable D is equal 1 on days following weekend and holidays, and 0 otherwise. X_t^2 are the most recent squared residuals derived from the MA (1)-GARCH(1,1)-M model applied to open-to-close returns on the previously opened market. Hamao et al. (1990) found evidence of spillover effect from the US and the UK to the stock market of Japan.

The study by Aityan, Ivanov-Schitz and Izotov (2010) introduced two correlation coefficients: same-day correlation (SDC) and next-day correlation (NDC). SDC measures the correlation between two indices at market close on the same calendar day, while NDC measures the correlation between two indices at market close on different days, i.e., “for the first component on the given trading day and for the other one on the following trading day” (Aityan et al., 2010, p. 593). The paper investigated the correlation between the US and markets from the Asia-Pacific region, Hong Kong, Japan, Singapore, South Korea, Taiwan, China, Malaysia and Indonesia, over the period from 1998 through to 2009. The results show that NDC is statistically significant and are higher than SDC, consequently giving an indication that the U.S. plays a pacesetting role on the markets in the Asia-Pacific region, with the exception of China. The low correlation between the markets of the US and China indicates that the Chinese equity market is relatively independent and insulated from foreign shocks.

Golosnoy, Gribisch and Liesenfeld (2015) present a novel approach to the analysis of intra-day information transmissions in their study of the volatility spillovers within the US, German and Japanese stock markets which allows chronological ordering of overlapping and non-overlapping trading hours. They employed a sequential phase model accounting for the four distinct geographical intra-day trading periods: (1) the Germany-US trading overlap period; (2) the US-only trading period; (3) the Japan-only trading period; and (4) the Germany-only trading period (Golosnoy et al., 2015, p.97). Golosnoy et al. (2015) report intensification of inter-market linkages after a crisis across all three markets in the sample. The findings show that the strongest linkages are between the markets of the US and Germany. Furthermore, the results indicate the existence of meteor shower and heat wave effects before the GFC, while after the crisis the meteor shower effect becomes more pronounced.

Maderitsch (2015) analysed return spillovers in Hong Kong, the US and Europe over the period 2000 to 2011. The study employed the Granger causality test to non-overlapped intraday equity index returns. The study provided evidence of both positive and negative spillovers across markets. Particularly, the positive spillovers are found from Hong Kong and the US to Europe and from Europe to the US during periods of high volatility, while negative spillovers are found from the US to Hong Kong. The author explained the sign of spillovers using a rational explanation, i.e. difficulties in assessing the information content, and psychological explanations, i.e. traders might underreact at market opening. However, the concepts of positive and negative spillovers are not well-defined in this paper and require further attention.

2.5 Asymmetry in return and volatility transmission mechanisms

2.5.1 Key concepts and definitions

The asymmetry in return and volatility transmission mechanisms may be hard to understand due to the fact that this phenomenon has not been well conceptualized or explained in finance literature to date. Therefore, this subsection provides a definition of asymmetry in return and volatility spillovers which are hypothesized in this thesis. Prior to doing so, it is important to explain how the term "*asymmetry*" has been used in previous studies on equity market behaviour, and why asymmetry in international information transmission mechanisms is different from those interpretations and, hence, require further attention.

Since the work by Black (1976) and Christie (1982), the presence of asymmetric volatility in financial markets has been well documented (e.g., Nelson, 1991; Bekaert & Wu, 2000; Ferreira, Menezes & Mendes, 2007; Scharth & Medeiros, 2009; Jackwerth & Vilkov, 2014; Xiang & Zhu, 2014). Although there is a long history of investigation of this phenomenon, "asymmetric volatility" and the associated term "asymmetry in volatility" has also been under consideration in the most recent literature. Albu, Lupu and Călin (2015) defined asymmetric volatility, as a stylized fact that manifests itself when volatility is higher in market downswings than in market upturns. It relies on the empirical evidence that there is a negative correlation between returns and innovations in expected volatility (Dennis, Mayhew, & Stivers, 2006). In other words, by asymmetry in volatility, researchers originally assumed that volatility is higher during bear markets and lower during the bull markets (Talpsepp & Rieger, 2010). Koulakiotis, Babalos and Papasyriopoulos (2015) further claimed that stock market volatility appears to rise more after a sharp fall in price (which is interpreted as bad news) than a respective rise in price (good news), which also describes the asymmetry in volatility. These two interpretations of asymmetry have been separated by El Babsiri and Zakoian (2001) into the terms "contemporaneous asymmetry", i.e. different volatility processes for down and up moves in equity market returns, and "dynamic asymmetry", i.e. asymmetric reactions of the volatilities to past negative and positive changes in returns (Palandri, 2015, p.486).

A similar understanding of asymmetry is evident in numerous studies analysing the impact of positive and negative news on stock market returns and the volatility of financial assets, where the term "asymmetric response" and "asymmetric effect" have also featured (e.g., Brzeszczyński, Gajdka & Kutan, 2015; Smales, 2015; Ning, Xu & Wirjanto, 2015; Bekaert, Engstrom & Ermolov, 2015). The, literature typically suggests that a negative market shock has a stronger impact on returns and volatilities than does a positive shock of the same magnitude, which is manifested in asymmetry (e.g, Liu, Wong, An & Zhang, 2014; Smales, 2015). An alternative interpretation of asymmetry has been used in relation to another well-known, stylized fact, volatility clustering. Ning et al. (2015) define volatility clustering as a phenomenon where:

"*High volatility movements (represented by large fluctuations in returns) tend to be followed by high volatility movements (characterized by a period of relative turbulence in the market), while low volatility movements (indicated by small fluctuations in returns) tend to be followed by low volatility movements (characterized by a period of a relative tranquillity in the market)*" (p.62).

Due to the fact that turbulent market periods tend to appear more frequently than tranquil market periods, Ning et al. (2015, p.62) claimed that high volatilities of returns tend to cluster more often than low volatilities of returns. He defines asymmetric volatility clustering as "asymmetry in the frequency of clusters of high volatilities and low volatilities".

This research investigates asymmetry in spillover effects across markets, therefore, none of the above definitions can be directly employed. Nevertheless, the interpretation of asymmetry in return and volatility spillovers used in this thesis is based on several ideas presented in the literature. First, Kundu and Sarkar (2016, p. 298) argue that it is an established fact that the correlation between markets is higher during periods of high volatility than periods of low volatility (e.g., Longin & Solnik, 2001; Ang & Bekaert, 2002, Forbes & Rigobon, 2002). The spillover effect is a dynamic process and may vary with market conditions such as whether there is a 'bull' or 'bear' market. Second, Koutmos and Booth (1995) investigated the impact of good news (market advances) and bad news (market declines) on volatility transmission, and found that the volatility spillover effect is more pronounced when the news arriving from the last market to trade is bad, providing evidence of asymmetry. Third, the paper by Hatemi-J (2012) suggested that the transmission of positive and negative shocks may have different causal impacts. Consequently, in this thesis asymmetry in spillovers is defined in the following way:

Asymmetry in spillover effect – is a phenomenon that occurs when the domestic financial market is more susceptible to negative (positive) than positive (negative) types of shocks transmitted from a foreign market.

It is important to clarify that asymmetry in volatility spillovers should be interpreted differently from asymmetry of return spillovers. 'Positive' and 'negative' volatility shocks indicate increases and decreases in the volatility of a market respectively, and do not necessarily provide information about the particular directions of return movements. While 'good' news causes growth of return, and 'bad' news causes decline in returns, regarding the volatility, both 'good' and 'bad' news may have a similar impact, i.e.an increase in market volatility. For example, Chen and Ghysels (2011) found that moderately good news reduces volatility' while ''both very good news (unusual high positive returns) and bad news (negative returns) increase volatility, with the latter having a more severe impact" (p.75).

It follows that information transmission mechanisms should be investigated separately for returns and for volatility. Referring to the study by Strohsal and Weber (2015), which analysed the dependency of intensity and direction of international volatility transmission on the degree of financial volatility of donor markets, the conclusion can be reached that the transmission of both positive and negative volatility shocks can be interpreted from two alternative perspectives. On the one hand, the volatility itself can be viewed as a sign of information flow, thus the increase in volatility of a donor's market generating intensive information flow, i.e. high spillover intensity, causing higher reactions in the recipient's market. For example, an increased volatility in China's market, increases the volatility of the South Korean market. On the other hand, volatility can be traditionally viewed as a reflection of uncertainty in the markets, thus the increasing volatility of a donor market increasing the uncertainty (noise) on the recipient market, leading to lower reactions in the target market. Consequently, the decline in volatility, i.e. negative volatility shock, can provide the signal to recipient market returns in the same way as an increase in volatility.

The paper by Segal, Shaliastovich and Yaron (2015) defined good and bad uncertainty, from the macroeconomic perspective, as the "variance associated with the respective positive and negative innovations of an underlying macroeconomic variable" (p.391). However, due to the fact that this thesis is based on the philosophical concepts of positivism, the terms "bad" and "good", are not used in construction of the definition of the transmission of positive and negative shocks since they are value laden, and hence subjective, terms. This thesis utilises the following definitions:

1) *Spillover (transmission) of positive return shocks is the effect when positive innovation, i.e. increase in returns on one market causes positive innovation, i.e. increase in returns, on another market;*

2) *Spillover (transmission) of negative return shocks is the effect when negative innovation, i.e. decline in returns, on one market causes negative innovation, i.e. decline in returns, on another market;*

3) *Spillover (transmission) of positive volatility shocks is the effect when positive innovation, i.e. increase in volatility, on one market causes positive innovation, i.e. increase in volatility, on another market;*

4) *Spillover (transmission) of negative volatility shocks is the effect when negative innovation, i.e. decline in volatility, on one market causes negative innovation, i.e. decline in volatility, another market;*

These effects are hypothesized in this thesis. Although there is still very limited empirical evidence on asymmetry in return and volatility transmission mechanisms, several useful techniques have been developed in the relevant literature to test this phenomenon. The next subsection focuses on these methodological advances.

2.5.2 Tests on causalities

The linear Granger Causality Test (Granger, 1969, 1981; Engle & Granger, 1987; Granger & Hallman, 1991) is one of the most popular techniques employed to test causality between stock markets. According to the Granger (1969) time-series Xt Granger Cause time-series Yt, if series Yt could be predicted by using past values of Xt series. Confirmation of Null Hypothesis means that Xt does not Granger Cause Yt if:

$$Pr\ (Yt + m|\ \Omega t)\ =\ Pr\ (Yt + m\ |\ \Psi\ t), \quad (2.5.1)$$

where $Pr\ (yt + m|\ \Omega t)$ - denotes conditional probability of Yt; Ωt - the set of all information available at time t; $Pr(yt + m|\ \Psi\ t)$ - denotes conditional probability of Yt obtained by excluding all information on Xt from Yt this set of information is depicted as Ψ. Causality between Xt and Yt time-series tested by using following equations:

$$Xt = \propto_0 + \sum_{j=1}^{k} \gamma_{1,j} X_{t-j} + \sum_{j=1}^{k} \gamma_{2,j} Y_{t-j} + \mu_{xt} \quad (2.5.2)$$

$$Yt = \propto_0 + \sum_{j=1}^{k} \beta_{1,j} X_{t-j} + \sum_{j=1}^{k} \beta_{2,j} Y_{t-j} + \mu_{yt} \quad (2.5.3)$$

where k is a suitably chosen positive integer, γ_j and β_j, j = 0, 1…k are parameters and α' are constants and μ_t's are disturbance terms with zero means and finite variances. The rejection of the Null hypothesis: $\gamma_{2,j} = \gamma_{2,2} = \gamma_{2,3=\dots} = \gamma_{2,j} = 0$ indicates that Yt does Granger cause Xt.

The Granger causality test was employed by Huang et al. (2000) in their analysis of the causalities among the stock markets of the US and the Asian stock markets of Japan, Hong Kong, Taiwan and China for the period from 2 October, 1992 to 30 June, 1997. The evidence provided by Huang et al. (2000) is particularly relevant to this thesis because all the markets analysed are under consideration in this thesis. Huang et al. (2000) demonstrated unidirectional Granger causality between the US and Japan, Hong Kong and Taiwan, and provided limited evidence of causality between China and other markets. The Granger causality technique become very popular among academics and practitioners due to its simple but sophisticated ability to capture short-term causalities across markets, and has been used by numerous researchers (e.g., Sheng & Tu, 2000; Masih & Masih, 2001; Climent & Meneu, 2003). Nevertheless, it was established, and confirmed, by many authors that financial time-series data have many nonlinear features, which could not be captured by the linear Granger causality test (e.g., Bekiros, 2014). Furthermore, the presence of autoregressive conditional heteroskedasticity can impact on linear test statistics. Furthermore, the studies that employed the Granger causality test failed to consider the causal impact of positive and negative shocks, therefore more recent studies tried to avoid this methodological limitation.

There are several existing methods to test the transmission of positive and negative return and volatility shocks across financial markets (e.g., Nelson, 1991; Granger & Yoon, 2002; Hatemi-J, 2012; Bekaert et al., 2015). The models developed to test asymmetry in spillover effects are often modifications of the more conventional methodologies. For example, Nelson (1991) introduced the EGARCH approach which is able to test asymmetries in return and volatility transmission mechanisms "because it allows own market and cross market innovations to exert an asymmetric impact on the volatility in a given market" (Koutmos & Booth, 1995, p.749). Another method is suggested by Granger & Yoon (2002), who proposed the idea of transforming data into both cumulative positive and negative changes. Although this approach was originally used to test time-series for co-integration, it had implications for asymmetric causality testing (e.g., Hatemi-J, 2012, 2014). The asymmetric causality with bootstrap simulation approach for calculating critical values suggested by Hatemi-J (2012) was selected for this thesis, due to the fact that it is able to capture the asymmetry in information transmission mechanisms, and also it is robust in that it takes into account the existence of the ARCH effect (e.g., Hacker & Hatemi-J, 2012). This approach is discussed in detail in Chapter 6.

2.5.3 Empirical evidence on asymmetry in return and volatility transmission

Although asymmetry in volatility has been actively tested and is referenced in finance literature (e.g., Albu et al, 2015; Koulakiotis et al, 2015; Bekaert et al., 2015), the discussion of asymmetric effect in return and volatility spillovers is very limited. One of the first attempts to investigate asymmetry in volatility transmission was performed by Bae and Karolyi (1994) and Koutmos and Booth (1995). Koutmos and Booth (1995) employed the multivariate EGARCH to investigate price and volatility spillovers across the equity markets of New York, Tokyo and London. The study utilized the daily open-to-close returns for the aggregate stock price indices, i.e. the S&P 500 for the USA, the FTSE-100 for the UK, and the Nikkei 225 Stock Index for Japan, for the period September, 1986 to December, 1993. The findings show the following channels of transmission: i) the price spillovers from New York to Tokyo and London, and from Tokyo to London; ii) volatility spillovers from New York to London and Tokyo, from London to New York and Tokyo, and from Tokyo to London and New York. Furthermore, the empirical results suggest that the impact of negative innovation is stronger than the impact of positive innovations for all channels of transmission, which confirms the existence of asymmetry in volatility transmission mechanisms.

The paper by Baruník, Kočenda, and Vácha (2015) examined the asymmetries in volatility spillovers that emerge due to bad and good volatility. The authors hypothesized that volatility spillovers might significantly differ depending on the qualitative nature of the preceding shock. Baruník et al. (2015) employed a new measure of volatility, so-called realized semivariance (Barndorff-Nielsen, Kinnebrock & Shephard, 2010), which measures the variation of the change in the asset price and reflects the direction of the change. Furthermore, the authors employed the Diebold and Yilmaz (2012) spillover index, i.e. directional and total, to test whether positive and negative spillovers are of the same magnitude. More specifically, the negative realized semivariance comes from the negative returns, while the positive realized semivariance comes from positive returns. Therefore, employing both positive and negative realized semivariance allows the testing of the asymmetry in volatility transmission in equity markets. The positive realized semivariance (RS^{+}), which is used as a proxy for 'good' volatility in Baruník et al. (2015), and negative realized semivariance (RS^{-}), which is used a proxy for 'bad' volatility, are defined as follows:

$$RS^{+} = \sum_{i=1}^{N} \mathbb{I}(\Delta r_{t+i/N} \geq 0)\Delta r_{t+i/N}^{2}, \tag{2.5.4}$$

$$RS^{-} = \sum_{i=1}^{N} \mathbb{I}(\Delta r_{t+i/N} < 0)\Delta r_{t+i/N}^{2}, \tag{2.5.5}$$

where $\mathbb{I}(.)$ is the indicator function; N is the number of observations; $\Delta r_{t+i/N}$ is daily returns; the sum of RS^{+} and RS^{-} gives a complete decomposition of the realized variance RV. This method first introduced by Barndorff-Nielsen et al. (2010) has also been employed to macroeconomic data by Segal et al. (2015).

However, Baruník et al. (2015) tested asymmetry in volatility spillovers utilizing daily data covering 21 U.S. stocks from seven sectors, rather than equity indices. They found asymmetric connectedness of markets at the disaggregated level, reporting that positive and negative spillovers are of different magnitudes in all sectors. Another study by Kundu and Sarkar (2016) analysed daily stock returns data from two developed markets, i.e. the US and the UK, and four emerging countries, i.e. BRIC (Brazil, Russia, India and China), to investigate asymmetry in information transmission mechanisms during periods of turmoil and turbulence , using daily data from January, 2000 to December, 2012. They proposed that STVAR-BTGARCH-M allows the smooth transition of behaviour to switch from one market condition to another. The empirical results show the strong connectedness between the developed markets of the US and the UK during both up and down market conditions. However, the signs of the spillover effect may vary. The evidence for the emerging markets is mixed, for some market pairs spillovers are negative, for others the combinations of market spillover effect is positive. For only one emerging market, i.e. China, the findings demonstrated persistence of only negative spillover effects to other markets. Kundu and Sarkar (2016) found strong evidence of asymmetric spillover effects among international equity markets in both periods of stability and crisis.

The investigations into asymmetry in return and volatility transmissions have important implications not only for international portfolio diversification, but also for stock market return predictability. Transmission of positive and negative shocks between markets may have remarkably different impacts on future returns. For example, the results enhancing understanding of the information transmission mechanisms can be used for signal extraction purposes, development of a trading strategy and the forecasting of returns, all of which are discussed in the next section.

2.6. Forecasting of returns on financial markets

2.6.1 Predictability of returns

The investigation of the forecasting of stock returns has a long history. Due to the highly practical significance of this task (i.e. the potential of achieving economic benefits through accurate prediction of future return movements), the forecasting of financial assets' returns has become one of the hottest topics in financial literature. It is not surprising that the background literature is vast, and it is impossible to discuss all the important research outcomes within this research area. This section does not aim to provide a comprehensive overview of all the techniques and methods currently available, due to the numerous forecasting methodologies that have been developed and tested over more than 80 years of research (The seminal paper by Cowles's (1933) "Can Stock Market Forecasters Forecast?" is one of the pioneering studies in this area, manifesting the starting point of forecasting research). The literature is still expanding today and, together with the increase in computer power, it is likely that this will be an area that continues to grow in the coming years. However, due to the fact that the forecasting of returns of financial assets is one of the primary implications of the meteor shower effect that is under investigation in this thesis, it is important to explain the main thrust behind the research question, is forecasting of domestic return possible by using foreign information transmission mechanisms?

Forecasting future returns is, undoubtedly, a difficult task for several theoretical, methodological and practical reasons. For example, the well-known market hypothesis (EMH) by Fama (1970) theorized restrictions to return predictability. Additionally, even the best forecasting models can explain only a relatively small part of future stock returns, in part due to the sizable unpredictable component of returns (e.g., Rapach & Zhou, 2013). Besides, as soon as any successful forecasting model is discovered, it will immediately be adopted by other market participants, affecting their investment decisions, changing the behaviour of the stock price, and, consequently, undermining the models' forecasting ability (e.g., Timmermann & Granger, 2004). The problem of model uncertainty and parameter instability may affect the performance of even the best models, over time (e.g., Pesaran & Timmermann, 1995; Paye & Timmermann, 2006). Nevertheless, the existing literature also provides out-of-sample empirical evidence demonstrating that some forecasting models are superior to others, and that the trading strategies based on these forecasts can outperform the market. These results of out-of-sample tests do not allow researchers and practitioners to relinquish the idea of forecasting once and for all, despite the existence of genuine theoretical and methodological challenges.

There is a wide variety of forecasting models that have been tested in literature, ranging from simple autoregressive methods to more complex non-linear models with time-varying parameters (Aiolfi & Timmermann, 2004). The single regressor model has been employed by Keim and Stambaugh (1986), Fama and French (1989), Fama (1990), Stambaugh (1999), Lewellen (2004), among others. The predictive regression model has been also used by Campbell and Shiller (1998) and Rapach and Wohar (2006):

$$y_{t+k} = \propto + \sum_{i=1}^{N} \beta_i x_{t,i} + \gamma y_t + \mu_{t+k}, \quad (2.6.1)$$

where y_t is the return for the period from $t-1$ to t, y_{t+k} is the return for the period from t to $t+k$, $x_{t,i}$ is the predictors used for forecasting of future returns; μ_{t+k} is the error term; N is number of predictors; β_i is coefficient estimates for each predictor for $i \epsilon [1, N]$. When $\beta_i = 0$ the variable $x_{t,i}$ does not have predictive power, alternatively, if $\beta_i \neq 0$ variable $x_{t,i}$ have predictive power for y_{t+k}.

Typically the predictive power of $x_{t,i}$ are assessed using t-statistics corresponding to β, ordinary least-squared (OLS) estimator of β, together with R^2 measure (Gupta & Modise, 2012). However, it was established that the method described by equation 2.6.1 may produce biased coefficient estimates of the predictive variable, particularly, in small samples (Nelson & Kim, 1993). There are also serial correlation and heteroskedasticity problems in forecasting error terms if forecasting horizon k is higher than 1 (e.g., Newey & West, 1987; Stambaugh, 1999), as well as "the potential for serious size distortions when basing inferences on standard asymptotic distribution theory" (Gupta & Modise, 2012, p. 910). Therefore, significant effort has been made to discover more sophisticated methods for β estimation (e.g., Amihud & Hurvic, 2004; Amihud, Hurvich & Wang, 2009).

One of the popular procedures introduced by Breiman (1996) is bootstrap aggregating (bagging) which has been used in numerous studies to estimate reduced-bias β coefficients (e.g., Kothari & Shanken, 1997; Rapach & Wohar, 2006a; Inoue & Kilian, 2008; Rapach & Strauss, 2008, 2010; Gupta & Modise, 2012). A detailed description of bagging methodology can be found in all of the above mentioned studies. The bagging methodology is particularly useful for forecasting variables with a large number of potential predictors because it allows the generation of a multiple version of a predictor which can be used to get an aggregated predictor (Breiman, 1996). Inoue and Kilian (2008) claimed that one of the basic problems of out-of-sample prediction is that "many potentially useful predictors are available to the forecaster, but few (if any) of these predictors have high predictive power, and many of the potential predictors are correlated" (p.511). The bootstrap procedure is often used as a control for data mining (Rapach & Wohar, 2006a). Generally, the data mining problem is especially pronounced for stock market data where researchers and practitioners are hoping to gain from any informational advantage it might give (Lucey & Whelan, 2001, p.80). Although the reliability of out-of-sample forecasting evidence is higher than an in-sample one, the data mining problem potentially persists in both in-sample and out-of-sample forecast tests (Inoue & Kilian, 2002). Therefore, Gupta and Modise (2012) argue that the critical values of test statistics have to be calculated using data mining-robust bootstrap procedure.

Besides the linear forecasting model, numerous studies have employed more complex non-linear models that took into account the fact that return time-series exhibit non-linear dynamics. The most extensively used models demonstrating significant forecasting performance are the GARCH-family models (e.g., Andersen, Bollerslev, Christoffersen & Diebold, 2006), as well as the heterogeneous autoregressive (HAR) model (e.g., Corsi, 2009; Jayawardena, Todorova, Li & Su, 2016), and artificial neural networks (ANN) models (Terasvirta, Tjostheim & Granger, 1994). However, even the most advanced and complex models can be misspecified due to the model instability problem (Stock & Watson, 1996). The misspecification may be especially pronounced in an international context due to the unique features of local stock markets, i.e. the returns can be susceptible to different factors, and the forecasting ability of these factors is also time-varying. Therefore, the model which is able to forecast stock return on one market simply does not work for other markets, where other predictors are more significant. Many academics suggest model combination methods to improve the accuracy of return forecasting (e.g., Bates & Granger, 1969; Granger & Ramanathan, 1984; Harvey, Leybourne & Newbold, 1998). Inoue and Kilian (2008) claim that in an environment when many predictors may potentially impact dependent variables, the combination forecast is a useful way of incorporating information.

Numerous combining methods are discussed in the literature: a simple averaging method, combining methods based on OLS or weighted least squares (WLS), discount MSFE, Bayesian shrinkage techniques, clusters, principal components, to name but a few (e.g., Granger & Ramanathan, 1984; Diebold & Pauly, 1987; Stock & Watson, 2004; Clemen & Winkler, 1986), as well as a comparison of those methods presented in Inoue and Kilian (2008) and Rapach and Strauss (2010). Some of these methods are employed in Chapter 7 in this thesis, where the methodological details can be found. There are two main questions that have to be addressed to build a successful combining forecast: 1) how many individual models to include? 2) how to estimate the optimal forecast combination weights? The idea of assigning equal weights to the individual forecasting models sounds reasonable, taking into account that the performance of a particular model is time-varying. Consequently, using past performance to identify "the best" model in any given time is a purely random process (Aiolfi & Timmermann, 2004). Aiolfi and Timmermann (2004) investigated forecasting performance across a large set of linear and nonlinear models and found significant consistency in forecasting performance. The top and bottom ranked models, based on their recent historical performance, have greater than average chance of remaining in these positions in the future. However, for several cases it was established that a previous best model could become the worst in the future and, conversely, the previous worst could become the best.

However, the majority of studies conducting bagging or combination forecasts used either financial or macroeconomic variables in their analysis of return predictability (e.g., Campbell & Yogo, 2006; Ferreira & Santa-Clara, 2011; Jordan, Vivian & Wohar, 2014), and the existing empirical evidence restricted to single country studies (e.g., Chen, Kim, Yao & Yu, 2010; Gupta & Modise, 2012; Kinnunen, 2013; Narayan, Narayan & Prabheesh, 2014; Phan, Sharma & Naraya, 2015). It is important to discuss further studies that have analysed the ability of foreign information to forecast returns on a domestic market.

2.6.2 Signal extraction problem

The testing of meteor shower hypothesis has implications for predictability literature. The existence of the meteor shower effect allows using foreign information for forecasting of returns and volatility on domestic markets. There are several important papers that tried to address the signal extraction problem and predict future price movements. However the methods employed vary significantly among studies (e.g., Henriksson & Merton, 1981; King & Wadhwani, 1990; Hamao et al., 1990; Ito et al., 1992; Melvin & Melvin, 2003; Ibrahim & Brzeszczynski, 2009, 2012; Ye, 2014; Strohsal & Weber, 2015;).

Ibrahim and Brzeszczynski (2009) introduced the foreign information transmission (FIT) model, which is a "conditional time-varying methodology that describes the effect some variables has on the relationships that exist between other variables" (Ibrahim & Brzeszczynski, 2012, p. 202). Using the same notations as in Ibrahim and Brzeszczynski (2009), the regression of y on x with time-varying coefficients α and β and an error term w can be described in the following way:

$$y_t = \propto_t + \beta_t x_t + w_t \tag{2.6.2}$$

The change of the parameters α and β for the period from t to $t+1$ are further specified by using endogenous variable z:

$$(\propto_{t+1} - \bar{\propto}) = [a + b(z_t - \bar{z})](\propto_t - \bar{\propto}) + v_{\propto,t+1}\,, \tag{2.6.3}$$

$$\left(\beta_{t+1} - \bar{\beta}\right) = [c + d(z_t - \bar{z})]\left(\beta_t - \bar{\beta}\right) + v_{\beta,t+1}\,, \tag{2.6.4}$$

where a, b, c, and d are constant parameters; $\bar{z}, \bar{\propto}$ and $\bar{\beta}$ are long-run average values of the variable z and the time-varying coefficients $\propto_t$ and β_t; $v_{\propto,t+1}$ and $v_{\beta,t+1}$ are associated error terms. The random variable x_t in equation (2.6.2) is multiplied by an AR(1) process for the slope coefficient given by equation (2.6.3). The model described by equations (2.6.2-2.6.4) represents volatility clustering phenomenon (e.g., Granger & Machina, 2006) but as one being generated by the structural (i.e., deterministic) properties of the system rather than by entering exogenously through its shocks (Ibrahim & Brzeszczynski, 2009, p.324).

Conditional on x_t and data observed through $t-1$, gathered in the vector Y_{t-1}, it is assumed that the vector of error terms $(v_{t+1} w_t)'$ has a Gaussian distribution, viz.,

$$\left[\begin{matrix} v_{t+1} \\ w_t \end{matrix}\middle|\ x_t, Y_{t-1}\right] \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} Q & 0 \\ 0' & \sigma_w^2 \end{bmatrix}\right), \tag{2.6.5}$$

where $v_{t+1} = (v_{\propto,t+1} v_{\beta,t+1})'$, and Q is diagonal. The slope parameter β_t is the intensity of the relationships between *y* and *x* at the time *t,* and the intercept parameter $\propto_t$ is the level of this relationships when $\beta_t x_t \neq 0$.

Ibrahim & Brzeszczynski (2009) employed FIT methodology to analyse return transmission across six stock markets located in Asia, Europe and USA. The paper highlighted the complexity of signalling mechanisms between large markets, because some of them can be immune to the transmission of foreign information. The writers also found that inter-regional information is more useful for predicting the direction of change in the stock market returns compared to region-specific information, i.e. the meteor-shower-like effect is stronger than the heat-wave-like effect. These findings are opposite to those provided by Melvin and Melvin (2003), who found evidence that heat waves are more important than meteor showers.

Besides the meteor-shower and heat-wave hypotheses, the recent paper by Strohsal and Weber (2015) also discusses two main interpretations of volatility-dependent cross-market spillover, testing “information” and “uncertainty” hypotheses. Under the first interpretation, the volatility itself can be viewed as a sign of information flow, i.e. the intensity of volatility spillovers stems from the intensity of transmission of information flow (e.g., Ross, 1989; Fleming, Kirby & Ostdiek, 1998). The second interpretation suggests that volatility has been, traditionally, viewed as a reflection of uncertainty in the markets (e.g., French, Schwert & Stambaugh, 1987; Bali & Engle, 2010.). Strohsal and Weber (2015) associated the former view with “information hypothesis” and the latter with “uncertainty hypothesis”. Both hypotheses assume that excess of volatility on a market can affect the volatility on another market, albeit in different directions. Under the information hypothesis, the high level of volatility on one market, generating intensive information flow, i.e. high spillover intensity, causes higher reactions in another market. Under the uncertainty hypothesis, the high volatility on one market increases the uncertainty (noise) on another market and leads to lower reactions in another market. Strohsal and Weber (2015) adopted the King and Wadhwani (1990) model using stylized economic models based on the signal extraction by rational agents to analyse how the level of volatility influences the spillover of shocks between markets.

The model by King and Wadhwani (1990) can be illustrated through the example of two stock markets, i.e. the former denoted by u and latter denoted by v. If information from both markets is fully revealed, than the changes in stock prices are assumed to be:

$$\Delta S_t^{(1)} = u_t^{(1)} + \alpha_{12} u_t^{(2)} + v_t^{(1)} \tag{2.6.6}$$

$$\Delta S_t^{(2)} = \alpha_{21} u_t^{(1)} + u_t^{(2)} + v_t^{(2)} \tag{2.6.7}$$

where $\Delta S_t^{(j)}$ denotes the percentage return in country j between time t-q and time t measured by the change in the logarithm of the stock market price index. The equation (2.6.6) and (2.6.7) are based on the assumption that $u^{(1)}$ and $u^{(2)}$ are independent, i.e. the news which affects both countries is always revealed first in one country or the other, but never simultaneously.

If information is not fully observable in both markets the changes in stock prices are assumed to be:

$$\Delta S_t^{(1)} = u_t^{(1)} + \alpha_{12}E_1(u_t^{(2)}) + v_t^{(1)} \tag{2.6.8}$$

$$\Delta S_t^{(2)} = \alpha_{21}E_2 u_t^{(1)} + u_t^{(2)} + v_t^{(2)} \tag{2.6.9}$$

where E_1 and E_2 denote the expectations operator conditional upon information observed in markets 1 and 2, respectively.

According to this model the equilibrium is not fully revelatory, because some information transmitted, for example, from market 1 to market 2, is idiosyncratic and irrelevant to market 2. Hence, the signal extraction problem can be solved by agents through finding the minimum-variance estimator:

$$E_1(u_t^{(2)}) = \lambda_2[\Delta S_t^{(2)} - \alpha_{21}E_2(u_t^{(1)})] \tag{2.6.10}$$

$$E_2(u_t^{(1)}) = \lambda_1[\Delta S_t^{(1)} - \alpha_{12}E_1(u_t^{(2)})] \tag{2.6.11}$$

$$\lambda_i = \frac{\sigma_{u(j)}^2}{\sigma_{u(j)}^2 + \sigma_{v(j)}^2}, \quad j = 1,2 \tag{2.6.12}$$

where σ_x^2 denotes the variance of *x*. The higherλ_i, the larger the information shock variance σ_x^2. In order to extract the signals from markets from price movement, the following equations have to be simultaneously obtained:

$$\Delta S_t^{(1)} = \eta_t^{(1)} + \beta_{12}\eta_t^{(2)} \tag{2.6.13}$$

$$\Delta S_t^{(2)} = \eta_t^{(2)} + \beta_{21}\eta_t^{(1)} \tag{2.6.14}$$

where $\beta_{ij} = \alpha_{ij}\lambda_j$;$\eta^{(i)} = u^i + v^i$;$i,j = 1,2$; the shocks results as $\Delta S_t^{(1)} = (1 - \alpha_{12}\alpha_{21}\lambda_1\lambda_2)\left(u_t^{(1)} + v_t^{(1)}\right) + \alpha_{12}\lambda_2\Delta S_t^{(2)}$ and $\Delta S_t^{(2)} = (1 - \alpha_{12}\alpha_{21}\lambda_1\lambda_2)\left(u_t^{(2)} + v_t^{(2)}\right) + \alpha_{12}\lambda_2\Delta S_t^{(1)}$ for market 1 and 2 respectively.

Strohsal and Weber (2015, p.30) use equations (2.6.13) and (2.6.14) to test information and uncertainty hypotheses: if spillover intensity β_{ij} depends *positively* on the level of volatility in the respective other market it would support the information hypothesis. Alternatively, if β_{ij} depends *negatively*, it would support the uncertainty hypothesis. Information and uncertainty hypotheses have been tested on markets with overlapping trading hours and on markets with sequential trading times. The authors found different results across countries, showing that a combination of 'donors', i.e. the source country of volatility, and the 'recipient', is critically important. For example, the US market is often assumed to be a major source of volatility shocks but, "even though the 'sender of volatility' remains the same in all cases, in times of high volatility this importance decreases for some 'receivers', whereas for others it increases" (Strohsal & Weber, 2015, p. 35). Consequently, the models used for signal extraction will provide different results in pairwise estimations and for different estimation periods.

Ye (2014) analysed interactions of the non-overlapping stock markets of the US and China providing evidence of the predictive power of the US market on the stock market of China. The study employed the statistical procedure developed by Henriksson and Merton (1981). This method uses returns on one market as a signal to forecast returns on another market, i.e. a positive return will give a buying signal, while a negative will give a selling signal.

2.6.3 Trading strategies and trading rules

The signal extraction methodologies are particularly relevant for construction of a trading strategy. The conveyance of information contained in both returns and volatility across borders creates the opportunity for investors to use this mechanism to forecast stock market returns and to design a trading strategy based on foreign information transmission. Farmer and Joshi (2002) defined a deterministic trading strategy as a "signal processing element that uses external information and past prices as inputs and incorporates them into future prices" (p.149). The ultimate goal of the trading strategy is to achieve a higher rate of return than a passive "buy and hold" approach could provide. While in forecasting literature, there are several ways to measure the accuracy of out-of-sample forecast, a relatively few actually offer the methodology to evaluate the economic benefits of a trading strategy.

One of the approaches that can be used for this purpose is to simulate investors' decisions in real time, using publicly available information. However, Pesaran and Timmermann (1995) highlighted that two problems have to be addressed. First, although the majority of papers in the topic area report excess return regressions, estimated on the basis of the entire sample of available observations, in real time investors could not obtain parameter estimates on the entire sample, which makes this assumption inadequate for the construction of a trading strategy. Second, the model's uncertainty problem does not allow the use of the same forecasting model for the whole sample period as it raises the possibility that the choice of the model has been made with the benefit of hindsight. Pesaran and Timmermann (1995) investigated the predictive power of the US excess returns and conducted their research based on assumptions that at any specific moment in time investors used only historical information to select a model capable of making one-step-ahead forecasts based on pre-identified model selection criterion and a set of financial variables. The writer's s claimed that these assumptions are far more realistic for the creation of a trading strategy in real time.

Several commonly used trading rules, using past information, are presented in the literature. Marshall, Cahan, and Cahan (2008) considered 7846 trading rule specifications from five rule families, i.e. filter rules, moving average rules, support and resistance rules, channel breakouts, and on balance volume rules. The classical filter rules (e.g., Alexander, 1961; Fama & Blume, 1966) suggests the investor should buy (sell) the selected security if its price increases (decreases) based on the predefined percentage points from its previous peak. Moving average rules are another family of technical trading rules, when buy (sell) signals are generated if the short term moving average rises above (falls below) the predefined percentage, the long term moving average. The family of the moving average rules includes, for example, the variable-length moving average rule, i.e. the investors holding position until the signal is no longer valid, and the fixed-length moving average rule, the investors holding position for a fixed number of days, ignoring signals appearing during this period (Zhu et al, 2015). Trading range break rules, which are also known as support and resistance rules or channel breakout, are technical trading rules that assumes that buy (sell) signals are generated when the stock price penetrates the resistance (support) level. Brock, Lakonishok and LeBaron (1992) used a moving average and the trading range brake rules extending standard statistical analysis through the use of bootstrap techniques. They compared the returns obtained from these trading strategies to returns from a simulated series constructed by using four popular models, i.e. the random walk, the AR (1), the GARCH-M, the EGARCH. The paper provided evidence that returns obtained from buy and sell signals could not be generated by any of four null models. The findings suggested that buying signals generate higher returns than selling signals, while the volatility of returns generated by selling signals are higher than those of buying signals.

The paper supported the evidence of the predictive power of technical trading rules, supporting the idea that these rules can be particularly relevant for futures markets, where transaction costs are comparatively low. The study by Pesaran and Timmermann (1994) also demonstrated the power of past information, contained in excess returns, to predict a statistically significant proportion of the signs of future returns. The paper analysed the predictability of excess returns on common stocks for the SP 500 and the Dow Jones portfolios at annual, quarterly, and monthly frequencies, and found evidence for all three time horizons. Alternative results obtained by a more recent study by Zhu et al. (2015) tested both moving average and the trading break rules by using the Shanghai Stock Exchange Composite Index (SHCI) from May 21, 1992 through December 31, 2013 and the Shenzhen Stock Exchange Component Index (SZCI) from April 3, 1991 through December 31, 2013. Zhu et al. (2015) showed that both trading rules cannot outperform standard buy-and-hold strategy, if transaction costs are taken into consideration, as this neglects the predictive power of simple technical trading rules. Ibrahim and Brzeszczynski (2009, p.201) investigated the advantages of using foreign information over domestic information in a trading strategy, measuring economic benefit by the performance of trading strategies that had been constructed using the signals extracted from domestic and foreign market information.

The performance of trading strategies is often compared with a domestic benchmark, i.e. the returns on the selected securities for the same estimation period (e.g., Pesaran & Timmermann, 1994, 1995; Gencay, 1998). However, the disadvantages of an active trading strategy are the costs involved in every transaction. Indeed, any active strategy will be more costly than “buy and hold strategy”, and only by taking into account transaction costs can the true value of the economic benefit of a trading strategy be evaluated (Marshall et al., 2008). It is not surprising that much has been written on this subject, given how relevant this topic is for practitioners and academics. However, there is a lack of accessible evidence that any particular trading strategy can consistently outperform a passive one.

One of the popular beliefs is that stocks that have outperformed the average stock return in a previous period will continue to perform better in the future. This phenomenon is often explained by fact that stock prices underreact to the information contained in past returns, which creates opportunities for the generation of momentum in trading strategies (Jegadeesh & Titman, 1993; Hameed & Kusnadi, 2002). In contrast to the phenomenon of stock price underreaction to past information, numerous researchers have analysed the overreaction phenomenon, i.e. investors tending to "overreact" to new information by giving higher weight to recent information as compared to prior information (e.g., Kahneman & Tversky, 1982; Atkins & Dyl, 1990; Bowman & Iverson, 1998; Otchere & Chan, 2003). In general, construction of a trading strategy based on these beliefs falls within the overlapping area between quantitative finance and behavioural and experimental finance. The benefits of a trading strategy are often linked to the goals and values of a particular group of investors. Several notable studies analysed the behavioural aspects of employing a trading strategy, providing evidence that the trading strategy depends on investors' goals and risk tolerance (e.g., Daniel, Hirshleifer & Subrahmanyam, 1998; Conrad & Kaul, 1998; Hong & Stein, 1999).

2.6.4 International information transmission and efficient market hypothesis

Forecasting of financial asset returns is fascinating not only for practitioners, but for academics as well, due to its implications for tests of market efficiency. In an efficient market new information generates signals that can be interpreted rationally by all market participants, leading to an optimal allocation of capital. The weak-form of efficient market hypothesis (EMH) suggests that past information cannot be used for predicting future returns because it is already fully incorporated into the current price of the assets (Fama, 1970). The 'semi-strong form' efficiency suggests that prices incorporate all public information, however some private information, which is hidden from the majority of market participants, can still cause deviation of asset prices from their intrinsic values. 'Insiders', i.e. market participants who have access to private information, can predict the behaviour of prices and achieve greater returns. Alternatively, 'strong form' efficiency postulates that prices incorporate all public and private historical information entirely, which makes the forecasting of future returns a completely unrealistic task. The history of testing EMH is quite long but the majority of papers tested weak-form of efficiency, due to the fact that "the rejection of the weak form of efficiency automatically implies rejection of the 'semi-strong' and 'strong' forms" (Lagoarde-Segot & Lucey, 2006, p.8).

Granger (1986) claimed that long-run relationships among financial markets may lead to the rejection of the efficient markets hypothesis (EMH). The majority of papers on return and volatility transmission and financial forecasting, consequently, contribute to evidence on EMH. For example, Maderitsch (2015, p.14) argued that under strong form efficiency the cross-market return spillovers are not statistically distinguishable from zero, because "information generated in chronologically preceding foreign markets should be fully incorporated into market opening prices". Referring to Lo's (2004) Adaptive Market Hypothesis, Maderitsch (2015) suggests that the degree of market efficiency may vary across markets and over time. The confirmation of the predictive power of foreign information transmissions, i.e. the meteor showers effect, may provide evidence of stock market inefficiency. The EMH, consequently, makes technical analysis invalid. The superior forecasting performance of a statistical method itself will invalidate the idea that stock market prices fully reflect all available information and analysis of historical data (e.g., Henriksson & Merton, 1981; Masteika & Rutkauskas, 2012) The creation of a trading rule that will outperform the passive "buy and hold", taking into account the transaction costs, will suggest that it is possible to outperform the market, which contradicts the EMH (Pesaran & Timmermann, 1994).

Besides the empirical evidence which confirmed the forecasting abilities of econometric models, and the literature that presented successful trading strategies able to outperform the market, so providing significant economic benefits to investors, there are certain theoretical explanations as to why forecasting can still be possible.

The first explanation relies on the role of macroeconomic indicators in the prediction of the stock returns and is provided by Rapach and Zhou (2013):

> Theoretically, asset returns are functions of the state variables of the real economy, and the real economy itself displays significant business-cycle fluctuations. If the quantity and price of aggregate risk are linked to economic fluctuations, then we should expect time-varying expected returns and return predictability, even in an efficient market (p. 331).

Another explanation is provided by Lagoarde-Segot and Lucey (2008, p.95) who claimed that investors may adopt alternative behaviour patterns due to uncertainties caused by the lack of information on company performance, which consequently creates disturbances in the economy's allocation function and in the corporate control mechanisms (Hirota & Sunder, 2002). The authors argue that this process can be especially pronounced in emerging markets, where information flow can be restricted due to several factors. Lagoarde-Segot and Lucey (2008) summarised some of the reasons for market inefficiency citing:

> i) illiquidity problems; ii) low degree of competition; iii) a lack of market transparency, low auditing experience, lax disclosure requirements, and overall weak regulations; iv) the fragmentation of capital markets and the presence of

political and economic uncertainties; v) a lack of a 'culture of equity' tends to slow the reaction of market participants to information (p.95).

Overall, there are some theoretical justifications for the claim that forecasting of future returns is possible. This thesis hypothesizes the ability of foreign information to forecast domestic stock index futures returns, with the further expectation that the forecasting ability of foreign information may vary between developed-developed, emerging-emerging, and developed-emerging market combinations.

2.7 Return and volatility spillovers across stock index futures

2.7.1 Lead-lag relationships between stock indices and stock index futures

In theory, according to the efficient markets hypothesis, the returns on stock index futures and underlying stock indices have to be perfectly correlated since the information is simultaneously incorporated by both spot and futures prices (e.g., Brooks, Rew & Ritson, 2001). In reality, empirical evidence shows that the relationship between futures and spot returns are often instable, especially during crisis periods, and may vary among markets across the globe, due a country's specific market regulations and different degrees of economic development. Hence, the existence of lead-lag relationships between spot and futures markets investigated, for example, by Harris (1989), Chan, Chan and Karolyi (1991), Antoniou, Holmes and Priestley (1998), Antoniou, Pescetto and Violaris (2003), among others, challenges the financial regulators and policy makers, due to the common belief that futures trading increases the volatility of underlying stock markets. Indeed, Antoniou and Holmes (1995) analysing the impact of futures contracts on underlying stock market volatility found that futures trading expanded the channels over which information can be transmitted to the market and so increased the volatility of the spot market. Due to the lower costs of trading and greater leverage potential, futures markets become attractive for both uninformed and informed traders (e.g., Antoniou et al., 2005; Chen & Gau, 2010). Futures trading, then, can destabilize the underlying spot market due to the impact of uninformed investors (Bohl, Diesteldorf & Siklos, 2015). An alternative viewpoint, i.e. of the stabilizing role of futures trading, is provided by Turnovsky (1983). Many studies have analysed the volatility of spot markets in pre-futures and post-futures periods providing evidence of increased volatility after the introduction of futures to the market (e.g., Harris, 1989; Chang et al., 1999).

Tu, Hsieh, and Wu (2016) claimed "that theoretical grounding on the linkage between volatility and futures pricing was provided by Hemler and Longstaff (1991)" (p.79), who found that "the difference between actual futures prices and spot prices is significantly related to volatility" (p.80). The issue of volatility spillovers between spot and futures markets has been actively studied in respect to price discovery. Continuous development of new methodologies, supported by the increase in computer capabilities, allows researchers to develop knowledge in this area. However, the existing literature is often presented through single country studies and is restricted to developed markets. For example, Gannon and Choi (1998) analysed volatility transmissions between futures and equity markets in Hong Kong. Tse (1995) and Chang et al. (1999) focused on Japan, and Brooks et al. (2001) provided evidence for the UK. Antoniou et al. (2005) investigated these phenomena in the industrialised markets of Canada, France, Germany, Japan, the UK, and the US, and Antonakakis, Floros and Kizys (2015) provided evidence for the UK and the US. The pattern of spot-futures linkages may vary: i) across different regions, i.e. due to the existence of trading agreements between countries, some markets can be donors or recipients of foreign shocks, increasing the volatility on futures and spot markets and, consequently, changing the intensity of spillovers between them; ii) due to the level of economic development, i.e. the intensity of information transmission between stock indices and stock index futures could be higher on developed markets than emerging markets; iii) due to different degrees of market openness and trading volumes on futures markets between countries. The introduction of stock index futures in emerging markets sparked the debate about the spot-futures relationship in markets with different degrees of financial development.

For example, in China financial futures were first traded in April 2010, potentially expanding the channels of information transmission in the Asian region and beyond. Yang, Yang and Zhou (2011) utilized high-frequency data to investigate intraday price discovery and volatility transmission between the stock index and the recently introduced stock index futures markets in China. First, the empirical findings suggest that the Chinese futures market, as an equity market, is in its infancy in terms of its development, despite the fact that CSI 300 dropped immediately after the futures contracts had been introduced. Second, the paper found strong bidirectional intraday volatility dependence between futures and stock markets in China. Yang et al. (2011) analysed data from 16 April, 2010 (introduction of stock index futures on CSI 300) to 30 July, 2010, which is a relatively short period, and when the Chinese futures markets was at a very early stage of development. Later, Bohl et al. (2015) investigated the same phenomenon for 8 April, 2005 (Introduction of CSI 300) till 24 June, 2013, which makes the post-futures period, i.e. 16 April, 2010 – 24 June, 2013, much longer than was analysed by Yang et al. (2011). The findings provided by Bohl et al. (2015, p. 218) show a stabilizing role for futures-spot volatility spillovers, because the introduction of CSI300 index futures had a significant and negative impact on the volatility of the CSI 300 spot index. Similarly, the stabilising role of futures trading in China is shown in a study by Zhou, Dong and Wang (2014). In contrast, a study by Hou and Li (2014) demonstrated that the introduction of stock index futures in China has tended to destabilise the underlying stock index.

Zhong et al. (2004) analysed futures-spot relationships in Mexico and found that the introduction of a futures market significantly increased volatility of the underlying equity index. The findings support the position of a destabilising role for futures trading. The role the futures market plays in price discovery, in the Mexican context, was also confirmed by Zhou et al. (2004). The authors employed a modified EGARCH, providing evidence of co-integration between the futures and spot markets in Mexico. Alternative evidence, provided by Kang, Cheong and Yoon (2013), analysed the spot-futures relationship in Korea. They found evidence in favour of the efficient market hypothesis, highlighting the fact that information incorporated by both futures and underlying index was done simultaneously. The results indicate strong bidirectional causalities between futures and spot markets, suggesting that none of the markets demonstrated a strong leading role in futures-spot relationships in Korea. For the emerging market of Taiwan, a study by Chiang and Wang (2002) found that futures trading has a major effect on spot price volatility, whereas the trading of MSCI Taiwan futures does not.

The literature on futures-spot market linkages is restricted primarily to single country studies, or the largest industrialised markets. Nevertheless, a few papers provided international evidence based on analyses of a broader country panel, including both emerging and developed markets. For example, Qiao, Wong and Fung (2013) analysed the stochastic dominance (SD) relationships between stock indices and their corresponding index futures for 10 countries from different regions, i.e. Asia (Japan, Hong Kong, Singapore, and Taiwan), Europe (the UK, Germany, and France), the Americas (the US, Canada, and Brazil), considering the period from 03 January, 2000 to 31 December, 2007. The empirical results show the absence of SD relationships between spot and futures markets in developed countries, providing evidence of the efficiency of these markets. However, the results for the emerging markets suggest that spot dominates futures for risk averters, while futures dominate spot for risk seekers in the second- and third-order SD.

Although the evidence for the stabilising and destabilising effects of futures trading on the underlying financial market is contradictory, many studies supported the argument proposed by Lien and Zhang (2008) who claimed that financial derivatives markets have helped to support capital inflows into emerging market economies. One of the common limitations of this literature field is that the majority of existing empirical papers employing futures data do not consider whether spot-futures relationships depend on the existence of an overlap in stock exchange trading hours, with the possible exception of a study by Chan (1992), that provided evidence demonstrating that this "lead-lag effect of futures-spot relationship is not caused by nonsynchronous trading in the spot index" (Pan & Hsueh, 1998, p.212). Furthermore, the question whether futures trading affects global financial market interconnectedness is correctly, was raised but left unanswered. While the literature about spot-futures relationship is relatively broad (see Lien & Zhang, 2008) the evidence for return and volatility spillovers across futures markets is very limited and requires further investigation.

2.7.2 Information transmission across futures markets

The contagion and spillover effects across stock indices have been rigorously studied, however, the cross-border return and volatility transmissions between stock index futures is relatively unexplored. Analysis of futures data can, still, provide more realistic practical implications. First of all, stock index futures are attractive financial instruments for those traders who are willing to invest in a diversified portfolio, corresponding to index. Since stock indices cannot be traded by investors as financial instruments (investing in constituent stocks is costly and time-consuming), investors would prefer stock index futures that could be traded in a single transaction (Subrahmanyam, 1991). Floros and Salvador (2014) claimed that trading stock index futures have advantages over trading the portfolio of stocks, for several reasons. These include easy short selling, low transaction costs, high leverage and liquidity, known price and taxation (Sutcliffe, 2006).

Pan and Hsueh (1998) analysed inter-regional returns and volatility spillovers between markets with non-overlapping trading hours utilizing the U.S. and Japanese stock index futures data for the period from 03 January, 1989 through to 30 December, 1993, and employed a two-step GARCH approach. The researchers found significant return and volatility transmissions from the US to Japan, while the spillovers for the reverse direction, i.e. from Japan to the US are not evident. The empirical results demonstrated the asymmetry in spillover across stock index futures, i.e. negative innovations have a stronger lagged spillover effect than positive innovations. Kao, Ho and Fung (2015) analysed price discovery and the dynamic of information transmission between the Nikkei 225 index futures and E-mini S&P 500 index futures, finding evidence supporting the trading-place-bias hypothesis. The authors used minute-by-minute data from 2011 to 2013 demonstrate the Nikkei 225 index futures price is susceptible to information on the location of trading rather than the home market. Contrary to Pan and Hsueh (1998), the results show that the leading role in information transmission changed over time, from the United States in 2011–2012 to Japan in 2013 (Kao et al., 2015, p. 331). Gannon (2005) also analysed spillover effect across stock index futures focusing on the markets without any overlap in stock exchange trading hours, i.e. the US and Hong Kong. There is strong evidence of volatility spillovers from the overnight U.S. index futures to the Hong Kong index futures.

The US market seems to be the most influential, not only among stock indices, but also among stock index futures. Besides US-Japan, and US-Hong Kong channels of transmission, Wu, Li and Zhang (2005) analysed short-run information transmission between the US and the UK stock index futures, employing the MA(1)-GARCH(1,1) model to high-frequency data. The results provide supporting evidence for the "heat wave" hypothesis regarding return spillovers, because no significant return spillovers are found between the US and the UK futures. However, the results support "meteor shower" hypothesis for volatility, because bidirectional volatility spillovers are identified for the US-UK market pair.

Some evidence for the European region is also presented in literature. For example, Albulescu et al. (2015) examined the co-movements between the selected European futures markets (the UK, Germany and France) for the period from 15 October, 2009 to 27 August, 2013, utilizing a continuous wavelet transform framework. Albulescu et al. (2015) demonstrated that, according to the WTC approach, the UK futures lead Germany and France in the long-run. This study also analysed the impact of the EDC on the correlation structure between markets. The findings suggest that the European futures markets are strongly correlated, where the correlation is increased after a crisis episode. These results are different from those provided by Karim and Jais (2011) who analysed the impact of the GFC on the integration of stock index futures markets and found that crisis does not affect the co-movements between stock index futures markets.

Regarding emerging markets, several studies also analysed the impact of crisis episodes on the dynamic of cross-markets linkages. Dooley and Hutchison (2009) formulated the decoupling-recoupling hypothesis that suggests the intensification of financial linkages between markets after crisis episodes, and this was supported by many studies (e.g., Levy-Yeyati & Williams, 2012; Korinek, Roitman, & Végh, 2010). Alternatively, Floros, Kizys and Pierdzioch (2013) claimed that the decoupling-recoupling hypothesis does not apply to the risk premium on the stock index futures market, citing the evidence from the Greek market. Instead, Floros et al. (2013,p. 172) provided evidence for the recoupling-decoupling hypothesis, demonstrating that the risk premium on the Greek stock index futures market was mainly driven by its regional (European) component before the EDC, while the local (Greek) component became more important for the risk premium after the recent Greek debt crisis. Similar evidence provided by Floros and Salvador (2014) claimed that the Greek stock market futures was globally priced before the EDC, but has become more segmented after the EDC. The paper by Hou and Li (2015) employed an asymmetric DCC GARCH approach to analyse information transmission between stock index futures of the US and China. Contradictory to the studies reporting that the Chinese equity market is comparatively isolated from external shocks (e.g. Huang et al., 2000), Hou and Li (2015) found that the US has a significant impact on the volatilities of stock index futures in China. This relationship is unidirectional, however, because China does not seem to affect the US.

The above-mentioned papers do not explain whether the difference in patterns of return and volatility transmissions exists between stock indices versus stock index futures. Only a few studies demonstrated any attempt to handle this issue. For example, the paper by Clements, Hurn and Volkov (2015) investigated patterns of volatility and news spillovers between Japan, Europe, and the US in global markets. The paper provided evidence from continuously-traded futures contracts from the equity, bond and foreign exchange markets. Clements et al. (2015) contributes to the literature analysing the 'same day effect' discussed earlier, or 'intra-day effect' providing evidence that:

> Returns to the futures contracts from different trading zones form a hypothetical global trading day in which developments in Japan can influence Europe and the United States on the same calendar day (p.16).

The empirical results provided supporting evidence for the meteor shower hypothesis. The application of realized semivariance measure (e.g., Barndorff-Nielsen, Kinnebrock & Shephard, 2010; Baruník et al., 2015) for stock index futures revealed the asymmetry in volatility transmission, because volatility related to negative news is transmitted quicker than volatility linked to good news. The results from the decomposition of realised volatility into its continuous and jump components indicated that "jumps in volatility are not as readily transmitted as might be expected a priori" (Clements et al., 2015, p.17). Although it was found that the diffusive component generally has more explanatory power than the jump component, for the stock index futures, the jump component, which reflects the arrival of more extreme news, is significant. The issue of co-jumps was also analysed by Wang, Yue & Zhao (2015), and earlier by Evans (2011), regarding news announcements. Both papers investigated co-jumps in stock indices and stock index futures markets in the same country, rather than providing evidence from international markets as done by Clements et al. (2015). Wang et al, (2015) analysed co-jumps across China's spot and futures markets and their association with macroeconomic news announcements. The paper employed the five-minute high-frequency data for spot and futures markets from 16 April, 2010 to 30 June, 2014. The findings suggest that Chinese stock index futures jump more frequently and, to a greater degree, than the underlying stock index does. Both stock indices and stock index futures experience positive jumps more frequently than negative ones. Evans (2011) analysed to what extent the intraday jumps in US futures markets (i.e. E-Mini, T-Bond and EUR-USD contracts) are associated with US macroeconomic news announcements. The results show "little evidence that intraday jumps help to predict returns, but substantive evidence that they precede volatility persistence and that the presence of news-related jumps generates stronger volatility than non-news-related jumps" (Evans, 2011, p. 2526). Although, the predictive ability of macroeconomic news announcements on futures markets have been investigated in several papers, the predictive ability of foreign information transmitted is left unexplained.

Smales (2015) analysed to what extent the trading decisions and measures of investor sentiment impact on market volatility. The paper investigated whether the net position of speculators and small traders have an ability to forecast future market returns. These two research questions are tested in the context of the US futures contracts, i.e. E-Mini and S&P 500. The results indicated that both speculators and small traders tend to follow positive feedback strategies, while hedgers adopt a strategy which is consistent with a dynamic hedging of their underlying portfolio, therefore supporting the position that hedgers help to stabilize the market. The linkages between investment sentiments and trading behaviour are significant for the futures markets analysed and have similar patterns. The findings demonstrated that trader behaviour is not static, because it has been changed after the GFC. Smales (2015) reports that the net position of both trader-types has predictive power, and is particularly strong in the prediction of upward trends over the short term.

The study by Smales (2015) also belongs to another literature section that considers whether sentiment indicators can impact future returns (e.g., Simons & Wiggins, 2001; Brown & Cliff, 2004; Bohl, Goodfellow & Bialkowski, 2010; Yang & Gao, 2014). Yang and Gao (2014) analysed sentiment spillover effect and sentiment aggregate effect in the context of the Chinese stock index futures market. The authors defined a sentiment spillover effect as the effect of stock market sentiment on stock index futures returns, while the sentiment aggregate effect was identified as "the relationship between futures contracts price and futures sentiment" (p. 172).

While the previous section demonstrated that the predictive abilities of stock indices have been analysed by employing different statistical techniques, and the economic significance of foreign information transmission has been tested by the generation of trading strategies, the evidence from stock index futures is very limited. The majority of papers that employed stock index futures data tested hedging strategies, rather than strategies based on the meteor-shower-like effect (e.g., Lindahl, 1992; Pattarin & Ferretti, 2004; Floros & Vougas, 2004; Chiu, Wu, Chen, & Cheng, 2005; Pok, Poshakwale & Ford, 2009; Wei, Wang & Huang, 2011; Smales, 2015). Significant elements of papers on hedging analyse commodity futures rather than financial futures (e.g., Chng, 2009; Nguyen, Sousa & Uddin, 2015; Joseph, Suresh & Sisodia, 2015.). The reason for the popularity of this literature is the fact that the opportunity to short sell futures contracts allows the investor to significantly hedge the risk of the portfolio of assets. Hedging is a key area in terms of the implications of stock index futures data. Pok et al. (2009) analysed the hedging effectiveness of the GARCH (1,1) and TGARCH models in the Malaysian context, utilizing daily stock index data from December, 1995 to April, 2001. The study by Wei et al. (2011) compared the hedging effectiveness of the copula–MFV model with several popular copula–GARCH models. The paper utilized high-frequency (5 minutes) data of the Chinese spot and index futures markets from 19 April, 2010 to 26 January, 2011, providing evidence in favour of the MFV hedging model.

This section illustrates that there are very few papers which analysed the return and volatility transmissions to provide evidence from stock index futures. The next section will highlight those issues relating to international information transmission mechanisms that have to be explored further.

2.8 Literature gap

Even though there is a plethora of empirical literature on return and volatility spillovers across various financial assets, it is surprising how much is still left unknown about the channels, intensity and origin of the transmission of information flows on the global markets. The existing evidence on return and volatility transmission mechanisms can be enriched by utilising evidence from stock index futures. The literature on stock market interconnectedness is very broad. The stock market linkages have been assessed to test integration (e.g., Portes & Rey, 2000; Bekaert et al., 2003; Kearney & Lucey, 2004; Coelho et al., 2007; Aggarwal et al., 2010; Cajueiro et al., 2009; Singh et al., 2010) contagion (e.g., Zhang, Li & Yu, 2013; Bekiros, 2014; Karanasos et al., 2014; Luchtenberg & Vu, 2015; Petmezas & Santamaria, 2014; Albulescu et al., 2015) and meteor shower hypotheses (e.g., Engle et al., 1990; Hamao et al, 1990; Melvin & Melvin, 2003; Ibrahim & Brzeszczynski, 2009, 2012). The majority of studies employed stock indices in the analysis of spillovers. The question of which data is appropriate to use in analyses of international information transmission and global market linkages is still a matter of debate between academics and supervisory bodies.

Barari, Lucey and Voronkova (2008) argued that stock market indices are not easily investible assets, due to the higher cost of trading, potential trading and entry barriers (Li et al., 2003). As a result the extent of diversification benefits available on the global market can be overestimated if only stock index data is utilized. Therefore, Barari et al. (2008) suggested that the results of the earlier studies, based on stock indices, should be interpreted with caution. As indicated earlier, this thesis postulates the position that employing only stock indices data, limits understanding of the practical implications of empirical results, because a trading strategy based on investing in various stock indices is an approximation that only makes sense in a theoretical context. In reality, stock indices cannot be traded by investors as financial instruments. Investors with diversification goals can only buy constituent stocks (which is not only costly but also time-consuming) and such trades are not possible to execute in a single transaction, which, on the other hand, can be done using stock index futures (Subrahmanyam, 1991). Employing stock index futures data in an analysis of international information transmission is more realistic from the point of view of the construction, testing and execution of actual trading strategies and, therefore, the results of such empirical research are more useful for practitioners.

Although existing literature employed futures data in the analysis of spillovers and addressed several important issues in finance, the evidence about global return and volatility transmission across futures markets is still very limited. This thesis focuses on the three main gaps in knowledge, identified following the survey and review of current literature.

I. *There is a lack of global empirical evidence on differences in patterns on return and volatility transmission across stock indices and stock index futures*.

Futures can offer several obvious advantages for investors, such as lower costs of trading or high trading volume (i.e. high liquidity). The existing literature employed futures and stock indices data in one empirical study and focused mainly on spot-futures interactions (e.g., Zhou et al., 2004; Yang et al., 2011; Qiao et al., 2013; Bohl et al., 2015), cojumps (Evans, 2011;Wang et al., 2015), or hedging risk of the portfolio (e.g., Lindahl, 1992; Pattarin & Ferretti, 2004; Floros & Vougas, 2004; Chiu et al., 2005; Pok, Poshakwale & Ford, 2009; Wei et al., 2011; Smales, 2015). Besides these reasonable applications of futures data in contemporary researches, from the perspective of international information transmission mechanisms, this thesis presumes that futures markets can provide more efficient channels for the conveyance of information flows. However, the issue of whether the patterns of information transmission across stock index futures are different from the patterns of information spillovers on equity indices is not investigated in literature, despite the theoretical and practical significance of this question. This question is relevant to the execution of a trading strategy, portfolio diversification, and for financial stability. Furthermore, the investigation of the difference in patterns of return and volatility spillovers across two interlinked, but different, asset classes, i.e. stock index futures and stock indices, can provide new results for the testing of the contagion hypothesis and spillover effects in the global context.

Although the return and volatility spillovers across stock market indices have been widely studied over the last two decades, this topic is even more relevant now due to its practical significance and the nature of volatility itself, which varies over time. The existing empirical evidence about intra- and inter-regional return and volatility spillovers around financial crises focuses mainly on information transmission across the largest developed stock markets. For example, the markets in Japan, the UK and the US were considered in the early literature by Engle et al. (1990), King and Wadhwani (1990), Becker, Finnerty and Gupta (1990), Hamao, Masulis and Ng (1991) or more recently by Ibrahim and Brzeszczynski (2009, 2014). On the other hand, globalization and the development of new technologies have caused an increase in the integration of emerging markets with the world economy. This effect has many practical implications. For example, the increasing economic integration of emerging and developed stock markets has become a crucial issue for portfolio managers because volatility spillovers tend to diminish the opportunities for international diversification in emerging economies. Moreover, the Global Financial Crisis, together with the European Debt Crisis, has resulted in a new stream of academic literature on contagion and stock market integration in the periods before, during, and after these episodes.

It is necessary to study return and volatility spillovers across both emerging and developed markets in order to explore the new geography of financial information transmission mechanisms across markets around recent crisis episodes. The selection of countries has to represent different regions, i.e. Asia, the Americas, Europe and Africa, and has not been restricted to the mature markets. The validity and necessity of this research is further strengthened by the fact that existing empirical evidence is not readily accessible for practitioners for two reasons. The first is that existing literature and research provides ambiguous results based on a variety of methodologies and employs data with different frequencies and time periods. Secondly, the studies that employed futures data more commonly conduct single country analysis or provide evidence from very limited numbers of markets. There is a clear need for accessible evidence based on a large number of countries obtained using a suitable methodology that allows the presentation of the results in an understandable format.

II. *The issue of asymmetry in return and volatility transmission across stock index futures of the markets with non-overlapping stock exchange trading hours is left uncommented in this topic area.*

While the concept of asymmetric volatility has been analysed by numerous papers (e.g., Nelson, 1991; Bekaert & Wu, 2000; Ferreira et al., 2007; Scharth & Medeiros, 2009; Jackwerth & Vilkov, 2014; Xiang & Zhu, 2014; Koulakiotis et al., 2015), the asymmetry in return and volatility transmission is not well-discussed, nor has it so far been investigated in the literature. A few papers, for example Koutmos and Booth (1995), Baruník et al. (2015), and Kundu and Sarkar (2016) analysed the transmission of positive and negative shocks from one market to another, shedding light on the concept of asymmetry in volatility spillovers. However, these papers provide evidence for only a small number of markets and employed stock indices. The issues of information transmission across markets with non-overlapping stock exchange trading hours, i.e. same day effect and meteor shower effect, are not explored well in literature employing futures data (e.g., Pan & Hsueh, 1998; Wu et al., 2005; Gannon, 2005; Kao et al., 2015). The paper by Clements et al. (2015) provided supporting evidence on the meteor shower hypothesis on futures markets, but analysed just the three largest markets, i.e. Japan, the US and Europe. There is a lack of international evidence on asymmetry in return and volatility spillovers across markets with non-overlapping trading hours. A study which analyses the transmission of positive and negative return and volatility across markets situated in different time zones would help to enhance our understanding of asymmetry in information transmission mechanisms. The utilization of the futures markets of both developed and emerging countries will make the results more practically significant.

Due to the existence of heteroskedasticity in futures time-series, the study needs to employ a methodology that is robust under the ARCH effect. One of the most utilised methods belongs to the ARCH-family of models. However, the recently developed asymmetric causality test, as suggested by Hatemi-J (2012), which used bootstrap procedure to estimate critical values, and provides robust results on the ARCH effect, have not yet been employed in an analysis of return and volatility transmission across stock index futures. Hence, there is an opportunity to provide original empirical results.

III. *The ability of international information contained in stock index futures returns to forecast the return on domestic futures markets has not been investigated in the international context.*

As demonstrated in previous sections, the evidence for the forecasting ability of foreign information over domestic information to predict futures returns is very limited. The existing papers on the predictive power of meteor shower and heat wave effects are, again, restricted mainly to the largest developed markets (e.g., Pan & Hsueh, 1998; Gannon, 2005; Wu et al., 2005; Albulescu et al., 2015), omitting the emerging markets. Normally, only a few markets are analysed and this caused the mutual ambiguities in the results reported by existing papers. There is a lack of a comprehensive study covering this issue. The difference in the forecasting performance of markets with, and without, overlap in trading hours has not been investigated, neither on stock indices, nor stock index futures markets.

Due to the fact that returns on stock index futures may have a large number of potential predictors and the significance of these predictors varies over time, the bagging and combination forecasting methodology suggested by Inoue and Kilian (2008), and further employed by Rapach and Strauss (2010), can provide interesting and practically significant results. This methodology has been employed to the large number of macroeconomic predictors, but has not been tested in the context of international return and volatility transmissions. Recent literature employing the same methodological framework includes the studies by McAleer and Medeiros (2010), Hillebrand and Medeiros (2010), Clark and McCracken (2010), and Jordan, Vivian and Wohar (2012, 2014, 2016).

For example, Hillebrand and Medeiros (2010) analysed the ability of bagging methodology to improve the forecasting performance of realized volatility, utilising data for 23 stocks from the DJIA index over the sample period from 1995 to 2005. The paper by Jordan et al. (2016) analysed whether commodity returns could forecast eight Canadian sector equity returns, using the bagging and combination forecast methodology to provide the out-of-sample evidence. The earlier paper written by the same authors, Jordan et al. (2012) generated out-of-sample bagging and combining forecasts for 12 Asian countries, using macroeconomic and financial variables as predictors. Although all these papers employed a similar methodology, none of them shed any light on international transmission mechanisms across stock index futures. The one notable exception, to the best of our knowledge, is the paper by Jordan et al. (2014) that analysed the ability of 13 foreign stock markets, i.e. India, Japan, Korea, Malaysia, Singapore, Thailand, the UK, and the US to predict the returns on the stock market in China. However this paper employed stock indices data only.

Due to the lack of studies employing bagging and combining forecasting methods to international stock index futures data, this research will be able to provide results on return predictability.

2.9 Chapter summary

This chapter has dealt with the background literature utilised in this PhD thesis. The main concepts used for the specification of the research questions and research hypothesis are also explained. Although the relevant literature is very broad, and contains work from many overlapping, but related literature strands, in fact, significant gaps in knowledge have been identified which underlines the necessity, and value, of this thesis at this time.

In addition to addressing these identified gaps in the literature, a major aim is to enhance understanding of the return and volatility transmission mechanisms in emerging and developed stock markets. The next section explains the structure of the thesis and the process of acquiring, and creating, new knowledge.

Chapter 3 Research design and philosophical assumptions

3.1 Introduction

A discussion of the philosophical underpinning of this research is an essential step in the understanding of the process of new knowledge creation. This chapter explains the design of the thesis which is in accordance with a chosen philosophical paradigm. It also identifies the position, values and role of the author as an independent researcher.

Section 3.2 discusses the problem of paradigm unity in finance science, providing an insight into the existing debate regarding ontology, epistemology and the methodology of research in this topic area. This section presents the philosophical paradigm underpinning the thesis in order to clarify the author's perceptions of the surrounding environment, explain what was assumed as an incontrovertible truth in this research, and to justify the choice of methodology employed.

Section 3.3 provides the set of research questions and hypotheses in regard to the aims and objectives of this study as identified in Chapter 1. This section aims to enhance the understanding of the research hypotheses before any viewing of the empirical chapters and results.

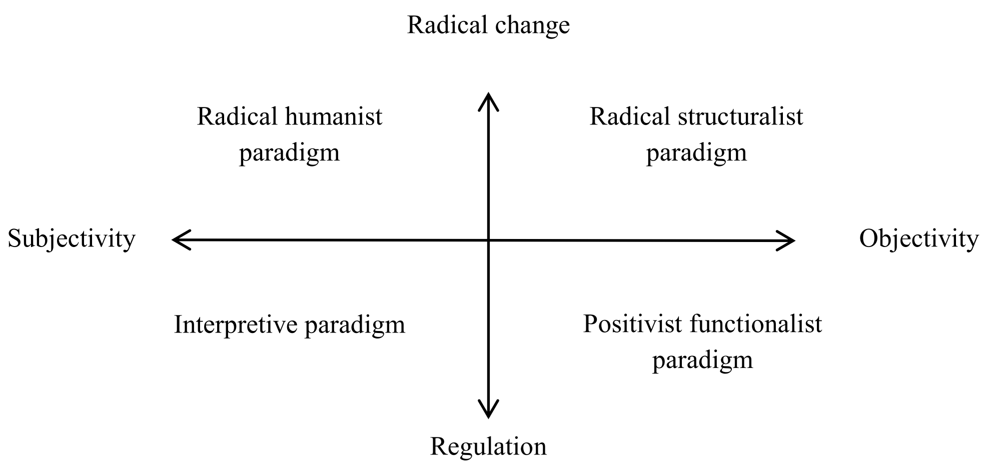
Section 3.4 clarifies how the thesis is filling the gap in literature investigated in Chapter 2. It aims to enhance the understanding of research design by the academic community, both within, and outside, the finance area.

An analysis of secondary data retrieved from public available sources is presented. As people are not involved in this research, there are no ethical issues that need to be specified. Consequently, an ethical consideration section is excluded from this chapter.

3.2 Philosophical assumptions

The description of the process of new knowledge creation in the finance field plays a crucial role in the justification of the accuracy, reliability and originality of the research results. Clarification of the assumptions regarding ontology, epistemology and the methodology of research is critically important. There are several studies that introduced paradigm matrices that can be used to describe the philosophical position of the researcher, for example, Burrell and Morgan (1979), and Chua (1986). In this thesis, the Burrell and Morgan (1979) framework is used due to the high regard in which it is held in the finance field (e.g., Ryan, Scapen & Theobald, 2002; Adler, Forbes & Willmott, 2007; Lagoarde-Segot, 2014, 2015.).

Figure 3.1 The matrix of social science by Burrell and Morgan (1979).



This thesis was conducted in the broad tradition of academic finance research and fits into the positivist, functionalist paradigm that dominates in this area. Indeed, paradigm unity in financial science has been highlighted by Lagoarde-Segot (2015, 2014), Schinckus (2015), as well as others. Although ontological, epistemological and methodological assumptions of modern finance are widely accepted by finance academics, according to Laoarde-Segot, they remain controversial outside the finance area regarding the intertwined nature of facts and values, social ontology, and performativity (Lagoarde-Segot, 2015). It is important to demonstrate what philosophical assumptions are settled to achieve the aims of this research and to place the results in the context of existing knowledge.

Since the acclaimed book by Kuhn (1962), entitled *The Structure of Scientific Revolutions*, paradigm-related debate has spread across different areas of science (e.g., Feyerabend, 1975; Latour, 1987). More recently, Locke and Lowe (2008), Vollmer (2009), and Lukka (2010) discussed the philosophical assumptions of accounting research, while Dharmapala and McAleer (1996), Lagoarde-Segot (2015, 2014), and Schinckus (2015) contributed to the philosophical debate in finance and econometrics. The main Kuhnian argument, to think "outside the current box", is a key message running through contemporary philosophical discussion. The relevance of this argument in finance relies on the changing role of financial research in society. Lagoarde-Segot (2015) argues: "In spite of its positivist affiliation and regardless of how diligently one eliminates normative biases from quantitative research, financial theory necessarily plays a sociopolitical role" (p. 4).

The traditional position of positivists is very clear: the purpose of science is to describe what can be observed and measured (Uebel, 2006). This position relies, first, on an ontological assumption that reality is external and objective, i.e. investigated phenomenon is objective and external to an individual and, second, on epistemological assumptions that knowledge is significant only if it is based on observation of this external reality (Easterby-Smith, Thorpe & Jackson, 2012). This objectivist approach implicitly favours the development of an econometrics-based research (Schinckus, 2015). However, taking into account the sociopolitical role of finance, the investigated phenomenon may be viewed in the subjective spectrum as well. The critique of a positivist paradigm, employed particularly in the finance area, relies on the fact/value dichotomy, and on the closely related analytic/synthetic dichotomy, posited by positivists.

To demonstrate the interlinked nature of facts and values, the aims of this thesis can be taken as an example. On the one hand, the thesis aims to investigate return and volatility transmission across 21 markets. This spillover effect is investigated through empirical analysis of the data, where the data is assumed as 'fact', which is true in nature and reflects reality. This assumption places the research within positivism epistemology and realism ontology i.e. that a single reality exists and can be measured by quantitative methods. On the other hand, an important part of this thesis is an investigation of the practical implications of international information transmission mechanisms. In other words, to identify the 'implications' of investigated phenomenon for practice, which means to the lower strand of difficulty, this research aims to demonstrate how the phenomenon of information transmission across borders can be useful for practitioners, policy makers and financial regulators. The 'usefulness' of the investigated phenomenon already belongs to ‘value’ categories rather than ‘fact’ categories, which are more subjective in nature. “Indeed, positivism posits a dichotomy between ‘facts’ and ‘values’: ‘facts’ are tangible, measurable and verifiable, whereas ‘values’ belong to the metaphysical realm, and, as such, cannot be the object of rational inquiry” (Lagoarde-Segot, 2015, p.3).

The value/facts dichotomy has deep roots in philosophical literature. It relies on the main question: what can be assumed as ‘truth’ in social science? Within positivism traditions, the ‘true’ statements should be empirically found by analysis of observations, which makes the idea of logical empiricism a fundamental in the positivist dimension (Schinckus, 2015). Carnap (1937, 1966) introduced two types of statements: analytic and synthetic. According to analytic/synthetic dichotomy, every true judgment must be either analytic or synthetic. Analytic statements are ‘true’ by definition and do not need to be proved, because they are true or false by virtue of their logical forms, i.e. analytic statements are “propositions whose predicate concept is contained in their subject concept” (Schinckus, 2015, p. 104). Lagoarde-Segot (2015) claims that analytic statements can be assumed as truth a priori, for example, logical tautologies, such as mathematical deductions, while synthetic statements are substantive claims which have to be proved only by empirical testing. Schinckus (2015) further argues that synthetic statements could not be viewed as a priori ‘true’ statements by positivists because they create knowledge without an empirical base, due to the synthetic proposition referring to observational facts. The truth or falsehood of these statements can only be determined through the conducting of experiments. Alternatively, Block (2003, p.65) argues that analytic statements have no application to the real world. They indicate, merely, how we choose to use words, while synthetic claims are specifically about the real world.

The stylized facts in finance literature are good examples of synthetic statements which are often taken as a priori, true, without empirical investigation, contrary to a positivist perspective (e.g., Boland, 2014). The assumptions of statistical models also demonstrate how the contemporary positivist paradigm employed in the area of finance conflict with traditional epistemological assumptions. Lagoarde-Segot (2015) highlights that ‘value’ judgements do not fit into an analytical/synthetic classification because they are not analytic, i.e. could not be taken for granted, but not synthetic either, i.e. could not be empirically investigated. ‘Value’ statements, which are an important category in contemporary financial science, are often excluded from finance research as they cannot be viewed as ‘true’ statements within a positivist paradigm.

The alternative view presented in the book *The Collapse of the Fact/Value Dichotomy and Other Essays* by Putnam (2002), addressed this philosophical value/fact controversy. Putnam claims that there cannot be any value-free judgment of facts and further "there is no value-neutral way of separating the descriptive and evaluative aspects of discourse" (Lagoarde-Segot, 2015, p.3). This thesis aims, not only to the capture facts of the investigated phenomenon, but also to provide logical judgements about its practical implications. Lagoarde-Segot (2015) claims: "Finance is an ambiguous discipline seeking to simultaneously analyse the functioning of financial markets, and guide the decisions of actors" (p.4).

Lagoarde-Segot (2015) analysed philosophical assumptions in mainstream finance studies and found that contemporary research in finance often combines both objectives formulated by Merton (1995): a "macro-normative" objective, that seeks to understand how asset prices are formed in a hypothetical world characterized by perfect rationality, and a "micro-normative" objective, which seeks to investigate the ways in which an economic agent can maximize their utility function in the market, without focusing on the mechanism of asset price formation. This ambiguity in financial research has resulted in debate over the future direction of financial science and how new knowledge has to be created in order to be accepted as valid and truthful.

The first group of authors, (e.g., Mantegna & Stanley, 1999; McCauley, 2006; Schinckus, 2010), suggests that financial analyses should use more data-driven methodologies and minimize the number of a priori statements used in research. This approach would compel researchers to use more sophisticated econometric techniques, and also to pay extra attention to the data used by researchers in order to justify how well data reflects the reality. For example, McCauley (2006) argues:

> Economists have not understood how to model markets mathematically in an empirically correct way…What is now taught as standard economic theory will eventually disappear, no trace of it will remain in the universities or boardrooms because it simply does not work (Soros, 1998; Stiglitz,2002): were its engineering, the bridge would collapse (p.606).

In this case, to describe adequately the real economic and finance phenomenon by mathematical models, researchers have to deal with true mathematical complexity which, so far, has been handled only in biology, i.e. the genetic code and its consequences, where there are numerous facts but few equations (McCauley, 2006, p.607). McCauley believes that further development of research in finance and economics relies on collaboration with econophysics, as well as a better understanding of mathematical modelling by researchers. This point of view supports the position taken by Mantegna and Stanley (1999).

A second, and alternative viewpoint, on the future of finance research, is a paradigm shift from positivist functionalist framework to a higher order of subjectivity, i.e. radical humanism or interpretive paradigm (e.g., Lagoarde-Segot, 2015), which causes diversification of finance studies. The second route allows researchers to integrate 'value' categories in financial theories and to adapt financial knowledge to what Schinkus calls "socio-economic reality" (Schinckus, 2015, p.105). This position is supported by authors who provide a critique on philosophical paradigms in finance and econometrics (e.g., Dharmapala & McAleer, 1996; Rayner, 2011). Boland (1997) showed that, for all practical purposes, an empirical test would require far too many observations than it is possible to make in order to take any economic model seriously. Following this logic, in his more recent book, Boland (2014) claims that model-builders should address the issue of the realism of their assumptions.

This thesis supports the view point provided by Schinckus (2015, p.105), who claims that if it is impossible to separate 'facts' from 'values' in finance research (Putnam, 2002), the use of an a priori statement as a starting assumption for studying social reality empirically is not a problem, per se. Therefore, despite the fact that 'value' categories are viewed as intangible, they can be described by synthetic statements, i.e. research hypotheses, and can be justified by empirical tests. The confirmation of a research hypothesis will postulate that this statement is 'true', and this truth has to be accepted by the academic world unless the opposite position can be proven by other research. Block (1999, p. 30) postulates that the emergence of new ideas necessarily overthrows all previous patterns of behaviour. While Block's comment has been criticized by Caplan (2001, p. 8) for its "wide exaggeration", the underlying logic of this position, in the process of knowledge creation, sounds reasonable, especially in the finance field. Boland (2014, p.239) expressed the viewpoint that "models (and their assumptions) should not be judged as either true or false but only as better or worse according to the currently accepted conventional criteria". A priori assumptions, that become an integral part of mainstream finance, can be useful approximations of external reality, and allows the investigation of a phenomenon to be analysed by the quantitative methods of data analysis available to date. Supporting the view of Friedman (1953), presented in his famous methodological essay, this thesis assumes, along with Boland, that “the truth status of the assumptions – as instruments or tools – does not matter so long as they work” (Boland, 2014, p.239).

For example, the forecasting ability of foreign information transmissions across markets, with and without overlap in trading hours discussed in Chapter 7, relies on an explicit set of assumptions. For example, the pit trading times are considered, while electronic trading hours are ignored etc., which is, obviously, an approximation of reality. The forecasting performance of each predictor is a judged, not as ‘true’ or ‘false’, but only as ‘better’ or ‘worse’ in comparison with conventional criteria (Boland, 2014), e.g. AR model benchmark. This thesis avoids overuse of the value categories, such as ‘bad’ and ‘good uncertainty’ due to the high level of subjectivity of these terms. Instead, the thesis uses research metaphors of ‘positive’ and ‘negative’ volatility shocks which are more self-explanatory and less value laden. Lagoarde-Segot (2015) claims that: “By structuring the language of research, metaphors determine the researcher's stance on social reality and orient empirical research towards the analysis of similarities between the object of study and the common language” (p.5).

Finally, Diebold and Yilmaz (2014) use the quote from Kelvin (1891) as a preface for their study on stock return connectedness, which fits perfectly into the philosophical stance taken in this thesis and research design:

> When you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind: it may be the beginning of knowledge, but you have scarcely, in your thoughts, advanced to the stage of science (p.119).

3.3 Research questions and research hypotheses

This section outlines the research questions and hypotheses that are under consideration in this thesis. Bearing in mind identified gaps in literature, and the aims and objectives of this study, three research questions are investigated:

1) Do any differences exist in patterns of return and volatility spillovers across emerging and developed stock market indices and across stock index futures?

2) Do any asymmetric patterns exist in return and volatility spillovers across futures markets with non-overlapping stock exchange trading hours?

3) Does foreign information help forecast the return of stock index futures on domestic markets?

Following positivism research paradigms, the list of research hypotheses has been developed in accord with each research question. This set of research hypotheses is general and tested for all markets by using different methodologies; therefore further hypotheses regarding the particular econometric method employed can be further specified in the empirical chapters. Due to the ambiguity of the definition of 'contagion hypothesis', 'spillover hypothesis', and others, this thesis specifies research hypotheses using the research metaphors, concepts and other terminology, defined in the literature review. The hypotheses are used to clarify more exactly what is under investigation in this thesis regarding each research question.

From the first research question, the following eight research hypotheses are tested:

Hypothesis 1: *The dynamics of return spillovers across stock index futures is similar to that of spot markets.*

This hypothesis assumes that cyclical movements of total spillover indices for returns are similar for both futures and spot markets. The rejection of this hypothesis provides further evidence of differences in patterns of return transmission across stock indices and stock index futures.

Hypothesis 2: *The dynamics of volatility spillovers across stock index futures is similar to that of spot markets.*

This hypothesis assumes that cyclical movements of total spillover indices for volatilities are similar for both futures and spot markets. The rejection of this hypothesis provides further evidence of differences in patterns of volatility transmission across stock indices and stock index futures.

Hypothesis 3: *The magnitude of return spillovers is higher across stock indices than across stock index futures.*

This hypothesis suggests that stock indices are more efficient channels of return transmission, while stock index futures are less efficient. The rejection of this hypothesis provides the opposite conclusion.

Hypothesis 4: *The magnitude of volatility spillovers is higher across stock indices than across stock index futures.*

This hypothesis suggests that stock indices are more efficient channels of volatility transmission, while stock index futures are less efficient. The rejection of this hypothesis provides the opposite conclusion.

Hypothesis 5: *The intensity of intra-regional return and volatility spillovers is higher than the intensity of inter-regional spillovers.*

This hypothesis assumes that markets from the same geographical region have stronger financial linkages; therefore markets are more susceptible to a shock transmitted from the same region rather than from other regions. This hypothesis can be confirmed for one region or rejected for another one.

Hypothesis 6: *The magnitude of return and volatility spillovers for developed-developed market pairs is higher than for emerging-emerging market pairs.*

This hypothesis assumes that the financial linkages are stronger between developed markets than between emerging markets.

Hypothesis 7: *The intensity of return and volatility spillovers from developed to emerging markets is higher than from emerging to developed markets.*

This hypothesis postulates that developed markets are the net-contributors of international return and volatility transmissions, while emerging markets are net-recipients.

This hypothesis can be confirmed or rejected for individual market pairs. The rejection of this hypothesis supports the 'decoupling hypothesis' discussed in the literature.

Hypothesis 8: *There are no bursts in return and volatility spillovers during crisis periods.*

This hypothesis assumes that the magnitude of return and volatility spillovers increases significantly after crisis shocks occur in one of the markets. The rejection of this hypothesis provides the supporting evidence for the 'contagion hypothesis' discussed in the literature.

Further to the second research question, the following four research hypotheses are tested in this thesis:

Hypothesis 9: *The transmission of negative return shocks across markets with non-overlapping trading hours is more pronounced than the transmission of positive shocks.*

This hypothesis presumes that domestic market returns are more susceptible to negative than positive types of shocks transmitted from a foreign market. The proof of this hypothesis provides supporting evidence to the asymmetry in return spillover effect. This hypothesis is tested for every country in the sample, and it can be rejected for one market and accepted for another market.

Hypothesis 10: *The transmission of positive return shocks across markets with non-overlapping trading hours is more pronounced than the transmission of negative shocks.*

This hypothesis suggests that domestic market returns are more susceptible to positive than negative type of shocks transmitted from a foreign market. The proof of this hypothesis provides supporting evidence for asymmetry in return spillover effect. This hypothesis is tested for every country in the sample, because it can be rejected for one market and accepted for another market.

Simultaneous rejection of H9 and H10 indicates the absence of asymmetry in return spillovers for the analysed market.

Hypothesis 11: *The transmission of negative volatility shocks across markets with non-overlapping trading hours is more pronounced than the transmission of positive shocks.*

This hypothesis assumes that domestic market volatility is more sensitive to negative than positive types of shocks transmitted from a foreign market. The proof of this hypothesis provides supporting evidence for asymmetry in the volatility spillover effect. This hypothesis is tested for every country in the sample, because it can be rejected for one market and accepted for another market.

Hypothesis 12: *The transmission of positive volatility shocks across markets with non-overlapped trading hours is more pronounced than the transmission of negative shocks.*

This hypothesis suggests that domestic market volatility is more susceptible to positive than negative types of shocks transmitted from a foreign market. The proof of this hypothesis provides supporting evidence for the asymmetry in volatility spillover effect. This hypothesis is tested for every country in the sample, because it can be rejected for one market and accepted for another market.

Simultaneous rejection of both H11 and H12 indicates the absence of asymmetry in volatility spillovers for the analysed market.

The third research question suggests the following six research hypotheses that are tested in this thesis:

Hypothesis 13: *There is no predictive power of information transmitted from markets with non-overlapping trading hours to forecast domestic market return.*

This hypothesis assumes that return spillovers across markets that open and close successively to each other could not be used as predictors of domestic market returns. The rejection of this hypothesis provides supporting evidence for 'same day effect' and meteor-shower hypotheses for returns. This hypothesis is tested for every country in the sample, because it can be rejected for one market and accepted for another market.

Hypothesis 14: *There is no predictive power of information transmitted from markets with overlapping trading hours to forecast domestic market return.*

This hypothesis assumes that return spillovers across markets that have an overlap in trading hours could not be used as predictors of domestic market returns. This hypothesis is tested for every country in the sample, because it can be rejected for one market and accepted for another market.

Hypothesis 15: *The predictive power of return transmission across markets with non-overlapping trading hours is stronger than the predictive power of return transmission across markets with overlapping trading hours.*

This hypothesis assumes that information transmitted from markets situated in different time-zones, which do not have any overlap in trading hours, is more significant for the prediction of domestic returns than information transmitted from markets that have an overlap in trading hours with the target market. This hypothesis is tested for every country in the sample, because it can be rejected for one market and accepted for another market.

Hypothesis 16: *The combination of information transmitted from several foreign markets can improve the forecasting performance of domestic market returns.*

This hypothesis assumes that the application of bagging methodology, i.e. the procedure of reducing the number of predictors by sequentially re-estimating the forecasting model and removing insignificant predictors, to improve forecasting performance, as well as the application of combination forecasts methods to the large number of foreign predictors, can demonstrate a better relative forecasting performance of domestic returns than individual forecasting models. This hypothesis is tested for every country in the sample, because it can be rejected for one market and accepted for another market. Furthermore, this hypothesis can be confirmed for some of the bagging methods, and rejected for combination methods, or vice versa.

Hypothesis 17: *The bagging model contains information useful for the prediction of domestic market returns beyond that contained in the combination forecasts.*

This methodologically driven hypothesis assumes that the bagging model encompasses the combining model for out-of-sample forecasts. This hypothesis is tested for every country in the sample, because it can be rejected for one market and accepted for another market.

Hypothesis 18: *The combination forecasts contain information useful for the prediction of domestic market returns beyond that contained in the bagging model.*

This methodologically driven hypothesis assumes that the combining model encompasses the bagging model for out-of-sample forecasts. This hypothesis is tested for every country in the sample, because it can be rejected for one market and accepted for another market.

The simultaneous rejection of H17 and H18 indicates that both sets of forecasts contain information useful for the forecasting of stock index futures returns of the target country which is not contained in the other.

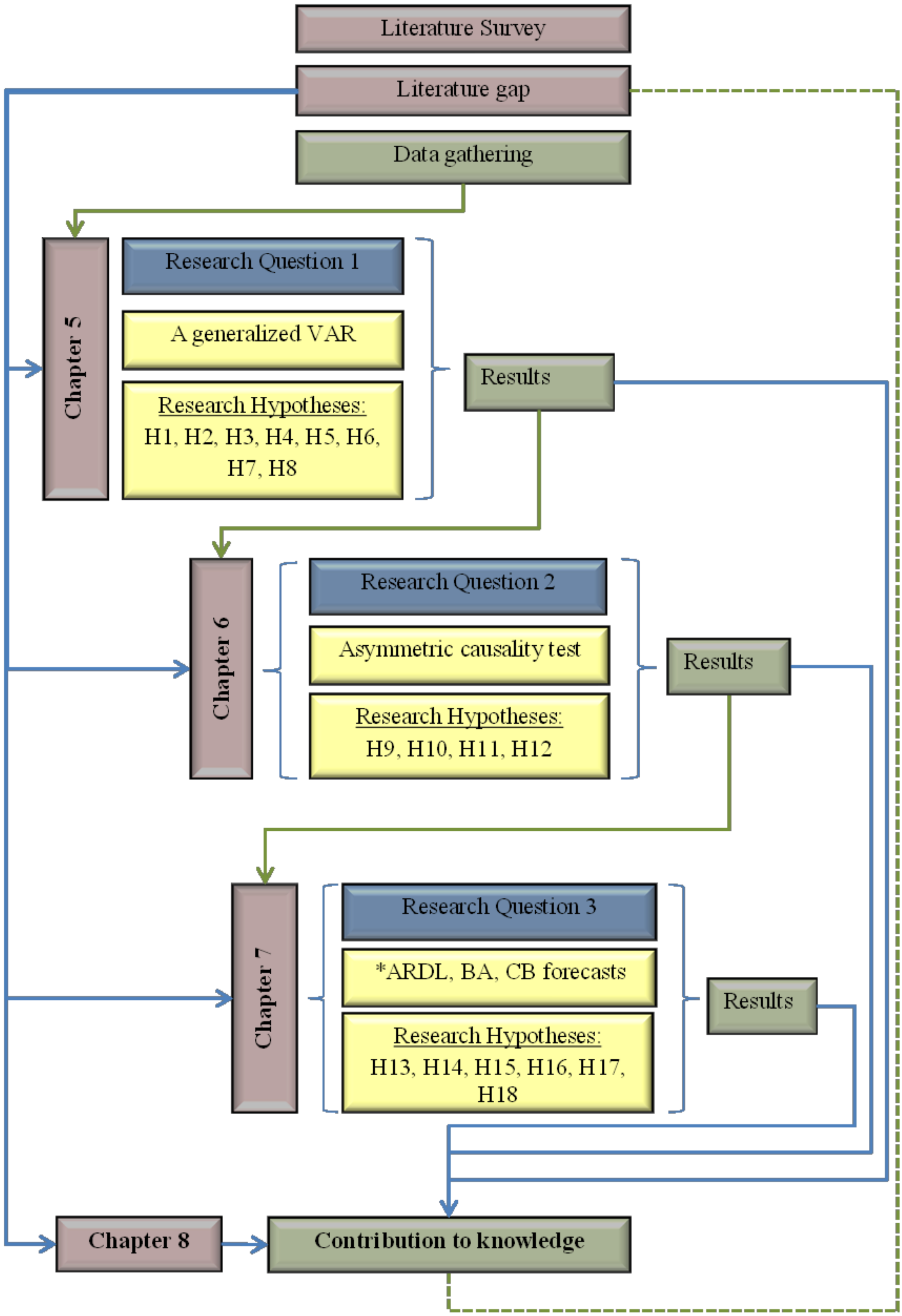
3.4 Designing quantitative research

In accordance with the chosen philosophical paradigm, this thesis tests the research hypotheses using the quantitative method of data analysis. There are three empirical chapters in this thesis, i.e. Chapter 5, Chapter 6 and Chapter 7, each aiming to answer one of the research questions specified above. However, the empirical results obtained by each empirical chapter can, in addition, provide further evidence relating to other research questions. Chapter 8 summarizes all the empirical evidence and discusses the findings regarding the research questions and, more specifically, the research hypotheses. Every empirical chapter employs its own methodological framework to test a research hypothesis. Confirmations or rejections of the research hypotheses generate evidence which is significant for the target research question, filling the gap in literature.

The results of each empirical chapter separately form the contribution to knowledge of this thesis. At the same time, all empirical chapters are appropriately related to each other through data, i.e. the application of stock index futures, the most important of those being highlighted by the literature survey, and a comparison of findings obtained for each market or region from different methodologies.

Figure 3.2 illustrates the process of new knowledge creation, starting from the literature survey and identification of the literature gap, and ending with a discussion of the results and contribution to knowledge. Chapter 5 provides the evidence relevant to answering the first research question and employs the Diebold and Yilmaz (2009, 2012) framework based on the generalized VAR to test the research hypotheses H1-H8. Chapter 6 provides the evidence relevant to the second research question and employs the Hatemi-J (2012) asymmetric causality technique to test the research hypotheses H9-H12. Chapter 7 considers the third research question and generates ARDL individual forecasts, the BA (bagging) forecast and CB (combination) forecasts following the Rapach and Strauss (2010) framework to test hypotheses H13-H18. The rejection or acceptance of hypotheses is discussed in Chapter 8, forming the contribution to knowledge and filling the gap in literature.

Figure 3.2 Design of the quantitative research.



Notes: *See List of Acronyms for abbreviations.

3.5 Chapter Summary

This chapter demonstrates how this research aims to fill the literature gap identified in the previous chapter. The thesis links together predictability literature and spillovers literature through an analysis of return and volatility transmissions across emerging and developed stock markets, providing original evidence using stock index futures data. An explanation for both, how the research was conducted to provide a contribution to our knowledge, and what the underlying logic for this research design was, has been provided. In addition the research questions and research hypotheses targeted for investigation in this thesis are articulated. The sequence testing the research hypotheses is explained through a discussion on research design. The chapter also provides an overview of the recent debate on paradigm unity in finance research. Finally, justifications of the process of new knowledge creation, as well as this author's beliefs regarding ontological, epistemological and methodological assumptions, are outlined.

Chapter 4 Data and preliminary analysis

4.1 Introduction

This chapter explains data gathering and discusses the main challenges of the data filtering process. The design of this thesis requires both stock indices and stock index futures data to be considered. The observation sample is divided into full sample, subsample, and out-of-sample periods. The selection of a broad range of countries, i.e. 10 developed and 11 emerging markets allows, on the one hand, the provision of a global perspective of investigated phenomenon. On the other hand, it causes the complexity of the data filtering process, both of which are discussed and addressed in this chapter. The chapter is organised as follows:

Section 4.2 shows the selection of countries included in this study and explains the logic for this choice. It describes the full sample estimation period and data gathering process for stock indices. Challenges regarding stock exchange trading hours, non-synchronous holidays and day light saving time are also examined. This section considers the data gathering process of stock index futures for the subsample estimation period. The length of the subsample period is also justified. The trading hours of stock index futures differ from the trading hours of underlying spot markets, and how this mismatch in trading hours is dealt with, is explained.

Section 4.3 specifies the equations for returns and volatility estimation used in this thesis. It also discusses the advantages of range volatility estimators over the classic volatility measure.

Section 4.4 provides descriptive statistics for return and volatility time-series for the full sample and the sub-sample estimation periods. It also discusses the values of skewness and kurtosis, an analysis of normality, multicollinearity, and heteroskedasticity.

Section 4.5 presents the results of preliminary data analysis, i.e. correlation analysis of stock indices and stock index futures data. This section also tests data for stationarity, using Augmented Dickey-Fuller (ADF) and the Phillips-Perron (P-P) unit root tests.

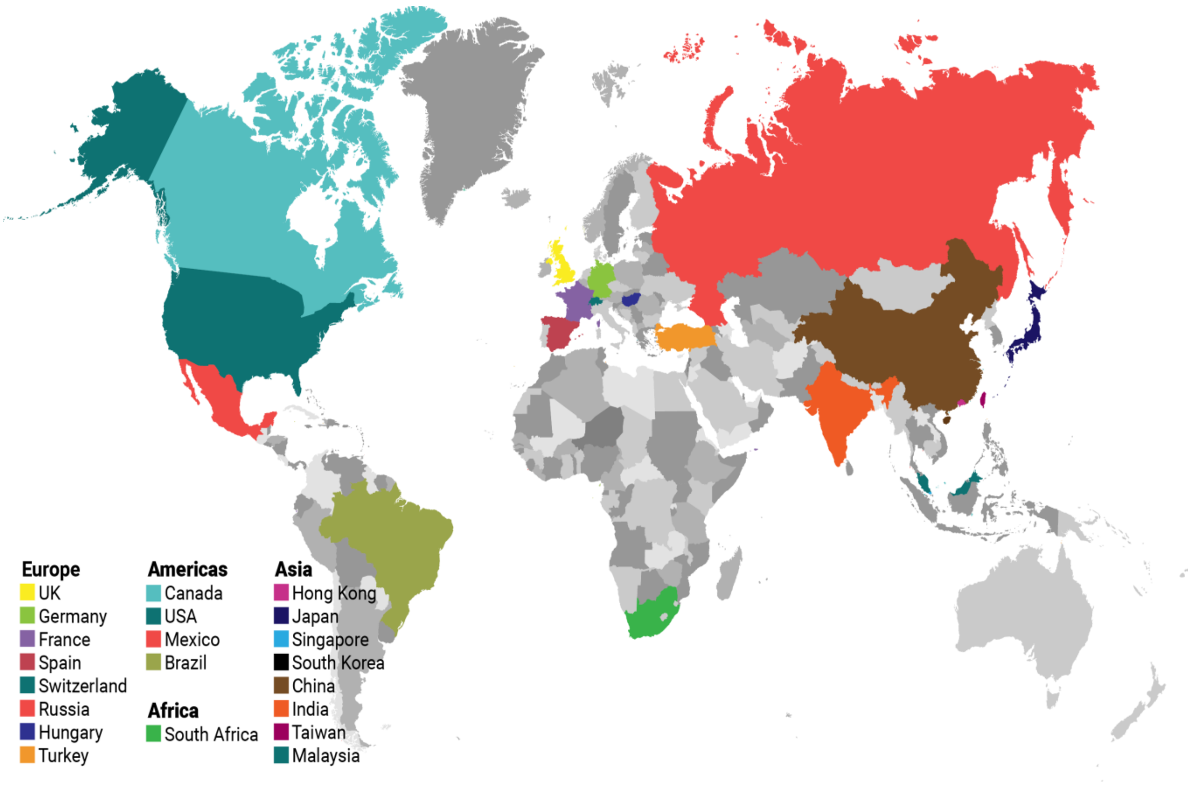
Section 4.6 summarises and draws conclusions.

4.2 Data

4.2.1 Selection of countries and estimation period

There are 21 countries selected for investigation in this thesis. The data sample contains 10 developed, and 11 emerging, markets from four geographical regions: Europe (the UK, Germany, France, Spain, Switzerland, Russia, Hungary and Turkey), Africa (South Africa), Asia (Hong Kong, Japan, Singapore, South Korea, China, India, Taiwan, and Malaysia) and the Americas (Canada, the US, Mexico and Brazil). This intensive country panel allows the provision of international evidence.

Figure 4.1 Selection of countries.



Source: Designed through http://www.freepik.com

This thesis contributes to existing literature by providing evidence of return and volatility transmission, not only across stock indices, but also across stock index futures, hence data for two asset classes are collected for analysis. Since stock index futures is a comparatively new instrument for emerging markets, for example, financial futures were recently introduced in China in April, 2010, the length of the estimation period for futures is significantly shorter than for stock markets. The opening, closing, high and low prices of stock indices have been obtained from the Bloomberg database for the period from 3 October, 2005 to 3 October, 2015, and for stock index futures from 3 October, 2010 to 3 October, 2015. The choice of estimation period was driven, first, by the desire to analyse the most recent data sample covering two crisis episodes, i.e. the Global Financial Crisis and the European Debt Crisis, and, second, by data availability, because there is a trade-off between the number of markets in the sample and the number of observations available for each market.

For the purposes of this research the estimation period is divided into in-sample and out-of-sample periods.

In-sample period:

- Full-sample period from 03 October, 2005 to 03 October, 2014, stock indices data only;
- Subsample period from 04 October, 2010 to 03 October, 2014, both stock index futures data and stock indices data for comparison purposes.

Out-of-sample period:

- From 04 October, 2014 to 02 October, 2015 to be used to test the ability of foreign information to forecast domestic futures returns.

4.2.2 Data collection

The opening, closing, high and low prices of stock indices were obtained from the Bloomberg database for the period from 03 October, 2005 to 03 October, 2014. This period covers two recent crisis episodes, i.e. the Global Financial Crisis and the European Debt Crisis. All indices are market value weighted indices, which are denominated in local currency.

Table 4.1 explains the time zone of the selected markets, providing trading hours for futures contracts and their underlying indices.

Table 4.1 Trading hours and time-zone description.

Country	Stock Index	Time zone	DST (Summer time)	Stock index trading hours (GMT)	Futures trading hours Local	Futures trading hours (GMT)	Futures trading hours during DST
Asia							
Hong Kong	HSI	GMT +8	N/A	01:15- 08:15 Lunch 04:00–05:00	09:15-12:00; 13:00-16:15	01:15-04:00; 05:00-08:15	01:15-04:00; 05:00-08:15
Japan	NKY	GMT +9	N/A	00:00 – 06:00 Lunch 02:30–03:30	09:00-15:15	00:00-6:15	00:00-06:15
Singapore	SIMSCI	GMT +8	N/A	01:00-09:00	08:30-17:15	00:30-09:15	00:30-09:15
China	SHSN 300	GMT +8	N/A	01:30-07:00	9:15-11:30; 13:00-15:15	01:15-03:30; 05:00-07:15	01:15-03:30; 05:00-07:15
South Korea	KOSPI2	GMT +9	N/A	00:00- 06:00	09:00-15:15	00:00-06:15	00:00-06:15
Malaysia	FBMKLCI	GMT +8	N/A	01:00 – 09:00	08:45-12:45; 14:30-17:15	00:45-03:45; 06:30-08:15	00:45-03:45; 06:30-08:15
Taiwan	TWSE	GMT +8	N/A	01:00 - 05:30	08:45-13:45	00:45-05:45	00:45-05:45
India	NIFTY	GMT +5.5	N/A	03:45-10:00	09:00-18:15	03:30-12:45	03:30-12:45
Europe and South Africa							
UK	UKX	GMT 0	Mar–Oct: GMT+1	08:00 – 16:30	06:00-20:00	06:00-20:00	05:00-19:00
Germany	DAX 30	GMT +1	Mar–Oct: GMT+2	07:00– 16:00	07:50-22:00	06:50-21:00	05:50-20:00
France	CAC 40	GMT +1	Mar–Oct: GMT+2	08:00-16:30	08:00-22:00	07:00-21:00	06:00-20:00
Spain	IBEX 35	GMT +1	Mar–Oct: GMT+2	08:00 -16:30	09:00-20:00	08:00-19:00	07:00-18:00
Switzerland	SMI	GMT +1	Mar–Oct: GMT+2	08:00-16:30	07:50-22:00	06:50-21:00	05:50-20:00
Russia	RTSI$	GMT +3	N/A	06:00-14:45	10:00-18:45; 19:00-23:50	07:00-15:45; 16:00-20:50	07:00-15:45; 16:00-20:50
Hungary	BUX	GMT +1	Mar–Oct: GMT+2	08:00-16:00	09:02-17:00	08:02-16:00	07:02-15:00
Turkey	XU030	GMT +2	Mar–Oct: GMT+3	07:30 -15:30 Lunch 10:30–12:00	13:55-17:45	11:55-15:45	10:55-14:45
South Africa	JALSH	GMT +2	N/A	07:00-15:00	08:30-17:30	06:30-15:30	06:30-15:30
Americas							
Canada	SPTSX60	GMT -5	Mar–Nov: GMT-4	14:30 – 21:00	06:00-16:15	11:00-21:15	10:00-20:15
USA	SPX	GMT -5	Mar–Nov: GMT-4	14:30 – 21:00	08:30-15:15	13:30-20:15	12:30-19:15
Mexico	MEXBOL	GMT -6	Apr–Oct: GMT-5	14:30-21:00	07:30-15:00	13:30-21:00	12:30-20:00
Brazil	IBOV	GMT -3	Oct–Feb: GMT-2	13:00 -20:00	08:00-16:55	11:00-19:55	10:00-18:55

Notes: *Time zones were identified using wwp.greenwichmeantime.com; **Trading hours were obtained from exchange trading hours reported in Bloomberg database with following conversion to GMT.

Futures contracts on equity indices for selected countries were retrieved from the Bloomberg data base. Daily opening, closing, high and low prices were collected for the in-sample estimation period from 03 October, 2010 to 03 October, 2014 to investigate the return and volatility spillovers, not only across equity indices but also across stock index futures of the selected emerging and developed markets.

There are several problems with the data collection process that occur in an analysis of information transmission mechanisms across international stock markets situated in different geographical time-zones. First, the conversion of local trading time to absolute time reference is important in order to record time accurately. Table 4.1 highlights trading hours of the world's stock exchanges, including lunch breaks which are common in Asian markets. The lunch break is not significant within this thesis, because only opening and closing prices, i.e. first and last prices, in which a security is actually traded on the particular day, are used to calculate daily returns. All local trading times, i.e. times along with the time zone within which the exchange is located, are presented in Table 4.1 and correspond to Greenwich Mean Time (GMT). For example, the local time of Singapore stock exchange trading hours is from 9:00 to 17:00. The Singapore Standard Time zone is 8 hours ahead of GMT (+8), therefore, the working hours of Singapore stock exchange is from 01:00 to 09:00 GMT. Employing the conversion of local trading time to GMT time for all selected stock markets is essential to achieve consistency of timing and to identify the pairs of markets with no-overlapping trading hours. A similar conversion has been employed for stock index futures trading hours.

Second, it is also necessary to identify pairs of countries with non-overlapping trading hours. Daylight Saving Time (DST) periods are taken into consideration, as switching from winter to summer time may cause, or remove, overlap in trading time for some cases. Since stock index futures for creation of the trading strategy are used, Table 4.1 also indicates futures trading hours during DST, i.e. summer time. The DST for selected countries is dealt with by adding one hour ahead of GMT during certain periods of time. This problem becomes more complex due to the changing government policies regarding DST. For example, in the Russian Federation, the DST took a place from March to October, from 2000 to 2010. However, since 2011, the DST has not been implemented.

Third, the existence of nonsynchronous holidays among selected markets may cause computation difficulties and negatively impact on the accuracy of results. The nonsynchronous holidays can be excluded from the data set or the return on the days with no trading activities can be assumed as zero. Alternatively, the linear model can be constructed to estimate the returns on markets' holidays and cover the gaps in the data set. For this thesis, the stock market returns on non-trading days are assumed as zero returns, because it reflects actual returns on non-trading days, rather than returns which could be obtained by using linear models. It is also inappropriate to simply ignore non-trading days, because days with no trading activities should be taken into consideration to make the data set closer to reality.

In comparison to stock indices, the collection of futures historical data is more complex. There are several futures contracts available for each stock market during the year with various maturity dates. This is done to give hedgers added flexibility in minimizing their risk (Eastman & Lucey, 2008). For the purposes of this research, the opening and closing prices were obtained from Bloomberg database, which are the first and last price on which this security has been actually traded on the specific day. These prices are used to calculate daily returns on stock index futures. Daily high and low prices are also collected to calculate the daily volatility using range volatility estimators. The high and low prices are the actual highest and lowest prices at which this security has been traded on the specific day.

The tickers of futures contract employ abbreviations for both the contract and its expiration date. The first two letters represent the contract, the next letter represents the contract expiration month, and a final number represents the expiration year. For example, the futures contract with DAX 30 has an underlying index and delivery date of 14 December, 2014, has a ticker GXZ4, where GX represents the contract, Z represents December and number 4 represents the year.

Table 4.2 Expiration month symbol codes

January - F	February - G	March - H	April – J
May - K	June - M	July - N	August – Q
September - U	October - V	November - X	December - Z

Due to the finite lifetime of a futures contract, both returns and volatility data must be transformed into a continuous time series. In order to generate continuous futures data series, several methods can be used, such as forward adjusted, proportionally adjusted, Gann series, perpetual series or backward adjusted series. The simplest way, and the one that was used by the majority of papers that employed daily futures data, is the 'role timing' method, i.e. roll timing determines when the near contract is dropped and replaced by the next one (Masteika & Rutkauskas, 2012, p.921). For this research, prices of futures contracts with the closest expiration dates were obtained, due to a higher trading volume on these securities. Contract expiration date is the moment when the futures contracts should be switched to the next. The same procedure was employed to generate continuous futures data for both the subsample period from 04 October, 2010 to 03 October, 2014 and the out-of-sample estimation period from 04 October, 2014 to 03 October, 2015, from the opening, high, low and closing daily prices obtained from the Bloomberg database.

Another challenge of futures data is that the trading hours of futures contracts do not match with the trading hours of its underlying index. As is clearly shown in Table 4.1, for the majority of countries, futures trading hours exceed the trading hours of their underlying indices. The additional electronic session makes some futures tradable for up to 23 hours per day, as is the case for example in the US. For the purposes of this research, only pit trading hours are considered.

4.3 Estimation of return and volatility

All returns were calculated as a difference between a natural logarithm of closing price and a natural logarithm of opening price:

$$R_t = LN(Closing\ price) - LN(Opening\ price) \tag{4.3.1}$$

The stock market returns on nonsynchronous holidays were assumed to be zero. Zero returns on nonsynchronous holidays reflect actual returns on non-trading days. This is a more realistic assumption than a calculation of the returns using linear models, or a simple exclusion of nonsynchronous holidays, from the observation sample.

Analyses of volatility are sensitive to the measure of volatility that is used. The advantages of range estimators over classical estimators of volatility are widely discussed in the literature (e.g., Parkinson, 1980; Garman & Klass, 1980; Rogers & Satchell, 1991, Yang & Zhang, 2000). The range estimators use information on daily trading range, the difference between the high and low prices for a particular security over certain time interval, while classic volatility estimators use close-to-close prices. The Rogers and Satchell (1991) volatility estimator has been used because it is more efficient than classical volatility and drift independent estimators, which is confirmed by Shu and Zhang (2006):

$$\delta_{RS}^2 = h_t(h_t - c_t) + l_t \times (l_t - c_t) \tag{4.3.2}$$

where: h_t - the normalized high price; l_t – the normalized low price; c_t - the normalized closing price on date *t*. Daily volatilities were calculated for futures and spot markets using equation (4.3.2).

The range volatility estimators are more suitable for capturing the time-varying nature of volatility than classic volatility measures. However, the underlying assumption of range estimators is that a security price follows a geometric Brownian motion, deviation from which will affect the accuracy of estimators. Nevertheless, the Rogers and Satchell range estimator allows a nonzero drift in the continuous return path and its accuracy is independent from the size of the drift.

4.4 Descriptive statistics

4.4.1 Stock index returns and volatility

Open-to-close returns for 10 developed, and 11 emerging markets, were calculated for the in-sample period from 3 October, 2005 to 3 October, 2014, providing 2350 observations in total. Table 4.3 gives a summary of the descriptive statistics on stock index returns.

Table 4.3 Descriptive statistics of stock indices returns.

Series		Mean	Variance	Skewness	Kurtosis	JB	LB(10)	ARCH
Hong Kong	HKG	-0.000473	0.000125	0.3549	16.1201	25493.5808	91.8201	157.314
Japan	JPN	-0.000285	0.000140	-0.6787	16.1214	25628.9362	35.5222	286.389
Singapore	SGP	-0.000160	0.000109	0.1811	8.6447	7330.3267	29.9749	104.949
China	CHN	0.001117	0.000272	-0.3677	3.1777	1041.7141	23.5777	43.425
South Korea	KOR	-0.000389	0.000118	-0.3125	10.3114	10449.2169	38.2961	142.246
Malaysia	MYS	0.000167	0.000038	-0.5187	7.0534	4976.7826	28.4938	74.252
Taiwan	TWN	-0.001110	0.000091	-0.0688	4.3586	1862.0193	27.8881	48.660
India	IND	0.000018	0.000236	0.0387	10.2232	10234.1755	28.7833	34.797
UK	GBR	0.000077	0.000154	-0.1336	8.3565	6844.5464	51.0849	132.823
Germany	GER	0.000013	0.000151	0.2411	8.6713	7385.1895	13.6901	57.011
France	FRA	-0.000384	0.000146	-0.3336	4.2120	1780.7115	23.1389	72.710
Spain	ESP	-0.000248	0.000191	0.0603	6.8150	4549.1029	9.9383	48.751
Switzerland	SUI	-0.000190	0.000085	-0.3328	6.6981	4436.4252	19.0082	113.169
Russia	RUS	0.000008	0.000469	-0.4720	12.6419	15736.0824	62.0699	67.104
Hungary	HUN	-0.000771	0.000210	-0.4969	4.6701	2232.2476	35.5889	69.073
South Africa	ZAF	0.000450	0.000165	-0.1893	3.9028	1505.4868	28.2537	107.821
Turkey	TUR	-0.000214	0.000283	-0.1678	2.0887	438.2098	18.8890	24.340
Canada	CAN	-0.000198	0.000108	-0.7688	10.5876	11207.7173	28.1940	169.851
USA	USA	0.000230	0.000156	-0.3998	10.8674	11626.6857	56.7757	136.674
Mexico	MEX	0.000396	0.000174	0.1175	6.3094	3903.2948	28.7805	69.029
Brazil	BRA	0.000201	0.000310	-0.0313	6.8414	4583.3511	13.6928	138.046

Notes: The statistic is significant at the 1% level. JB is the Jarque–Bera test for the null hypothesis of normality. LB (10) is the Ljung–Box test of the null hypothesis where the first 10 autocorrelations are zero. ARCH is the Lagrange Multiplier test proposed by Engle (1982), utilised with respect to first-order ARCH.

Table 4.3 shows that Jarque-Bera statistics reject null hypotheses for all markets, confirming that all series are not normally distributed. These results are not surprising. Since the early work by Fama (1963), Simkowitz and Beedles (1978), among others, it is evident that equity returns do not follow normal distribution. The rejection of the Null Hypothesis of the normality by the JB test and reveals that the residuals of the model have significant skewness or kurtosis. If the return distribution is perfectly symmetrical, i.e. neither negatively nor positively skewed, the mean, median and mode are equal. The positive value of skewness shows that time series are positively skewed, which means that there are many small values and few large values in stock market returns, i.e. the mean of the returns is greater than the median. The negative values of skewness indicate the opposite situation when time series contain many large values and fewer small values. Negative skewness occurs when the median is greater than the mean, which means that there are more returns higher than the mean, so the investor would prefer to buy a financial asset with negatively skewed returns (Eastman & Lucey, 2008).

As is clear from Table 4.3, there are both positively and negatively skewed time series in the sample. More specifically, 6 out of 21 markets (28.6%) have positively skewed returns, while 15 out of 21 markets (71.4%) have negatively skewed returns. According to Table 4.5, for the majority of markets in the sample for the period from 3 October, 2005 to 3 October, 2014, negative skewness is evident. An analysis of kurtosis, as a measure of 'peakedness' of time series data, demonstrates that there are sharp picks in stock returns. The positive excess kurtosis indicates leptokurtosis, while negative excess kurtosis indicates platykurtosis. There are only positive values of kurtosis for the selected time series, i.e. leptokurtosis, the kurtosis results of the daily returns vary from 2.0887 (Turkey) to 16.1214 (Japan).

Analysis of skewness and kurtosis indicates that there is a higher frequency of extreme values of returns for all 21 selected stock markets in the sample. Table 4.5 also shows that the Ljung–Box test statistics at lag 10, Q (10) and provides evidence of autocorrelation for the time series. The results of analysis of autocorrelation, skewness, kurtosis and normality of time series data are consistent with previous studies within this area. The Lagrange Multiplier test by Engle (1982) was employed to test series on autoregressive conditional heteroskedasticity. Conditional heteroskedasticity means that the variance of a return series changes over time, conditional on past information (Fernandez & Lucey, 2007). The test indicated the existence of the ARCH effect for the majority of time series. Generally, the log-returns exhibit the regular statistical properties identified for the daily frequency in many studies (Albu et al., 2015).

Table 4.4 provides a summary of the descriptive statistics on volatility. According to JB statistics, The Null Hypothesis of normality is rejected for all markets in the sample, which raises the question of the existence of high moments in volatility. The analysis of skewness shows that 9 out of 21 (42.9%) volatility time series are positively skewed, while 12 out of 21 (57.1%) cases are negatively skewed. In comparison with the returns, the distribution of positively and negatively skewed time-series is more equal. However, the analysis of kurtosis shows that there are only positive values for kurtosis for the daily stock index volatility. Analysis of both skewness and kurtosis provides the evidence of the predominance of the days with higher market volatility over days with lower market volatility.

Table 4.4 Descriptive statistics of stock indices volatility.

Series		Mean	Variance	Skewness	Kurtosis	JB	LB (10)	ARCH
Hong Kong	HKG	-0.004169	0.014328	-0.2953	11.4524	12876.7242	76.7253	158.943
Japan	JPN	-0.000017	0.013336	0.4698	12.5664	15548.8086	57.1156	263.393
Singapore	SGP	-0.000788	0.004269	-0.7551	11.8934	14073.9622	41.7884	89.899
China	CHN	-0.016895	0.021389	0.1314	2.8325	792.3373	53.1365	78.276
South Korea	KOR	-0.004912	0.003536	-0.2968	7.2053	5117.9790	74.3752	54.251
Malaysia	MYS	-0.004807	0.002139	-0.2043	5.5741	3058.6343	17.0638	57.714
Taiwan	TWN	0.002982	0.007780	0.1241	3.1831	998.1450	28.9523	50.153
India	IND	-0.005076	0.015594	-0.3091	7.6859	5821.6206	24.9198	21.783
UK	GBR	-0.003983	0.012026	-0.1506	6.0276	3566.4275	32.2127	131.945
Germany	GER	-0.007436	0.012960	-0.1500	5.3372	2798.0486	10.8235	101.548
France	FRA	-0.004402	0.012595	-0.0050	3.6399	1297.2925	12.5694	141.437
Spain	ESP	-0.010406	0.019325	-0.1077	5.1290	2580.4548	12.3494	76.582
Switzerland	SUI	-0.002732	0.008090	-0.0797	6.0383	3572.5844	22.4355	225.418
Russia	RUS	-0.001812	0.024423	0.5053	9.3821	8718.9497	30.6038	56.755
Hungary	HUN	-0.001663	0.024514	0.2677	3.3378	1118.9833	44.6279	91.415
South Africa	ZAF	-0.007941	0.017911	0.1867	2.9955	892.2639	14.3253	138.439
Turkey	TUR	-0.009095	0.039454	0.0201	1.3433	176.8326	29.5182	34.978
Canada	CAN	-0.004786	0.007291	0.2693	8.6032	7275.7335	85.0714	232.810
USA	USA	-0.006451	0.008971	0.1681	10.0198	9841.4621	127.4640	184.810
Mexico	MEX	-0.008273	0.020044	-0.0338	4.3533	1856.0491	17.3314	92.139
Brazil	BRA	-0.007521	0.039030	-0.1184	4.0234	1590.5435	40.1095	185.261

Notes: The statistic is significant at the 1% level. JB is the Jarque–Bera test for the null hypothesis of normality. LB (10) is the Ljung–Box test of the null hypothesis where the first 10 autocorrelations are zero. ARCH is the Lagrange Multiplier test proposed by Engle (1982).

Table 4.4 illustrates the evidence of autocorrelation for the time series according to the Ljung–Box test statistics at lag 10, Q (10), and is similar to that of returns. The results of the analysis of autocorrelation, skewness, kurtosis and normality of volatility time series are also consistent with previous studies within this area. The Lagrange Multiplier test indicates a pronounced ARCH effect for the majority of time series.

4.4.2 Stock index futures returns and volatility

For the in-sample period from 3 October, 2010 to 3 October, 2014, open-to-close daily returns of futures contracts were collected, giving 1046 observations. Table 4.6 summarizes the descriptive statistics for stock index futures returns and volatility. There are several differences identified by a comparison with descriptive statistics of futures and their spot market data for the same estimation period. Table 4.6 also summarises the descriptive statistics for volatility of futures and stock indices for the subsample from 4 October 2010, to 3 October, 2014, for comparison purposes, while Table 4.7 presents the results for volatility.

By comparison with basic statistics presented in Table 4.6, it was found that for the majority of countries, the average rate of return on futures markets was higher than the average rate of return on stock market indices for the same estimation period. However, standard deviations are also higher, i.e. 8 out of 10 developed countries and 7 out of 11 emerging countries have higher returns and standard deviations on futures markets than on stock equity indices. The UK and Spain, as well as South Africa, China, Mexico and Brazil demonstrate a reverse pattern (lower return and standard deviations of futures). The analysis of skewness and kurtosis demonstrates similar patterns for spot and futures markets, the predominance of negative skewness and positive kurtosis for returns, and positive skewness and positive kurtosis for volatilities.

The stock market returns in Russia demonstrate the highest volatility in the sample: the standard deviation of RTSI$ returns equal 3.47 percentage points. The average return on RTSI$ equals -0.11 per cent which makes RTSI$ the worst performing stock market index within the sample. However, futures contracts on RTSI$ demonstrate a better performance than its spot market, with a positive average return of 0.00574 per cent and a lower standard deviation of 1.7445 per cent which puts the performance of futures contracts on the Russian stock market just in line with the performance of other markets within the sample. The IPD benefits in emerging and developed stock markets, as well as the economic benefits of using international information in a trading strategy, should be assessed by analysing both stock equity indices and futures contracts data, providing further contributions to existing empirical evidence.

Table 4.6 Descriptive statistics for futures and spot market *returns* for subsample: 4 October 2010 - 3 October 2014.

Series	Futures markets returns							Stock indices returns						
	Mean	Variance	Skewness	Kurtosis	JB	LB(10)	ARCH	Mean	Variance	Skewness	Kurtosis	JB	LB(10)	ARCH
HKG	-0.000046	0.000080	0.0618	1.1555	58.7980	13.0745	2.394	-0.000597	0.000057	0.0893	1.2806	72.7962	13.4438	4.470
JPN	0.000480	0.000169	-0.6556	4.7114	1041.3870	16.3805	24.154	-0.000137	0.000090	-1.6491	15.8084	11354.9854	29.7982	11.236
SGP	0.000159	0.000072	-0.3024	1.5678	122.9537	15.3452	38.006	-0.000279	0.000038	-0.0836	3.0606	409.0767	26.3899	21.507
CHN	-0.000392	0.000127	0.2648	2.9110	381.1743	14.5219	1.642	0.000505	0.000138	0.1319	2.3689	247.3805	26.8470	1.905
KOR	-0.000098	0.000126	-0.2911	3.3975	517.3607	20.2770	34.838	-0.000594	0.000067	-0.3397	3.0478	424.5633	23.6268	43.478
MYS	0.000108	0.000029	-0.1166	3.5493	550.8823	26.6260	26.161	0.000079	0.000020	-0.3898	2.6076	322.5316	14.3407	13.824
TWN	-0.000033	0.000053	-0.0360	2.9264	373.1069	4.3247	12.797	-0.000943	0.000050	-0.2162	2.8661	365.8240	10.4127	20.603
IND	0.000195	0.000127	0.0025	0.8236	29.5362	12.5795	6.187	-0.000592	0.000086	-0.1962	1.1581	65.0979	15.6000	13.007
GBR	0.000128	0.000071	0.0764	5.9787	1557.4057	23.6851	52.247	0.000148	0.000087	-0.2520	2.7385	337.6012	12.0960	35.966
GER	0.000171	0.000115	-0.1284	4.6299	936.2159	11.9011	27.224	-0.000007	0.000114	-0.3051	5.1555	1173.5130	10.4761	35.716
FRA	0.000063	0.000127	-0.1227	3.3390	488.0746	15.9620	30.758	-0.000073	0.000123	-0.3401	4.3407	840.5354	10.8930	39.755
ESP	-0.000436	0.000189	-0.2483	3.2270	464.1624	10.0237	27.263	-0.000265	0.000191	-0.2302	3.3782	506.1530	10.8516	27.563
SUI	0.000205	0.000060	-0.0197	5.3376	1240.5632	34.1648	34.911	0.000154	0.000056	-0.6668	9.3181	3858.0322	21.6241	87.975
RUS	-0.000112	0.000307	-0.4624	3.3102	514.3454	10.9898	6.978	-0.000270	0.000253	-0.5510	4.3799	888.1439	15.8750	8.435
HUN	-0.000332	0.000142	-0.3061	4.0806	741.3342	17.4160	20.915	-0.000669	0.000134	-0.5972	4.2767	858.4762	16.3510	9.816
ZAF	0.000200	0.000068	-0.0667	2.1089	194.4341	20.5406	7.585	0.000486	0.000076	-0.2583	1.5491	116.1137	14.6892	18.665
TUR	-0.000210	0.000261	-0.4160	3.0563	436.8775	13.5127	17.782	-0.000821	0.000213	-0.2444	1.1792	70.9443	8.9423	20.704
CAN	0.000090	0.000057	0.1112	3.7144	602.8902	22.7195	10.046	0.000076	0.000043	-0.2450	2.0801	198.8620	36.0817	22.583
USA	0.000624	0.000085	-0.3459	4.6806	974.7690	38.3841	67.243	0.000466	0.000084	-0.6238	6.7990	2080.5688	60.5330	102.785
MEX	0.000124	0.000071	0.0035	2.0844	189.1801	20.7434	25.722	0.000244	0.000084	-0.3603	3.7416	632.1834	24.4081	29.446
BRA	-0.000545	0.000151	-0.0063	1.1523	57.8224	14.9228	27.267	-0.000249	0.000177	-0.2250	2.1131	203.2376	5.9161	20.161

Notes: The statistic is significant at the 1% level. JB is the Jarque–Bera test for the null hypothesis of normality. LB (10) is the Ljung–Box test of the null hypothesis that the first 10 autocorrelations are zero. ARCH is the Lagrange Multiplier test proposed by Engle (1982).

Table 4.7 Descriptive statistics for futures and spot markets *volatility* for subsample: 4 October 2010 - 3 October 2014.

Series	Futures markets volatility							Stock indices volatility						
	Mean	Variance	Skewness	Kurtosis	JB	LB(10)	ARCH	Mean	Variance	Skewness	Kurtosis	JB	LB(10)	ARCH
HKG	0.000386	0.009363	-0.0630	1.1979	63.1762	11.8892	5.276	-0.002882	0.006420	-0.1291	0.9360	41.0449	12.0104	9.484
JPN	-0.009450	0.018652	0.0637	4.2834	799.5783	35.3095	63.694	0.001266	0.008710	1.1064	11.6030	6075.1801	36.9934	6.881
SGP	-0.001587	0.002983	-0.137252	2.5815	293.4543	17.1828	20.330	0.000084	0.001521	0.0031	2.5196	276.4165	17.1988	27.128
CHN	0.004447	0.007166	-0.4118	2.1245	226.0521	19.4956	2.801	-0.005264	0.010364	-0.1706	1.7891	144.4446	28.1497	8.987
KOR	-0.001135	0.004377	0.1017	2.2535	222.9112	22.9178	36.944	-0.003888	0.002616	0.0549	3.4046	505.2318	31.2248	22.216
MYS	-0.002242	0.001904	-0.1656	3.6930	598.6087	17.8767	4.720	-0.003903	0.001444	-0.2192	8.0613	2837.9047	20.9649	2.449
TWN	-0.001614	0.004742	-0.0107	2.9641	382.5801	11.0855	22.440	0.002166	0.004752	0.2864	1.9069	172.6182	18.3977	10.077
IND	-0.006421	0.01259	0.0022	0.3416	5.0805	20.2068	10.442	-0.002578	0.009459	-1.7065	24.7313	27138.8026	10.7680	0.268
GBR	-0.007076	0.00453	-0.8378	10.7152	5121.5552	37.9671	23.159	-0.005115	0.007170	-0.0569	5.0409	1106.9674	13.5156	101.164
GER	-0.009241	0.008648	-0.0734	5.2173	1186.1487	26.4371	43.191	-0.007196	0.010681	0.1694	3.6258	577.3993	20.2388	91.028
FRA	-0.007977	0.008569	0.0201	3.5039	534.6449	14.2283	57.731	-0.005083	0.010509	0.1474	3.8727	656.8182	17.0136	118.796
ESP	-0.004155	0.01774	0.2479	3.3201	490.6619	12.9842	63.807	-0.009820	0.019088	0.2172	3.2022	454.7002	10.2892	67.296
SUI	-0.005528	0.004608	0.1859	9.1474	3649.3275	48.1257	96.113	-0.003827	0.005497	0.3274	10.1772	4528.4784	19.1657	239.042
RUS	-0.006912	0.05249	0.1483	2.0545	187.6248	17.3527	16.352	-0.002503	0.014942	0.3330	2.6726	330.3341	11.4051	15.536
HUN	-0.002759	0.012511	0.0304	2.2212	214.9848	16.4618	36.928	-0.002095	0.015453	0.3035	2.0920	206.5998	13.5072	17.991
ZAF	-0.006675	0.00832	0.0362	1.3850	83.7470	21.0209	14.897	-0.009409	0.008869	0.1800	1.1618	64.4161	19.3637	19.844
TUR	-0.001639	0.005904	0.0701	1.1532	58.7585	30.8709	21.024	0.003945	0.033920	0.0013	1.3558	80.0408	24.1537	30.699
CAN	-0.004236	0.002987	-0.1655	3.0748	416.4431	37.5372	31.036	-0.004196	0.002730	-0.1811	3.5407	551.5798	46.2796	43.521
USA	-0.009201	0.005559	0.0871	6.6460	1924.5497	38.9962	81.463	-0.008145	0.004676	0.4654	6.2085	1716.0575	58.5513	102.047
MEX	-0.003315	0.009511	0.0230	1.6909	124.5825	17.4786	34.758	-0.005704	0.010399	0.2726	1.7412	144.9551	16.5366	29.023
BRA	0.003618	0.020939	-0.0896	0.5611	15.1079	16.1826	18.635	0.001355	0.022897	0.0605	0.5441	13.5270	12.1669	23.082

Notes: The statistic is significant at the 1% level. JB is the Jarque–Bera test for the null hypothesis of normality. LB (10) is the Ljung–Box test of the null hypothesis that the first 10 autocorrelations are zero. ARCH is the Lagrange Multiplier test proposed by Engle (1982).

4.5 Preliminary data analysis

4.5.1 Correlation coefficient estimation

One of the most commonly used methods of evaluation of stock market co-movements is estimation of the unconditional correlation coefficient matrix (Pearson's r). Two cross-correlation matrixes built for indices and futures returns for the in-sample period are presented in Table 4.8 and Table 4.9. The results show that for the majority of market pairs correlation coefficients are positive, where the largest values of correlation coefficients are evident for the market combination of the UK and Germany, and also between developed European markets. The lowest correlation with other markets is evident for the Chinese market.

Forbes and Rigobon (2002) criticised studies that employed cross-market correlation coefficients to test contagion. The conditional correlation between two random variables r_1 and r_2 with mean equal zero can be described as follows:

$$\rho_{12,t} = \frac{E_{t-1}(r_{1,t}r_{2,t})}{\sqrt{E_{t-1}(r_{1,t}^2)E_{t-1}(r_{2,t}^2)}} \tag{4.5.1}$$

Forbes and Rigobon argue that the conditional correlation coefficient can increase after a crisis episode but this can be due, primarily, to the increase in market volatility, rather than unconditional correlation across markets. The presence of heteroskedasticity in returns makes estimates of cross-market correlation coefficient biased and unable to prove the contagion effect across markets. In this thesis, a more sophisticated methodology is employed.

Table 4.8 Correlation coefficient matrix for futures returns.

	HKG	JPN	SGP	CHN	KOR	MYS	TWN	IND	GBR	GER	FRA	ESP	SUI	RUS	HUN	ZAF	TUR	CAN	USA	MEX	BRA
HKG	1.00																				
JPN	0.28	1.00																			
SGP	0.48	0.46	1.00																		
CHN	0.43	0.15	0.26	1.00																	
KOR	0.35	0.46	0.59	0.24	1.00																
MYS	0.29	0.10	0.30	0.24	0.20	1.00															
TWN	0.34	0.15	0.24	0.26	0.35	0.32	1.00														
IND	0.38	0.24	0.48	0.17	0.37	0.29	0.20	1.00													
GBR	0.33	0.12	0.28	0.15	0.20	0.25	0.24	0.34	1.00												
GER	0.15	-0.01	0.15	0.01	0.04	0.12	0.01	0.27	0.76	1.00											
FRA	0.18	0.02	0.18	0.04	0.06	0.15	0.05	0.28	0.79	0.90	1.00										
ESP	0.45	0.15	0.26	0.94	0.25	0.26	0.27	0.17	0.15	0.02	0.05	1.00									
SUI	0.15	0.02	0.13	-0.01	0.03	0.13	0.01	0.24	0.70	0.72	0.72	0.00	1.00								
RUS	0.34	0.23	0.43	0.16	0.37	0.21	0.16	0.39	0.52	0.48	0.47	0.17	0.36	1.00							
HUN	0.19	0.08	0.23	0.07	0.21	0.23	0.13	0.25	0.46	0.48	0.48	0.09	0.36	0.47	1.00						
ZAF	0.14	0.03	0.15	0.05	0.11	0.11	0.04	0.19	0.39	0.38	0.38	0.04	0.37	0.33	0.31	1.00					
TUR	0.19	-0.02	0.18	0.10	0.12	0.12	0.05	0.28	0.59	0.56	0.55	0.11	0.49	0.47	0.35	0.33	1.00				
CAN	0.11	0.00	0.10	0.04	0.07	0.04	0.09	0.12	0.42	0.40	0.41	0.05	0.30	0.26	0.21	0.18	0.31	1.00			
USA	0.20	0.07	0.20	0.08	0.18	0.19	0.23	0.26	0.68	0.62	0.63	0.09	0.53	0.43	0.39	0.30	0.42	0.62	1.00		
MEX	0.11	0.03	0.07	0.08	0.11	0.11	0.10	0.13	0.28	0.22	0.22	0.08	0.22	0.18	0.16	0.17	0.24	0.38	0.45	1.00	
BRA	0.06	-0.04	0.04	0.05	0.10	0.07	0.09	0.09	0.28	0.25	0.26	0.05	0.24	0.18	0.17	0.16	0.22	0.42	0.44	0.42	1.00

Table 4.9 Correlation coefficient matrix for stock indices.

	HKG	JPN	SGP	CHN	KOR	MYS	TWN	IND	GBR	GER	FRA	ESP	SUI	RUS	HUN	ZAF	TUR	CAN	USA	MEX	BRA
HKG	1.00																				
JPN	0.30	1.00																			
SGP	0.61	0.34	1.00																		
CHN	0.40	0.15	0.27	1.00																	
KOR	0.46	0.43	0.48	0.26	1.00																
MYS	0.33	0.24	0.42	0.22	0.32	1.00															
TWN	0.43	0.28	0.42	0.24	0.55	0.32	1.00														
IND	0.39	0.27	0.49	0.17	0.28	0.32	0.19	1.00													
GBR	0.30	0.31	0.37	0.09	0.20	0.24	0.15	0.39	1.00												
GER	0.19	0.11	0.24	0.00	0.13	0.10	0.05	0.28	0.75	1.00											
FRA	0.12	0.00	0.17	-0.01	0.07	0.09	0.03	0.20	0.71	0.88	1.00										
ESP	0.11	0.04	0.19	-0.03	0.06	0.10	0.02	0.21	0.62	0.75	0.84	1.00									
SUI	0.07	0.01	0.13	-0.05	0.05	0.07	0.00	0.18	0.65	0.75	0.81	0.68	1.00								
RUS	0.20	0.24	0.26	0.08	0.17	0.20	0.12	0.27	0.42	0.32	0.29	0.26	0.22	1.00							
HUN	0.11	-0.01	0.11	0.00	0.06	0.11	0.02	0.19	0.39	0.50	0.52	0.47	0.44	0.24	1.00						
ZAF	0.09	0.00	0.16	-0.01	0.12	0.11	0.07	0.21	0.39	0.44	0.46	0.42	0.41	0.24	0.38	1.00					
TUR	0.28	0.34	0.37	0.12	0.23	0.27	0.17	0.42	0.68	0.51	0.44	0.38	0.38	0.46	0.30	0.31	1.00				
CAN	0.11	0.00	0.08	0.03	0.06	0.05	0.05	0.05	0.29	0.32	0.37	0.29	0.36	0.07	0.20	0.15	0.18	1.00			
USA	0.33	0.14	0.30	0.08	0.27	0.15	0.18	0.25	0.56	0.62	0.61	0.52	0.55	0.22	0.35	0.31	0.36	0.63	1.00		
MEX	0.34	0.19	0.34	0.13	0.26	0.22	0.16	0.30	0.56	0.56	0.51	0.43	0.46	0.29	0.32	0.32	0.46	0.50	0.71	1.00	
BRA	0.37	0.20	0.35	0.16	0.27	0.22	0.20	0.31	0.57	0.53	0.51	0.44	0.46	0.29	0.33	0.30	0.45	0.50	0.68	0.72	1.00

4.5.2 Unit root test

In order to test stationarity of the returns on futures and indices, a unit root test was conducted. There are two commonly used stationarity tests and these are both employed: Augmented Dickey-Fuller (ADF) and the Phillips-Perron (P-P).

The Augmented Dickey-Fuller test constructs a parametric correction for higher-order correlation by assuming that the Y series follows an AR (p) process and adding p lagged difference terms of the dependent variable Y to the right-hand side of the test regression:

$$\Delta y_t = \alpha y_{t-1} + x'_t\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \cdots + \beta_p \Delta y_{t-p} + v_t \qquad (4.5.2)$$

where t is a time trend and v_t is white noise.

The P-P test provides an alternative (nonparametric) method of controlling for serial correlation when testing for a unit root. It estimates the non-augmented DF test equation and modifies the t-ratio of α coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. The P-P test relies on the following equation:

$$\Delta y_t = \mu + \alpha t + (\rho - 1)\Delta y_{t-1} + v_t \qquad (4.5.3)$$

For both ADF and P-P tests, $Y(t)$ series is assumed to have a unit root under the null hypothesis, which means that data is nonstationary if a null hypothesis could not be rejected. Table 4.10 gives results of ADF and P-P stationary test for indices and futures returns respectively. It is evident that all variables under investigation are stationary because the null hypotheses that all series have a unit root (nonstationary) is rejected in both ADF and P-P tests.

Table 4.10 Stationarity test for stock indices and stock index futures returns, in-sample.

Markets	Returns				Volatility			
	Stock indices		Stock index futures		Stock indices		Stock index futures	
	ADF	P-P	ADF	P-P	ADF	P-P	ADF	P-P
HKG	-18.1558	-54.6064	-30.7693	-30.7354	-29.2012	-56.7520	-31.4742	-31.5139
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
JPN	-32.2937	-51.0246	-32.8074	-32.8055	-33.4731	-53.3182	-34.5470	-34.7345
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SGP	-52.8756	-54.0475	-34.0548	-34.0278	-38.2777	-52.0479	-34.0161	-34.2718
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CHN	-52.2238	-52.1453	-32.8973	-32.8932	-38.8773	-54.9375	-34.5652	-34.6408
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
KOR	-38.4691	-53.4729	-32.0013	-32.0072	-29.5095	-57.4679	-35.2245	-35.3350
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MYS	-45.2354	-45.3218	-35.4703	-35.7436	-49.0704	-49.3127	-35.3658	-35.5464
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
TWN	-51.5773	-51.5272	-33.3447	-33.3969	-53.3889	-53.8288	-33.6475	-33.8022
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
IND	-47.5667	-47.5614	-32.3992	-32.4008	-51.5290	-52.0936	-33.7002	-33.7705
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GBR	-24.7247	-51.1291	-36.0831	-37.1051	-51.7686	-51.8211	-36.7638	-37.6640
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GER	-46.9152	-46.8959	-34.0780	-34.3490	-49.0625	-49.2234	-34.5399	-35.7778
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FRA	-52.5488	-52.5384	-34.6510	-35.1821	-50.4852	-51.1041	-34.5756	-35.2547
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ESP	-48.5327	-48.5480	-33.0103	-33.0036	-49.4482	-49.5158	-32.0535	-32.1571
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SUI	-51.3556	-51.7142	-34.9969	-36.0815	-49.4876	-49.9752	-36.2774	-38.0675
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
RUS	-45.5011	-45.5031	-30.6574	-30.6162	-44.5117	-44.4338	-32.5682	-32.5987
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
HUN	-21.9143	-48.8184	-30.1057	-30.1106	-51.0116	-51.010	-32.9349	-32.9491
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ZAF	-47.4142	-48.0346	-34.8909	-35.9643	-48.5325	-48.9647	-33.9470	-34.9637
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
TUR	-50.7332	-50.7705	-34.6353	-34.6174	-52.8432	-53.1119	-36.8585	-37.0619
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CAN	-52.1198	-52.0337	-32.2931	-33.0516	-56.1863	-56.7389	-32.8704	-33.6060
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
USA	-38.4229	-54.9783	-34.7725	-35.5528	-58.0305	-58.8298	-35.5232	-36.1175
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MEX	-44.8263	-44.7544	-30.4863	-30.4341	-48.5768	-49.1538	-32.5140	-32.6776
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
BRA	-50.0773	-50.6363	-34.3436	-34.3330	-53.9046	-54.6998	-34.7474	-34.7469
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: Critical values: 1% level is -3.432959; 5% level is -2.86257; 10% level is -2.567368; Statistics is significant at the 1% level.

4.6 Chapter Summary

This chapter explains the data utilized in this thesis and rationalises the selection of the countries chosen for the investigation on the grounds that it allows the provision of global evidence on the investigated phenomenon. The chapter explains the length of estimation period considered in this thesis, with the underlying reasons for the choice of this time-frame.

The challenges of data gathering and data preparation processes are highlighted. The differences in trading hours for stock indices and stock index futures, with further clarification of the DST policies and existence of non-synchronous holidays are examined. This discussion, in particular, is helpful for an understanding of the sequences of trading on financial markets during a 24-hour time span, which is important for any investigation of the information transmission mechanisms across markets with, and without, overlap in trading times.

The chapter provides descriptive statistics on data employed in this work. The results showed that the returns of both stock indices and stock index futures are not-normally distributed, which is consistent with existing research and literature. The analysis of skewness and kurtosis demonstrates the predominance of the days with higher market volatility over days with lower market volatility during the estimation period. The existence of the ARCH effect for all time-series is also confirmed. The results of preliminary tests suggested that all data are stationary. The conventional correlation analysis indicated a positive correlation among financial time-series, with the highest correlation between developed European markets and the lowest correlation between the Chinese market and other markets.

Chapter 5 Return and volatility spillovers across emerging and developed markets: evidence from stock indices and stock index futures

5.1 Introduction

The international information transmission mechanisms across markets, through both returns and volatility, have both theoretical significance and a wide range of practical implications. The phenomenon of volatility spillovers occurs when volatility in one market triggers volatility in other markets. This effect can be especially visible during periods of turmoil which diminish the benefits of international portfolio diversification for investors. Recent technological advances have increased the accessibility of foreign information for domestic investors, and speeded up information flows. The investigation of return and volatility spillovers between stock markets within various geographical regions contributes to our knowledge about global financial interconnectedness.

There are various fields of literature to which the analysis of return and volatility spillovers is related, for example the literature on financial contagion, hedging, asset allocation and stock market efficiency. Ideas of transmission of volatility across markets underpinned the ‘heat-waves’ and ‘meteor showers’ hypotheses postulated by Engle et al. (1990) and have natural implications in the analysis of predictability of stock market returns (see, e.g., Ibrahim and Brzeszczynski, 2009; 2014, among others). Indeed, while return and volatility spillovers can limit the benefits of global diversification, the knowledge about international information transmission mechanisms can provide the opportunity to predict the behaviour of a domestic market by using foreign information. Therefore, the estimation of directional return and volatility spillovers is important in understanding the channels of intra- and inter-regional information transmission, which can be used to create successful trading strategies.

This Chapter provides the regional perspective of return and volatility transmission giving the insight on the new geography of financial integration testing the hypotheses H1-H8. First, empirical evidence from both stock indices and stock index futures data about differences in information transmission mechanisms is provided. The analysis contributes to the emerging literature which employs alternative data to simple stock indices in the analysis of international information transmission effects. The findings suggest that employing futures data makes the results more practically applicable in the construction of trading strategies based on transmission of foreign information. Second, the methodology of Diebold and Yilmaz (2009; 2012) is utilized to explore the new geography of financial linkages through an analysis of both intra- and inter-regional return and volatility spillovers across 21 developed and emerging markets from four regions: Asia, the Americas, Europe and Africa. Third, evidence about the changing intensity of return and volatility spillovers around the most recent crisis episodes with respect to structural breaks in the volatility of both futures and spot markets returns is found, which contribute to the contagion literature. The empirical results are also important for policy makers and financial regulators because they provide a global perspective on spillovers across financial markets from 2005 to 2014. This is crucial to an enhanced understanding of the new requirements for financial regulation.

5.2 Methodology

This chapter employs the Diebold and Yilmaz (2009) methodological framework which provides separate measures of return and volatility spillovers based on forecast error variance decompositions from a vector autoregressive (VAR) model. However, due to the fact that it relies on the Cholesky-factor identification of VAR, the results may be dependent on variable order. Subsequently, Diebold and Yilmaz (2012) replaced the Cholesky factorization on KPPS (Koop, Pesaran & Potter, 1996; Pesaran & Shin, 1998) variance decomposition, allowing the above methodological limitation to be avoided but retaining all the advantages of their general framework. In this chapter, therefore, return and volatility spillovers are estimated using a generalized vector autoregressive following the Diebold and Yilmaz method (2012).

A covariance stationary of N-variable VAR (p) can be described as follows:

$$X_t = \sum_{i=1}^{p} \Psi_i X_{t-i} + \varepsilon_t, \tag{5.2.1}$$

where X_t is a vector of returns or vector of volatilities of either spot or futures markets in our sample, Ψ_i is a parameter matrix and $\varepsilon \sim (0, \Sigma)$ is a vector disturbance.

The moving average representation of the VAR is given by:

$$X_t = \sum_{i=0}^{\infty} A_i \, \varepsilon_{t-i} \tag{5.2.2}$$

$$Q_i = \Psi_1 A_{i-1} + \Psi_2 A_{i-2} + \ldots \Psi_p A_{i-p}, \tag{5.2.3}$$

where A_0 being an N×N identity matrix and with A_i= 0 for i < 0.

N-variable VAR variance decomposition, introduced by Sims (1980), allows for each variable X_i to be added to the shares of its H-step-ahead error forecasting variance coming from shocks of variable X_j (where $\forall i \neq j$ for each observation). The record of these cross variance shares, under investigation in this Chapter, provides information of spillovers from one market to another. Additionally, the Diebold and Yilmaz (2012) framework allows for the examination of how variable X_i depends on its own shocks, and for a calculation of total volatility spillover.

As has been mentioned above, the employed framework relies on KPPS H-step-ahead forecast error, which is invariant to the ordering, and can be defined for H = [1, 2…+∞), as:

$$\vartheta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \Omega e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \Omega A'_h e_i\right)} \tag{5.2.4}$$

where Ω is the variance matrix for the error vector ε; σ_{jj} is the standard deviation of the error term for the jth equation; e_i is the selection vector, with one as the ith element and zero otherwise. $\sum_{j=1}^{N}\vartheta_{ij}^{g}(H) \neq 1$. This means that the sum of the elements in each row of the variance decomposition is not equal to 1. Normalization of each entry of the variance decomposition matrix by the row sum made as:

$$\tilde{\vartheta}_{ij}^{g}(H) = \frac{\vartheta_{ij}^{g}(H)}{\sum_{j=1}^{N}\vartheta_{ij}^{g}(H)} \tag{5.2.5}$$

where $\sum_{j=1}^{N}\tilde{\vartheta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N}\tilde{\vartheta}_{ij}^{g}(H) = N$.

The total volatility contributions from KPPS variance decomposition are used to calculate the Total Spillover Index:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N}\tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\vartheta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N}\tilde{\vartheta}_{ij}^{g}(H)}{N} \times 100 \tag{5.2.6}$$

Similarly, directional spillover indices are calculated to measure spillovers from market i to all markets j , and reverse direction of transmission from all markets j to market i, using equation (5.2.7) and (5.2.8) respectively:

$$S_{.i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N}\tilde{\vartheta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\vartheta}_{ij}^{g}(H)} \times 100 \tag{5.2.7}$$

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 \quad (5.2.8)$$

The difference between total shocks transmitted to market i and those transmitted from market i to all markets is defined as *net volatility spillover* (Eq. (5.2.8) – Eq. (5.2.7)). In a similar way, *net pairwise spillovers* are calculated for each K pairs of markets in the sample:

$$S_{ij}^{g}(H) = \frac{\tilde{\vartheta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\vartheta}_{ik}^{g}(H)} - \frac{\tilde{\vartheta}_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \tilde{\vartheta}_{jk}^{g}(H)} \times 100 =$$

$$= \frac{\tilde{\vartheta}_{ji}^{g}(H) - \tilde{\vartheta}_{ij}^{g}(H)}{N} \times 100 \quad (5.2.9)$$

The Total Spillover Index is applied to investigate the global and regional trends of spillover activity around the crisis episodes, while directional spillovers are used to demonstrate how much each market contributes to all the other markets, providing information about the channels of intra- and inter-regional information transmission across the selected markets.

5.3 Empirical results and discussion

5.3.1 Full-sample period

The first stage of current empirical analysis employs daily return and volatility data of 10 developed and 11 emerging markets for the full-sample period from 3 October 2005 to 3 October 2014 in order to investigate intra- and inter-regional information transmission. The empirical results are presented in the form of spillover tables. Table 5.1 reports ‘input-output’ decomposition of spillovers indices for stock markets returns and Table 5.2 deals with volatility. In contrast to Diebold and Yilmaz (2009) who report that return and volatility spillovers are of the same magnitude, it is found in this Chapter that the Total Spillover Index for returns (71%) is higher than the estimated Total Spillover Index for volatility (56%); therefore, the magnitude of returns spillovers is higher than volatility spillovers. These differences in magnitude in return and volatility spillovers are evident in all 21 markets in the sample, but especially so for the emerging market of Taiwan, where the results in the row, *Contribution to Others,* are 40.89% for return and only 1.0% for volatility. Similar significant differences are evident in Korea and India. The row *Contribution to Others* demonstrates which stock market is the most influential in the data sample. While Rapach, Strauss and Zhou (2013), among others, argued that USA tends to be the most influential market, in our sample the UK stock market had the highest value of spillovers (126%), with the American market only second highest (116.28%). Among emerging markets the highest return spillover was detected from Mexico (101.14%), Brazil (102.30%) and South Africa (82.76%). The lowest value of the return spillover index (contribution to others) in the whole sample had China (18.88%) and Japan (35.34%).

Table 5.1 Return spillovers across stock markets.

Region/ Market		Asia									Europe and Africa										Americas					From Others
		HKG	JPN	SGP	CHN	KOR	MYS	TWN	IND	Sum	GBR	GER	FRA	ESP	SUI	RUS	HUN	TUR	Sum	ZAF	CAN	USA	MEX	BRA	Sum	
Asia	HKG	31.92	3.64	11.64	5.18	6.17	3.74	5.54	5.22	73.04	4.40	1.30	0.66	0.50	0.31	3.10	0.39	0.32	10.99	3.63	0.64	3.60	3.68	4.42	12.34	68.08
	JPN	3.94	35.66	4.58	1.04	8.88	1.62	4.33	2.52	62.58	4.90	3.64	2.71	1.77	2.86	2.99	1.56	0.69	21.11	3.74	0.99	4.02	3.77	3.79	12.57	64.34
	SGP	11.20	3.76	28.68	2.16	6.67	5.11	5.40	6.43	69.41	4.87	1.98	1.22	1.19	0.80	3.92	0.55	0.80	15.33	4.22	0.63	2.88	3.59	3.94	11.04	71.32
	CHN	9.99	2.16	4.56	62.39	3.67	3.53	3.62	1.99	91.91	1.07	0.01	0.04	0.04	0.11	1.07	0.06	0.11	2.51	1.48	0.29	0.67	1.29	1.84	4.10	37.61
	KOR	6.92	9.09	7.40	2.14	33.92	3.33	9.32	2.69	74.81	3.66	1.13	0.58	0.38	0.39	3.23	0.49	0.61	10.47	3.73	1.08	3.51	3.00	3.40	10.99	66.08
	MYS	5.21	2.10	7.49	2.46	4.08	42.59	4.80	4.33	73.05	3.63	1.34	1.30	1.01	0.78	3.01	1.21	0.84	13.13	3.40	1.13	2.01	3.62	3.66	10.42	57.41
	TWN	7.22	5.20	7.51	2.33	11.62	4.69	40.68	1.82	81.08	2.87	0.63	0.56	0.36	0.40	2.38	0.18	0.25	7.64	3.15	1.00	2.72	2.01	2.41	8.14	59.32
	IND	5.62	1.95	7.45	1.18	2.68	2.85	1.52	33.39	56.64	5.21	3.29	2.59	2.24	2.12	3.89	1.69	1.98	23.02	5.06	1.83	3.98	4.90	4.57	15.28	66.61
Sub-total		82.00	63.56	79.33	78.87	77.68	67.47	75.22	58.39	582.52	30.61	13.32	9.67	7.50	7.76	23.59	6.15	5.59	104.19	28.41	7.59	23.39	25.87	28.03	84.88	490.77
Europe and Africa	GBR	2.10	1.32	2.61	0.25	1.50	1.22	0.85	2.27	12.12	15.52	9.27	9.00	6.78	7.39	4.67	2.83	2.73	58.18	6.56	2.85	8.26	5.90	6.12	23.14	84.48
	GER	0.76	0.22	1.16	0.00	0.50	0.28	0.12	1.27	4.31	10.21	17.04	13.62	10.02	9.63	3.54	4.30	3.39	71.74	4.76	2.03	7.22	5.21	4.74	19.20	82.96
	FRA	0.38	0.02	0.69	0.01	0.14	0.21	0.06	0.87	2.38	9.91	13.54	17.05	11.98	11.25	3.13	4.47	3.63	74.95	4.17	2.53	6.74	4.71	4.52	18.50	82.95
	ESP	0.37	0.05	0.87	0.02	0.16	0.23	0.05	1.01	2.76	9.14	12.22	14.68	20.77	9.61	2.83	4.48	3.71	77.45	3.62	1.90	6.13	3.97	4.17	16.17	79.23
	SUI	0.26	0.01	0.50	0.04	0.13	0.17	0.08	0.80	2.01	9.86	11.65	13.63	9.55	20.76	2.33	4.08	3.69	75.55	3.66	2.84	6.94	4.57	4.44	18.79	79.24
	RUS	2.43	1.67	3.17	0.43	2.10	1.36	1.23	2.77	15.16	7.46	5.77	4.78	3.57	2.95	23.54	3.51	3.29	54.88	7.67	3.16	6.32	6.31	6.49	22.29	76.46
	HUN	0.43	0.02	0.48	0.02	0.13	0.54	0.05	1.31	2.99	6.10	8.35	8.84	7.17	6.66	4.35	32.82	4.71	79.01	4.09	1.92	4.48	3.68	3.84	13.92	67.18
	TUR	0.30	0.02	0.95	0.01	0.53	0.36	0.23	1.66	4.06	6.34	7.12	7.67	6.37	6.59	4.79	5.09	35.42	79.37	3.98	1.09	3.90	3.85	3.75	12.59	64.58
Sub-total		7.04	3.34	10.43	0.78	5.18	4.37	2.68	11.97	45.79	74.54	84.97	89.28	76.21	74.82	49.18	61.57	60.55	571.13	38.50	18.32	50.00	38.20	38.07	144.59	617.09
	ZAF	2.35	1.78	3.00	0.45	2.14	1.55	1.36	2.99	15.62	8.88	6.15	5.32	3.74	3.94	6.58	2.52	2.29	39.40	20.27	4.06	6.77	7.00	6.88	24.71	79.73
Americas	CAN	0.50	0.18	0.45	0.07	0.24	0.37	0.23	0.24	2.28	4.66	4.21	5.27	3.26	4.87	0.81	1.60	0.89	25.58	2.12	36.01	15.04	9.63	9.35	70.03	63.99
	USA	1.81	0.60	1.80	0.10	1.26	0.68	0.46	1.47	8.19	8.31	7.68	7.33	5.46	6.17	2.94	2.44	1.98	42.30	3.87	7.97	18.70	9.78	9.19	45.64	81.30
	MEX	2.41	0.73	2.42	0.40	1.62	1.12	0.68	1.83	11.21	7.02	6.28	5.74	3.93	4.57	3.66	2.24	2.20	35.64	4.87	5.59	11.03	20.88	10.78	48.28	79.12
	BRA	2.82	0.82	2.80	0.60	1.91	1.17	0.94	2.16	13.20	7.50	5.73	5.40	4.08	4.38	3.80	2.29	2.04	35.22	5.00	5.33	10.04	10.66	20.54	46.58	79.46
Sub-total		7.54	2.32	7.46	1.17	5.03	3.34	2.31	5.70	34.87	27.49	23.91	23.74	16.72	19.99	11.20	8.57	7.11	138.74	15.85	54.90	54.82	50.95	49.87	210.53	303.87
Contr to Others*		67.01	35.34	71.53	18.88	56.12	34.14	40.89	45.66	369.57	126.00	111.30	110.96	83.41	85.76	67.01	45.98	40.13	670.55	82.76	82.76	116.28	101.14	102.30	368.58	1491.45
Contr incl own**		98.93	71.01	100.21	81.27	90.04	76.73	81.57	79.05	678.80	141.52	128.34	128.01	104.18	106.51	90.55	78.81	75.54	853.46	103.03	103.03	134.98	122.02	122.85	464.71	71.0%

Notes: *From Others - directional spillover indices measure spillovers from all markets *j* to market *i*; **Contribution to others - directional spillover indices measure spillovers from market *i* to all markets *j*; ***Contribution including own - directional spillover indices measure spillovers from market *i* to all markets *j* including contribution from own innovations of market *i*; Other columns contain net pairwise (*i*,*j*)-th spillovers indices. Total Return Spillover Index demonstrates that 71.0% of forecast error variance comes from spillovers.

Table 5.2 Volatility spillovers across stock markets.

Region/ Market		Asia									Europe and Africa										Americas					From Others
		HKG	**JPN**	**SGP**	**CHN**	**KOR**	**MYS**	**TWN**	**IND**	**Sum**	**GBR**	**GER**	**FRA**	**ESP**	**SUI**	**RUS**	**HUN**	**TUR**	**Sum**	**ZAF**	**CAN**	**USA**	**MEX**	**BRA**	**Sum**	
Asia	**HKG**	46.82	4.08	16.37	5.45	0.02	6.14	0.01	0.01	78.89	1.91	0.92	0.99	0.57	0.67	2.80	0.32	0.51	8.69	2.06	1.62	2.85	2.72	3.17	10.36	53.18
	JPN	4.82	61.35	5.48	1.70	0.06	2.81	0.08	0.04	76.34	3.23	2.28	1.82	1.37	1.89	2.98	1.37	0.43	15.37	2.59	1.09	1.48	1.73	1.40	5.70	38.65
	SGP	16.60	4.25	43.89	2.33	0.02	6.23	0.04	0.07	73.43	3.13	1.56	1.61	1.32	1.14	3.81	0.45	0.76	13.78	2.70	2.59	2.82	2.23	2.45	10.09	56.11
	CHN	8.64	2.56	3.73	77.92	0.10	3.37	0.05	0.06	96.43	0.17	0.02	0.06	0.03	0.05	0.38	0.18	0.21	1.11	0.29	0.47	0.31	0.65	0.74	2.16	22.08
	KOR	0.10	0.09	0.06	0.17	93.94	0.22	0.10	3.85	98.53	0.16	0.09	0.16	0.12	0.19	0.08	0.14	0.18	1.12	0.04	0.14	0.06	0.06	0.05	0.31	6.06
	MYS	7.91	2.88	7.88	2.63	0.03	59.96	0.01	0.06	81.37	2.06	0.76	1.03	0.79	0.65	2.81	0.71	0.61	9.43	2.24	1.60	1.44	1.78	2.14	6.96	40.04
	TWN	0.03	0.03	0.30	0.39	0.03	0.02	96.90	0.06	97.76	0.32	0.29	0.18	0.19	0.22	0.17	0.12	0.04	1.53	0.25	0.07	0.09	0.19	0.12	0.46	3.10
	IND	0.01	0.12	0.15	0.03	3.57	0.14	0.06	93.52	97.61	0.26	0.16	0.18	0.10	0.13	0.44	0.16	0.15	1.57	0.26	0.06	0.18	0.11	0.21	0.57	6.48
Sub-total		84.94	75.35	77.85	90.62	97.77	78.88	97.26	97.68	700.36	11.24	6.08	6.03	4.48	4.94	13.48	3.45	2.90	52.60	10.42	7.65	9.24	9.47	10.26	36.63	225.70
Europe and Africa	**GBR**	0.79	0.39	1.18	0.04	0.01	0.63	0.04	0.09	3.16	18.23	11.84	13.17	10.33	11.39	4.32	3.10	3.20	75.59	6.10	3.81	4.94	3.18	3.22	15.15	81.77
	GER	0.40	0.16	0.63	0.00	0.00	0.25	0.04	0.05	1.54	12.17	18.58	15.92	12.06	11.46	3.26	3.74	3.10	80.28	4.42	3.11	4.64	3.04	2.95	13.75	81.42
	FRA	0.37	0.08	0.58	0.01	0.01	0.24	0.04	0.05	1.36	12.78	15.06	17.65	13.38	11.90	3.35	3.59	3.09	80.81	4.64	3.11	4.38	2.82	2.88	13.19	82.35
	ESP	0.31	0.06	0.60	0.01	0.00	0.23	0.05	0.04	1.30	11.88	13.53	15.85	20.89	10.71	3.17	3.55	3.20	82.78	4.30	2.74	3.91	2.38	2.59	11.62	79.11
	SUI	0.34	0.03	0.47	0.01	0.01	0.20	0.05	0.06	1.17	13.01	12.72	13.97	10.64	20.78	2.59	3.26	3.22	80.19	4.33	3.32	4.80	3.12	3.07	14.31	79.22
	RUS	1.99	1.22	2.74	0.19	0.02	1.36	0.07	0.16	7.75	7.64	6.02	6.17	4.96	4.07	31.56	4.63	4.96	70.00	8.69	3.06	3.30	3.46	3.73	13.56	68.44
	HUN	0.32	0.05	0.39	0.03	0.16	0.40	0.05	0.11	1.52	6.67	7.84	7.94	6.61	6.19	5.40	38.27	4.49	83.40	5.16	2.20	2.88	2.40	2.45	9.92	61.73
	TUR	0.29	0.07	0.63	0.07	0.04	0.43	0.07	0.09	1.68	7.34	6.90	7.38	6.41	6.56	6.50	4.76	40.57	86.43	5.08	1.32	2.02	1.60	1.86	6.81	59.43
Sub-total		4.80	2.06	7.22	0.36	0.24	3.74	0.40	0.65	19.48	89.73	92.50	98.05	85.28	83.06	60.14	64.90	65.82	639.48	42.73	22.68	30.87	22.00	22.76	98.32	593.47
	ZAF	1.28	0.85	1.67	0.11	0.02	1.13	0.05	0.06	5.17	9.63	6.95	7.59	5.93	6.03	7.90	3.86	3.44	51.34	28.66	3.54	3.55	3.89	3.85	14.83	71.34
Americas	**CAN**	0.93	0.37	1.28	0.11	0.00	0.64	0.07	0.02	3.41	6.09	4.88	5.23	3.90	4.74	1.87	1.22	0.72	28.65	2.49	29.84	15.98	9.38	10.24	65.45	70.16
	USA	1.44	0.28	1.29	0.03	0.01	0.53	0.04	0.02	3.64	6.23	6.13	6.13	4.64	5.67	1.74	1.68	1.07	33.29	2.21	14.26	25.28	10.65	10.65	60.85	74.72
	MEX	1.77	0.25	1.37	0.26	0.02	0.70	0.07	0.01	4.44	4.99	4.91	4.81	3.39	4.52	2.14	1.49	1.21	27.46	2.83	9.66	12.87	30.12	12.61	65.26	69.88
	BRA	2.05	0.21	1.58	0.32	0.01	0.72	0.00	0.06	4.95	4.98	4.64	4.83	3.66	4.40	2.12	1.57	1.16	27.36	2.60	10.46	12.43	12.32	29.88	65.09	70.12
Sub-total		6.18	1.10	5.52	0.72	0.03	2.59	0.19	0.11	16.45	22.29	20.56	20.99	15.59	19.34	7.88	5.96	4.16	116.77	10.13	64.23	66.56	62.48	63.39	256.65	284.88
Contr to Others*		50.38	18.02	48.37	13.88	4.13	26.38	1.00	4.98	167.15	114.66	107.51	115.00	90.39	92.59	57.85	39.90	35.76	653.65	63.28	68.26	84.94	67.72	70.39	291.31	1175.38
Contr incl own**		97.20	79.37	92.26	91.80	98.07	86.34	97.90	98.50	741.45	132.89	126.09	132.65	111.28	113.37	89.40	78.17	76.33	860.18	91.93	98.09	110.23	97.85	100.27	406.43	56.0%

Notes: *From Others - directional spillover indices measure spillovers from all markets j to market i;**Contribution to others - directional spillover indices measure spillovers from market i to all markets j;***Contribution including own - directional spillover indices measure spillovers from market i to all markets j including contribution from own innovations of market i; Other columns contain net pairwise (i,j)-th spillovers indices; Total Volatility Spillover Index demonstrates that 56.0% of forecast error variance comes from spillovers.

Table 5.2 presents the results for volatility. For the majority of markets volatility spillovers are less intense than return spillovers (the values of spillover indices are lower for volatility). The lowest magnitude of volatility spillovers is from the emerging market of Taiwan to other markets, with 96.90% contribution from its own market innovations and just 1.0% contribution to other markets indicated. In contrast, the highest magnitude of volatility spillovers is found across developed European countries, such as the UK, Germany, France, Spain and Switzerland.

The column *From Others* can be used to show which market is the most sensitive to external shocks. Table 5.1 and Table 5.2 demonstrate the reverse direction of spillovers (from all foreign markets to a domestic market) which can be assessed by considering the entries of rows for each particular market (horizontal entries). For both the UK and the USA the value of return spillovers from others markets is very high (84.48% and 81.30% respectively). The lowest value of spillovers from other markets has the stock markets of China, with returns of 37.61%, and Taiwan, with a volatility of 6.06%. Analysis of both *Contribution to Others* and *From Others*, together with other entries in Table 5.1 and Table 5.2 provides an accurate picture of cross-region and region specific information transmission. Moreover, the *Sub-total* rows demonstrate total spillovers from market i to all markets j from a specific region, while the *Sum* columns demonstrate total spillovers from all markets j from a specific region to market i. Further discussion on some of the most important findings of the research is essential to explain their theoretical and practical implications. This has been done below.

The Asian region is characterized by a lower level of spillovers between stock markets within the region compared to Europe and the Americas. The strongest return spillovers for all Asian markets come from the UK. In regard to volatility spillovers, UK influence is strongest mainly on the developed markets of Hong Kong, Japan and Singapore. Similarly, these markets are influenced by shocks from markets from the Americas region, for example the USA and Brazil. This could be explained by the fact that developed Asian markets are more integrated into the world economy when compared with emerging markets from the same region. The row *Contribution to Others* indicates that the Hong Kong stock market is the most influential in the Asian region (67.01% for returns and 50.38% for volatility). This, however, is mainly due to the high spillovers from Hong Kong to other Asian markets. Consequently, the intensity of intra-region spillovers is higher than the intensity of inter-regional spillovers. It is found that the majority of Asian markets have the highest reaction to their own shocks, for example, Korea, Taiwan and India record 93.94%, 96.90% and 93.52% of their own forecast error variance respectively, making them the most independent markets in the sample. These results have a number of important implications. Firstly, they reveal diversification opportunities in emerging Asian stock markets which are less affected by external shocks. Secondly, independence from external shocks limits the opportunities to predict the volatility of those markets based on foreign information transmission. As a result, emerging Asian markets seem to be an attractive option for portfolio trading strategy, but less attractive for investors utilizing an active trading strategy based on the meteor shower effect introduced by Engle et al. (1990).

While the Asian region is relatively independent from other regions, the linkages between Europe and the Americas are much stronger for both directions of spillovers, providing the evidence for inter-regional information transmission. However, developed markets are more influential than emerging markets. The strongest linkages between emerging and developed stock markets are within the Americas region, where the USA accounts for 11.03% and 10.04% of error variance of the stock market of Mexico and Brazil respectively. One of the possible explanations for this phenomenon is that countries which are geographically close to each other have a higher level of volatility spillover, because the geographical location affects the economic and financial integration of the countries. Among four countries selected from the Americas region, Canada is the least impacted upon by foreign information transmission.

The South African stock market is representative of the African region and it is the third most influential emerging market in the sample after Mexico and Brazil. The greatest magnitude of spillovers is from South Africa to Russia (7.67% for return and 8.69% for volatility), while the magnitude of the reverse direction of spillovers is also high (6.58% for return and 7.90% for volatility). Additionally, South Africa has strong linkages with the UK stock market. South Africa also influences developed Asian markets and all four markets selected from Americas.

Overall, there is strong evidence of intra-regional and inter-regional returns spillovers across stock markets, while there is limited evidence of inter-regional volatility spillovers. The values of pairwise spillovers between markets from the same region are much higher than between markets from different regions. Furthermore, the magnitude of spillovers between developed and emerging stock markets is lower than between solely developed markets or emerging markets, providing opportunities for international portfolio diversification.

5.3.2 Subsample analysis: comparison of evidence from futures and spot markets

A major contribution of this Chapter is its analysis of information transmission mechanisms across stock index futures, which are a practical and more realistic alternative to stock market indices in determining trading strategies. Spillover tables were compiled for the subsample period from 4 October 2010 to 3 October 2014 to allow a comparison of the magnitude of return and volatility spillovers across stock index futures and across stock market indices. Table 5.3 and Table 5.4 provide evidence from futures markets for returns and volatility data respectively, while Table 5.5 and Table 5.6 provide evidence from underlying spot markets for the subsample period. The previous section explains the meaning of the rows and columns within the spillover tables and a similar interpretive logic of the empirical outputs is applicable for this section. As with the full-sample period the magnitude of return spillovers is higher than the magnitude of volatility spillovers for both futures and spot markets. The Total Return Spillover Index is equal 66.3% and the Total Volatility Spillover index is 58.3% for stock index futures. Total Spillovers indices for spot markets return and volatility are 65.5% and 52.0% respectively. The return spillovers, therefore, across futures and spot markets are at the same level of magnitude, but the intensity of volatility spillovers is higher across futures.

Table 5.3 Return spillovers across stock index futures.

Region/ Market		Asia									Europe and Africa										Americas					From Others
		HKG	JPN	SGP	CHN	KOR	MYS	TWN	IND	Sum	GBR	GER	FRA	ESP	SUI	RUS	HUN	TUR	Sum	ZAF	CAN	USA	MEX	BRA	Sum	
Asia	HKG	40.01	3.56	9.98	7.36	4.51	3.67	4.91	5.41	79.40	4.26	1.02	1.43	0.36	1.04	3.93	1.43	0.66	14.14	1.19	1.62	2.85	2.72	3.17	5.28	59.99
	JPN	2.85	32.17	3.87	0.99	2.89	0.92	1.78	1.63	47.12	6.70	6.36	6.75	4.28	4.59	3.28	1.84	1.15	34.94	3.10	1.09	1.48	1.73	1.40	14.85	67.83
	SGP	5.63	2.42	22.35	1.90	4.50	3.52	2.96	4.28	47.56	5.96	4.54	4.63	2.57	3.63	4.33	2.37	1.51	29.54	2.16	2.59	2.82	2.23	2.45	20.75	77.65
	CHN	11.25	2.08	5.43	61.18	4.49	3.81	3.96	1.76	93.96	1.18	0.06	0.11	0.19	0.15	1.78	0.25	0.30	4.02	0.46	0.47	0.31	0.65	0.74	1.56	38.82
	KOR	3.09	2.43	5.22	1.74	23.83	1.88	5.38	2.76	46.33	5.16	5.15	5.05	3.99	3.42	4.19	2.62	1.59	31.16	2.31	0.14	0.06	0.06	0.05	20.19	76.17
	MYS	5.01	1.85	8.69	2.83	3.68	50.61	4.96	5.06	82.71	3.09	0.67	1.19	0.23	0.67	3.18	2.65	0.61	12.28	0.66	1.60	1.44	1.78	2.14	4.35	49.39
	TWN	6.00	2.71	6.68	3.56	11.28	5.00	48.78	3.17	87.19	2.78	0.05	0.27	0.09	0.08	2.09	1.22	0.12	6.69	0.35	0.07	0.09	0.19	0.12	5.76	51.22
	IND	4.91	1.40	7.32	0.97	3.24	4.30	2.13	37.96	62.25	5.07	2.97	3.39	1.65	2.36	4.45	2.37	1.42	23.68	2.40	0.06	0.18	0.11	0.21	11.68	62.04
Sub-total		78.76	48.62	69.55	80.54	58.43	73.72	74.86	62.03	546.51	34.19	20.82	22.82	13.35	15.93	27.23	14.76	7.35	156.44	12.64	17.14	38.92	13.21	15.15	84.41	483.10
Europe and Africa	GBR	1.87	0.65	2.39	0.35	1.32	1.17	1.04	2.38	11.19	18.32	10.70	11.52	6.31	8.79	5.26	3.87	2.88	67.64	6.22	3.35	8.51	1.61	1.48	14.95	81.68
	GER	0.43	0.04	0.66	0.02	0.09	0.36	0.02	1.42	3.05	11.44	19.26	15.63	10.00	9.83	4.59	4.49	2.97	78.20	6.05	3.00	7.32	1.07	1.29	12.69	80.74
	FRA	0.59	0.06	1.05	0.06	0.16	0.45	0.06	1.58	4.00	11.76	14.99	18.51	11.60	9.64	4.33	4.21	2.79	77.82	5.73	3.07	7.15	0.98	1.26	12.46	81.49
	ESP	0.09	0.05	0.28	0.07	0.03	0.06	0.14	0.92	1.64	9.06	13.47	16.21	25.69	7.84	3.37	4.43	2.59	82.67	4.59	2.61	6.48	0.70	1.32	11.11	74.31
	SUI	0.48	0.07	0.73	0.08	0.15	0.40	0.06	1.49	3.48	11.86	12.45	12.75	7.49	24.39	3.38	3.23	3.30	78.85	5.90	2.35	6.72	1.16	1.54	11.78	75.61
	RUS	2.73	1.16	4.00	0.64	2.75	1.63	1.11	3.16	17.17	7.76	6.40	6.29	3.47	3.66	26.86	6.13	2.87	63.45	5.31	3.18	6.83	1.72	2.34	14.06	73.14
	HUN	1.12	0.21	1.74	0.17	1.50	1.81	0.82	2.03	9.41	7.22	8.06	7.78	5.75	4.41	7.39	33.65	3.26	77.51	4.00	1.54	5.38	0.96	1.20	9.08	66.35
	TUR	0.90	0.15	1.50	0.12	0.51	0.58	0.41	1.79	5.96	6.44	6.44	6.36	4.32	5.84	4.49	4.16	42.45	80.50	4.11	1.91	4.00	1.54	1.98	9.43	57.55
Sub-total		8.21	2.40	12.35	1.52	6.51	6.46	3.67	14.79	55.90	83.86	91.77	95.05	74.64	74.40	59.66	64.16	63.10	606.64	41.92	21.01	52.39	9.74	12.40	95.55	590.87
	ZAF	0.84	0.04	1.17	0.20	0.49	0.42	0.17	2.11	5.43	10.16	9.44	9.23	5.28	7.13	5.73	3.36	2.86	53.19	28.62	3.36	5.43	2.13	1.84	71.38	71.34
Americas	CAN	0.50	0.02	0.76	0.10	0.46	0.11	0.31	0.71	2.98	6.40	5.54	5.94	3.60	3.25	2.56	1.66	1.46	30.41	3.78	35.95	14.48	5.62	6.77	62.83	64.05
	USA	0.93	0.33	1.67	0.14	1.41	0.89	1.07	1.62	8.05	10.15	8.26	8.54	5.48	5.89	4.55	3.43	2.04	48.35	3.97	8.79	21.84	4.60	4.39	39.63	78.16
	MEX	0.65	0.15	0.67	0.40	1.23	0.69	0.65	0.98	5.43	4.01	2.52	2.71	1.40	2.22	1.83	1.17	1.58	17.44	2.61	7.51	10.18	47.63	9.20	74.52	52.37
	BRA	0.32	0.21	0.39	0.15	0.69	0.22	0.33	0.59	2.90	3.74	2.95	3.21	2.41	2.87	1.83	1.60	1.47	20.08	2.40	8.85	9.51	9.06	47.20	74.63	52.80
Sub-total		2.40	0.71	3.48	0.79	3.79	1.90	2.37	3.90	19.35	24.30	19.27	20.40	12.89	14.23	10.78	7.87	6.55	116.27	12.76	61.11	56.02	66.92	67.56	251.61	247.37
Contr to Others*		50.19	19.60	64.20	21.86	45.39	31.90	32.28	44.87	310.29	134.20	122.03	128.99	80.47	87.29	76.53	56.50	37.41	723.42	67.32	66.66	130.91	44.37	49.76	291.71	1392.73
Contr incl own**		90.20	51.77	86.55	83.05	69.22	82.51	81.06	82.83	627.19	152.51	141.29	147.50	106.16	111.68	103.39	90.15	79.86	932.55	95.93	102.61	152.76	92.00	96.96	444.33	66.3%

Notes: *From Others - directional spillover indices measure spillovers from all markets *j* to market *i*;**Contribution to others - directional spillover indices measure spillovers from market *i* to all markets *j*;***Contribution including own - directional spillover indices measure spillovers from market *i* to all markets *j* including contribution from own innovations of market *i*; Other columns contain net pairwise (*i,j*)-th spillovers indices; Total Return Spillover Index demonstrates that 66.3% of forecast error variance comes from spillovers.

Table 5.4 Volatility spillovers across stock index futures.

Asia	Europe and Africa	Americas	From Others

Region/ Market		HKG	JPN	SGP	CHN	KOR	MYS	TWN	IND	Sum	GBR	GER	FRA	ESP	SUI	RUS	HUN	TUR	Sum	ZAF	CAN	USA	MEX	BRA	Sum	
Asia	HKG	51.06	2.69	12.45	6.43	4.13	3.06	3.52	6.01	89.36	1.14	0.53	0.70	0.15	0.43	2.48	0.73	0.21	6.37	0.82	1.07	0.96	0.66	0.77	3.45	48.94
	JPN	2.43	53.25	3.32	1.84	5.06	1.63	2.90	0.89	71.32	3.07	3.12	2.95	2.25	1.91	2.01	1.45	0.60	17.36	1.37	2.50	5.17	0.40	1.88	9.96	46.75
	SGP	9.62	2.46	39.40	2.09	4.94	4.63	2.85	4.60	70.60	1.79	2.10	2.19	1.65	2.03	3.70	1.50	0.42	15.40	1.53	2.71	5.34	1.64	2.79	12.47	60.60
	CHN	8.89	2.89	3.90	71.65	4.36	2.15	2.57	1.07	97.49	0.10	0.05	0.04	0.23	0.18	0.69	0.07	0.19	1.55	0.24	0.14	0.29	0.25	0.04	0.72	28.35
	KOR	3.61	4.41	5.48	2.67	42.97	1.81	10.45	2.26	73.66	1.93	2.00	1.80	1.67	0.97	2.62	1.62	0.70	13.32	1.10	3.22	4.73	1.72	2.25	11.92	57.03
	MYS	3.82	2.21	7.44	1.18	2.91	64.48	2.92	4.39	89.35	0.67	0.29	0.64	0.31	0.43	2.80	1.57	0.16	6.86	0.45	0.22	1.26	1.28	0.58	3.34	35.52
	TWN	3.85	3.51	4.26	2.21	14.31	2.65	59.61	2.09	92.48	0.69	0.15	0.32	0.38	0.43	0.93	0.27	0.14	3.32	0.51	0.91	2.01	0.34	0.42	3.69	40.39
	IND	6.20	0.81	7.08	0.62	2.08	4.72	1.23	53.60	76.34	2.49	1.88	2.52	1.18	1.75	4.01	1.50	0.64	15.98	2.36	1.25	1.83	1.15	1.09	5.32	46.40
Sub-total		89.49	72.23	83.32	88.70	80.75	85.13	86.05	74.92	660.59	11.89	10.11	11.16	7.82	8.13	19.25	8.72	3.07	80.16	8.38	17.14	38.92	13.21	15.15	50.87	364.00
Europe and Africa	GBR	0.52	0.34	0.85	0.04	0.61	0.36	0.22	1.09	4.02	22.78	14.25	13.84	8.63	11.21	5.09	4.26	2.84	82.91	5.99	1.42	4.20	0.68	0.78	7.08	77.22
	GER	0.21	0.03	0.38	0.02	0.13	0.24	0.02	0.97	2.00	13.58	21.19	16.19	10.85	10.08	5.03	4.61	2.81	84.33	5.56	1.65	4.98	0.70	0.77	8.10	78.81
	FRA	0.26	0.10	0.68	0.03	0.15	0.22	0.03	1.00	2.47	12.56	15.64	20.48	12.99	9.64	5.20	4.64	2.98	84.14	5.59	1.69	4.72	0.68	0.71	7.80	79.52
	ESP	0.06	0.04	0.23	0.01	0.07	0.08	0.06	0.63	1.18	9.93	13.20	16.24	25.49	7.81	4.11	5.17	2.78	84.72	4.35	2.07	5.48	0.91	1.29	9.75	74.51
	SUI	0.19	0.20	0.52	0.07	0.32	0.21	0.03	1.04	2.57	13.61	12.79	12.65	8.16	26.82	4.25	3.77	3.32	85.36	5.28	1.09	4.13	0.70	0.86	6.79	73.18
	RUS	1.53	0.63	2.57	0.27	1.30	1.38	0.40	2.29	10.38	7.16	7.57	8.14	5.17	4.85	31.53	5.74	3.09	73.25	7.22	2.21	4.35	1.09	1.50	9.15	68.47
	HUN	0.38	0.06	0.45	0.05	0.34	0.90	0.17	1.36	3.70	7.36	8.26	8.35	7.37	5.14	6.51	35.55	3.98	82.51	6.01	1.33	4.28	0.85	1.33	7.79	64.45
	TUR	0.16	0.14	0.24	0.18	0.16	0.10	0.14	0.76	1.89	5.71	6.52	7.10	5.39	5.98	4.42	5.19	47.43	87.75	4.87	1.01	2.84	0.85	0.80	5.50	52.57
Sub-total		3.32	1.52	5.93	0.66	3.08	3.50	1.06	9.14	28.21	92.68	99.43	102.99	84.05	81.53	66.13	68.93	69.23	664.97	44.87	21.01	52.39	9.74	12.40	61.96	568.73
	ZAF	0.53	0.07	0.87	0.07	0.29	0.39	0.08	1.55	3.86	8.81	8.58	8.85	5.47	6.36	7.41	5.26	3.15	53.19	32.42	2.27	4.07	1.95	1.53	9.82	67.58
Americas	CAN	0.43	0.23	0.49	0.04	0.38	0.14	0.54	0.37	2.62	2.31	3.10	3.24	3.35	1.33	1.91	1.64	0.74	17.62	2.05	42.20	19.80	7.75	7.95	77.71	57.80
	USA	0.30	0.20	0.72	0.11	0.84	0.40	0.49	0.77	3.83	5.29	6.68	6.72	6.28	3.99	3.76	3.19	1.70	37.62	3.31	13.51	29.02	6.13	6.59	55.24	70.98
	MEX	0.35	0.07	0.17	0.16	0.68	0.41	0.19	0.66	2.69	1.10	1.44	1.45	1.88	0.91	1.38	1.31	0.80	10.29	1.72	10.07	11.74	53.66	9.82	85.30	46.34
	BRA	0.47	0.20	0.31	0.17	0.72	0.23	0.24	0.47	2.80	1.69	1.70	1.71	2.52	1.49	1.37	1.81	0.56	12.86	1.57	9.78	11.81	9.18	52.01	82.77	47.99
Sub-total		1.55	0.70	1.68	0.48	2.62	1.18	1.46	2.27	11.94	10.40	12.93	13.12	14.04	7.72	8.42	7.95	3.80	78.39	8.65	61.11	56.02	66.92	67.56	301.03	223.11
Contr to Others*		43.83	21.27	52.42	18.27	43.77	25.72	29.04	34.28	268.59	101.01	109.86	115.64	85.89	76.92	69.68	55.31	31.82	646.13	61.90	60.13	104.01	38.90	43.76	246.79	1223.41
Contr incl own**		94.89	74.52	91.81	89.91	86.74	90.20	88.64	87.87	704.60	123.79	131.05	136.13	111.38	103.74	101.21	90.86	79.24	877.41	94.32	102.33	133.03	92.56	95.76	423.68	58.3%

Notes: *From Others - directional spillover indices measure spillovers from all markets *j* to market *i*;**Contribution to others - directional spillover indices measure spillovers from market *i* to all markets *j*;***Contribution including own - directional spillover indices measure spillovers from market *i* to all markets *j* including contribution from own innovations of market *i*; Other columns contain net pairwise (*i*,*j*)-th spillovers indices; Total Volatility Spillover Index demonstrates that 58.3% of forecast error variance comes from spillovers.

Table 5.5 Return spillovers across stock markets subsample.

Region/ Market	Asia									Europe and Africa										Americas					From Others
	HKG	JPN	SGP	CHN	KOR	MYS	TWN	IND	Sum	GBR	GER	FRA	ESP	SUI	RUS	HUN	TUR	Sum	ZAF	CAN	USA	MEX	BRA	Sum	

Asia	HKG	37.63	3.18	10.47	8.70	5.77	2.81	5.80	2.46	76.82	4.29	0.42	0.62	0.20	0.48	3.71	0.59	0.24	10.54	4.32	0.64	2.17	2.63	2.88	8.32	62.37
	JPN	4.70	58.50	4.05	1.49	7.24	3.05	5.87	0.36	85.26	3.09	0.56	0.68	0.27	0.38	2.62	0.06	0.02	7.67	3.61	0.06	1.40	1.46	0.54	3.47	41.50
	SGP	10.29	2.56	37.26	3.16	4.59	3.06	5.02	3.09	69.04	5.86	1.95	2.07	0.79	1.87	4.75	0.74	0.52	18.55	4.18	0.71	3.29	2.14	2.09	8.24	62.74
	CHN	13.33	2.09	5.15	57.20	3.47	2.39	4.26	0.85	88.73	1.50	0.11	0.11	0.28	0.05	1.91	0.10	0.05	4.12	3.10	0.50	0.68	1.68	1.19	4.04	42.80
	KOR	6.33	4.84	5.49	2.60	40.85	3.03	10.04	1.43	74.61	4.10	0.61	0.74	0.36	0.74	3.83	0.76	0.44	11.59	3.31	1.07	3.70	3.12	2.60	10.48	59.15
	MYS	4.01	2.60	3.54	1.67	3.32	53.66	4.38	1.78	74.96	2.65	1.87	1.92	0.78	1.34	2.45	1.53	0.74	13.28	1.48	1.51	2.34	3.77	2.65	10.27	46.34
	TWN	7.04	4.76	5.92	3.47	11.19	3.50	45.40	1.71	83.00	2.47	0.15	0.21	0.37	0.10	2.49	0.16	0.11	6.06	3.33	0.87	3.01	1.69	2.03	7.61	54.60
	IND	3.26	0.36	4.19	0.56	1.13	1.26	1.23	51.69	63.68	5.56	2.59	3.22	1.78	2.53	3.64	1.16	1.35	21.82	4.68	1.11	3.07	2.89	2.76	9.83	48.31
Sub-total		86.59	78.89	76.06	78.85	77.56	72.76	82.00	63.37	616.09	29.52	8.26	9.56	4.84	7.49	25.39	5.10	3.46	93.63	28.01	6.47	19.66	19.38	16.76	62.27	417.80
Europe and Africa	GBR	1.89	0.85	2.67	0.41	1.44	0.50	0.94	1.41	10.10	16.96	8.87	9.51	5.71	7.63	5.75	2.81	2.58	59.82	7.75	3.12	9.27	4.94	5.00	22.32	83.04
	GER	0.31	0.04	0.79	0.03	0.20	0.04	0.09	0.84	2.33	9.63	18.51	15.28	10.33	10.28	4.47	4.62	3.61	76.71	4.74	1.92	7.36	3.72	3.22	16.22	81.49
	FRA	0.34	0.03	0.90	0.04	0.18	0.05	0.06	0.95	2.56	9.99	14.72	17.85	12.27	10.35	4.05	4.26	3.28	76.76	4.44	1.81	7.22	3.73	3.49	16.24	82.15
	ESP	0.14	0.01	0.39	0.08	0.09	0.01	0.19	0.77	1.68	8.02	13.35	16.50	23.94	8.71	3.31	4.92	3.34	82.10	3.03	1.43	5.92	2.68	3.15	13.18	76.06
	SUI	0.29	0.09	0.95	0.06	0.40	0.09	0.10	0.89	2.86	9.96	12.40	12.95	8.09	22.44	3.61	3.84	3.65	76.93	4.83	1.82	6.62	3.60	3.33	15.38	77.56
	RUS	2.60	1.03	3.23	0.74	1.87	0.87	1.38	1.47	13.20	8.74	6.17	5.82	3.54	4.11	25.36	4.22	2.14	60.11	7.21	2.30	7.28	4.78	5.11	19.47	74.64
	HUN	0.57	0.02	0.53	0.01	0.53	0.35	0.13	0.90	3.04	6.10	9.16	8.79	7.27	6.30	5.71	35.64	3.59	82.56	3.99	0.68	4.05	3.05	2.63	10.41	64.36
	TUR	0.25	0.04	0.54	0.06	0.22	0.14	0.20	0.93	2.37	6.10	8.03	7.70	5.85	6.92	3.48	4.06	41.24	83.38	3.85	0.75	3.58	2.94	3.13	10.40	58.76
Sub-total		6.38	2.11	10.01	1.43	4.92	2.06	3.08	8.16	38.14	75.50	91.22	94.40	76.99	76.75	55.74	64.35	63.43	598.39	39.85	13.83	51.29	29.45	29.06	123.63	598.06
	ZAF	2.39	1.51	2.57	1.12	1.72	0.57	1.60	1.97	13.44	10.54	5.91	5.75	2.93	5.05	6.56	2.51	2.18	41.44	22.94	3.92	7.35	5.60	5.31	22.19	77.06
Americas	CAN	0.61	0.04	0.77	0.39	0.58	0.22	0.55	0.62	3.78	5.20	4.30	4.15	2.51	3.26	1.37	0.80	0.75	22.33	2.93	41.20	14.18	8.11	7.47	70.95	58.80
	USA	1.04	0.40	1.68	0.28	1.34	0.37	1.18	1.01	7.30	9.76	7.77	8.13	4.96	5.80	4.72	2.19	1.67	45.00	4.98	6.96	20.30	8.28	7.18	42.73	79.70
	MEX	1.90	0.59	1.39	0.69	1.93	0.83	0.89	1.29	9.52	7.16	5.28	5.58	2.99	4.22	4.41	2.29	1.80	33.73	5.47	5.26	11.09	26.83	8.10	51.28	73.17
	BRA	2.06	0.23	1.27	0.67	1.58	0.43	1.05	1.45	8.73	7.49	4.88	5.50	3.70	4.17	4.41	2.10	1.95	34.19	4.81	5.17	10.12	8.54	28.43	52.26	71.57
Sub-total		5.61	1.25	5.12	2.03	5.42	1.86	3.66	4.37	29.33	29.60	22.23	23.36	14.16	17.45	14.91	7.37	6.17	135.25	18.20	58.58	55.69	51.77	51.18	217.23	283.23
Contr to Others*		63.34	25.26	56.50	26.22	48.77	23.59	44.94	26.18	314.80	128.19	109.11	115.23	74.98	84.31	77.24	43.70	34.00	666.76	86.06	41.60	113.69	79.37	73.88	308.54	1376.16
Contr incl own**		100.97	83.76	93.75	83.42	89.62	77.25	90.34	77.87	697.00	145.16	127.62	133.08	98.92	106.75	102.60	79.34	75.24	868.70	108.99	82.80	134.00	106.21	102.31	425.31	65.5%

Notes: *From Others - directional spillover indices measure spillovers from all markets *j* to market *i*;**Contribution to others - directional spillover indices measure spillovers from market *i* to all markets *j*;***Contribution including own - directional spillover indices measure spillovers from market *i* to all markets *j* including contribution from own innovations of market *i*; Other columns contain net pairwise (*i,j*)-th spillovers indices; Total Return Spillover Index demonstrates that 65.5% of forecast error variance comes from spillovers.

Table 5.6 Volatility spillovers across stock markets subsample.

Region/	Market	Asia									Europe and Africa										Americas					From Others
		HKG	JPN	SGP	CHN	KOR	MYS	TWN	IND	Sum	GBR	GER	FRA	ESP	SUI	RUS	HUN	TUR	Sum	ZAF	CAN	USA	MEX	BRA	Sum	
Asia	HKG	57.21	2.73	12.73	9.09	0.12	3.67	0.10	0.02	85.67	1.33	0.35	0.64	0.14	0.35	2.86	0.51	0.13	6.31	2.48	1.79	1.06	1.13	1.55	5.54	42.79
	JPN	3.04	78.98	3.22	1.89	0.04	3.17	0.27	0.07	90.68	1.91	0.33	0.69	0.35	0.73	1.66	0.08	0.06	5.82	1.52	0.73	0.62	0.52	0.11	1.98	21.02
	SGP	12.08	2.67	54.51	3.19	0.19	2.86	0.05	0.04	75.59	3.20	1.77	2.37	1.03	2.09	4.15	0.45	0.33	15.38	3.00	1.79	2.50	0.80	0.94	6.03	45.49

	CHN	11.63	2.50	4.67	73.44	0.11	1.98	0.05	0.60	94.97	0.36	0.07	0.19	0.33	0.09	1.05	0.22	0.07	2.39	1.17	0.48	0.31	0.53	0.15	1.47	26.56
	KOR	0.17	0.21	0.19	0.20	93.09	0.97	0.03	1.85	96.70	0.24	0.17	0.19	0.10	0.04	0.34	0.06	0.22	1.35	0.23	0.52	0.41	0.47	0.32	1.71	6.91
	MYS	4.66	3.24	3.12	1.52	0.68	77.42	0.37	0.07	91.08	0.91	0.06	0.25	0.04	0.30	2.56	0.70	0.40	5.21	0.39	0.61	0.61	1.30	0.80	3.32	22.58
	TWN	0.22	0.05	0.14	0.05	0.54	0.06	95.47	0.16	96.69	0.19	0.13	0.31	0.48	0.14	0.44	0.21	0.27	2.17	0.07	0.18	0.26	0.39	0.24	1.07	4.53
	IND	0.12	0.39	0.30	0.02	1.28	0.38	0.48	93.16	96.12	0.52	0.61	0.74	0.27	0.49	0.32	0.14	0.05	3.15	0.13	0.24	0.15	0.11	0.10	0.60	6.84
Sub-total		89.13	90.76	78.88	89.40	96.05	90.51	96.82	95.97	727.50	8.65	3.50	5.37	2.73	4.24	13.38	2.37	1.53	41.78	9.01	6.34	5.92	5.26	4.19	21.71	176.73
Europe and Africa	**GBR**	0.61	0.44	1.16	0.09	0.05	0.22	0.01	0.16	2.72	19.03	12.57	13.31	8.89	11.27	5.31	2.75	3.08	76.20	6.96	3.72	5.55	2.20	2.65	14.12	80.97
	GER	0.18	0.04	0.68	0.03	0.11	0.06	0.01	0.13	1.22	12.63	18.80	16.18	11.64	10.90	4.66	3.44	2.97	81.21	5.22	3.04	5.23	1.98	2.09	12.34	81.20
	FRA	0.25	0.11	0.84	0.04	0.10	0.06	0.00	0.16	1.56	12.72	15.46	18.09	12.94	10.76	4.69	3.29	2.91	80.86	5.26	3.04	5.06	1.99	2.23	12.32	81.91
	ESP	0.08	0.06	0.48	0.03	0.11	0.02	0.04	0.07	0.89	10.95	14.38	16.68	23.26	9.24	3.94	3.62	2.85	84.93	3.92	2.54	4.16	1.53	2.03	10.26	76.74
	SUI	0.18	0.19	0.84	0.04	0.07	0.11	0.02	0.19	1.64	13.19	12.67	13.11	8.70	21.92	4.22	2.81	3.57	80.19	5.33	3.16	5.21	1.96	2.51	12.84	78.08
	RUS	1.60	0.63	2.30	0.36	0.24	0.85	0.07	0.15	6.20	8.59	7.60	7.96	5.23	5.80	30.52	4.81	3.44	73.94	7.88	2.71	4.11	2.31	2.85	11.98	69.48
	HUN	0.28	0.00	0.41	0.05	0.36	0.40	0.03	0.41	1.95	6.55	7.80	7.68	6.40	5.32	6.46	39.99	3.88	84.08	5.41	1.18	3.28	1.93	2.17	8.56	60.01
	TUR	0.17	0.11	0.24	0.07	0.29	0.21	0.09	0.04	1.23	7.24	7.13	7.47	5.71	7.47	4.92	4.18	43.46	87.59	5.01	0.88	2.16	1.39	1.74	6.17	56.54
Sub-total		3.35	1.58	6.95	0.71	1.31	1.93	0.26	1.31	17.41	90.90	96.41	100.48	82.78	82.68	64.72	64.87	66.17	649.01	44.99	20.26	34.77	15.29	18.28	88.60	584.93
	ZAF	1.10	0.64	1.53	0.34	0.09	0.13	0.11	0.25	4.20	10.65	8.05	8.41	4.96	7.09	7.45	3.84	3.34	53.79	29.32	3.10	3.77	3.30	2.53	42.01	70.68
Americas	**CAN**	0.78	0.28	1.01	0.20	0.02	0.15	0.12	0.20	2.75	5.93	5.40	5.53	3.57	4.52	2.10	0.94	0.68	28.67	2.56	33.97	16.85	7.66	7.53	66.01	66.03
	USA	0.36	0.18	0.85	0.11	0.10	0.17	0.07	0.01	1.86	7.54	7.33	7.58	4.79	6.15	3.30	1.88	1.14	39.70	2.92	13.39	26.94	7.47	7.71	55.51	73.06
	MEX	0.80	0.28	0.33	0.44	0.18	0.43	0.08	0.08	2.63	4.24	4.15	4.34	2.55	3.40	2.73	1.79	1.15	24.34	3.69	9.17	11.33	40.31	8.53	69.34	59.69
	BRA	0.99	0.12	0.49	0.11	0.11	0.30	0.04	0.16	2.33	5.13	4.25	4.73	3.29	4.19	2.66	1.96	1.33	27.54	2.21	8.90	11.29	8.19	39.53	67.92	60.47
Sub-total		2.94	0.86	2.69	0.86	0.41	1.06	0.31	0.45	9.57	22.84	21.12	22.18	14.19	18.25	10.80	6.56	4.31	120.25	18.20	11.39	65.44	66.41	63.64	258.79	259.24
Contr to Others*		39.31	14.86	35.53	17.88	4.77	16.20	2.03	4.81	135.40	114.02	110.27	118.36	81.40	90.35	65.82	37.66	31.89	649.76	65.38	61.17	83.93	47.17	48.76	241.03	1091.58
Contr incl own**		96.53	93.84	90.04	91.31	97.87	93.62	97.50	97.98	758.68	133.05	129.08	136.45	104.66	112.27	96.34	77.65	75.35	864.84	94.70	95.14	110.87	87.49	88.30	381.79	52.0%

Notes: *From Others - directional spillover indices measure spillovers from all markets *j* to market *i*;**Contribution to others - directional spillover indices measure spillovers from market *i* to all markets *j*;***Contribution including own - directional spillover indices measure spillovers from market *i* to all markets *j* including contribution from own innovations of market *i*; Other columns contain net pairwise (*i*,*j*)-th spillovers indices; Total Return Spillover Index demonstrates that 52.0% of forecast error variance comes from spillovers.

For example, Table 5.6 shows that Korea, Taiwan and India have the lowest values of *Contribution to Others,* 4.77%, 2.03% and 4.81% for volatility spillovers across stock market indices, while for stock index futures these values are 43.77%, 29.04% and 34.28% (see Table 5.4). Volatility spillovers from Korea, Taiwan and India, in relation to other markets, are higher for futures data. This may be explained by lower cost of trading on futures markets and, therefore, the higher speed of international information transmission (Antoniou, Holmes and Priestley, 1998). Table 5.6 indicates that the total volatility spillovers from the USA to other markets is 83.93%, while volatility spillovers from the UK to other markets is 114.02%, making the UK much more influential than the USA. However, analysis of futures data reveals a different outcome and is presented in Table 5.4. The magnitude of volatility spillovers from the USA is higher than that from the UK, being 104.01% and 101.01% respectively.

Again, as with the full-sample analysis, there are stronger financial linkages across markets from the same region in the subsample period for both futures and indices data. The strongest magnitude of volatility spillovers was between developed European countries; the UK, Germany, France, Spain and Switzerland, developed Asian countries, Hong Kong and Singapore, and developed countries from the Americas, USA and Canada. The values of the pairwise spillovers indices are much lower between emerging markets within the sample. The linkages between emerging and developed markets are weaker, and in the majority of cases the main direction of spillover of both return and volatility is from developed to emerging stock markets, for example from Hong Kong to China, from the UK to South Africa and from the USA to Mexico and Brazil. The intensity of intra-region volatility spillovers across stock index futures is higher than the intensity of inter-region volatility spillovers. The main channels of inter-regional information transmission are from the Americas to Europe and from Europe to the Americas. There is some evidence of inter-regional return spillovers from America and Europe to Asia. However, there is a very low magnitude of volatility spillovers from Asian countries to other regions. South Africa has strong spillovers into European markets. South Africa is from the same geographical time-zone as European markets and, therefore, the trading hours of these markets overlap almost exactly. These channels of international information transmission are similar for both futures and stock indices. However, the magnitude of spillovers are higher for futures markets, so the conclusion can be made that information transmission mechanisms work more efficiently across futures.

Nonetheless, the spillovers tables do not demonstrate additional significant differences between the information transmission mechanisms across futures markets (see Tables 5.3 and 5.4) and spot markets (see Tables 5.5 and 5.6) apart from those discussed above. Additionally, spillovers tables cannot be used to observe the dynamic of return and volatility spillovers during the full-sample and subsample estimation periods. The contagion across markets has to be considered to provide a clear picture of the behaviour of spillovers during periods of turmoil, which can further explain some of the findings outlined earlier. For example, the high intensity of spillovers across developed European countries can be explained by contagion between those markets during the Eurozone crisis. It is useful, therefore, to plot return and volatility spillovers to investigate the behaviour of spillovers across futures and stock indices around the most recent crisis episodes.

5.3.3 Intensity of return and volatility spillovers around the recent crisis episodes

The behaviour of total return and volatility spillovers around the Global Financial Crisis and the European Debt Crisis is investigated in this section and contributes to current literature on these topics. Rolling window estimation is used to analyse the time-varying behaviour of spillovers over the full-sample and subsample periods. It is important to consider cyclical movements and burst in spillovers that could not be captured by the results presented in previous tables. The behaviour of return and volatility spillovers across stock index futures and stock equity indices for the sub-sample period are compared. Figure 5.1 presents the spillover plot for stock index futures and stock indices data from October 2010 to October 2014 based on the 200-day rolling window estimation following the methodology developed by Diebold and Yilmaz (2012). While the cyclical movements of spillovers are similar for futures and spot markets, the magnitude of spillovers is higher for futures markets during the subsample period, confirming the findings discussed in a previous section. Figure 5.1 provides information that confirms that the magnitude of volatility spillovers is lower than the magnitude of return spillovers for both futures and spot markets. The significant increase in total spillovers during 2011 was caused by the European Debt Crisis, while from 2012 to 2014 a decrease in spillovers across futures and spot markets can be seen, a sign of the global economic recovery.

Figure 5.1 Subsample total spillovers plot: futures and spot markets.

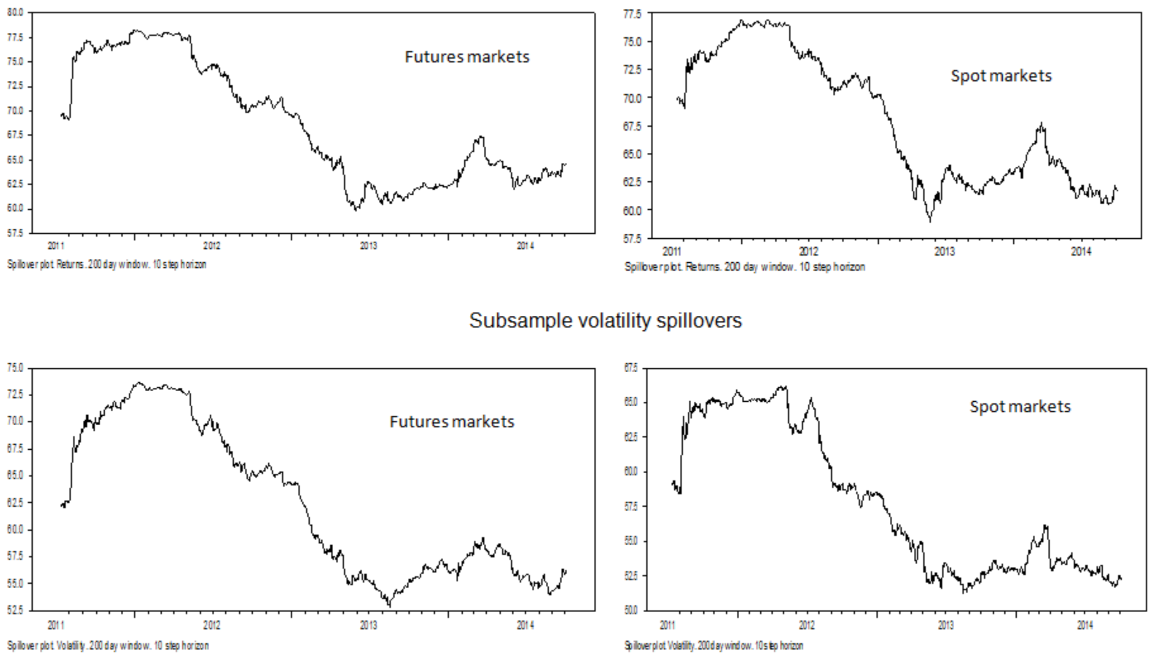
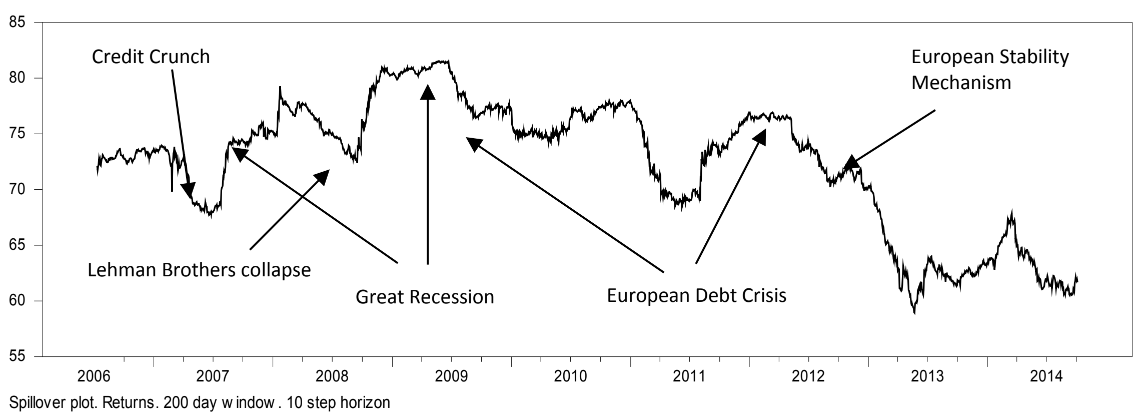


Figure 5.2 presents the return spillover plot for stock indices data from 2005 to 2014.

Figure 5.2 Return spillover plot, stock indices, full-sample.



Several cycles are identified from October 2005 to October 2014. Starting with the value of around 72%, the total return spillover plot fluctuated from 82% (from third quarter 2008 to first and second quarters 2009) to 58% (second quarter 2013). There are significant decreases in total return spillovers from 2012 to 2013 and during 2014. Total volatility spillovers follow a similar trend but the values of volatility spillover is lower than return spillover during the full-sample period, confirming the difference in Total Spillover Indices analysed in previous sections. Starting at a value around 59% (significantly lower than the starting point of return spillovers at 72%), total volatility spillover rises to 69% during 2009, and drops below 52% during 2013 (in the third quarter of 2013 and the end of 2014).

Figure 5.3 presents volatility spillover plot for stock indices data from 2005 to 2014:

Figure 5.3 Volatility spillover plot, stock indices, full-sample.

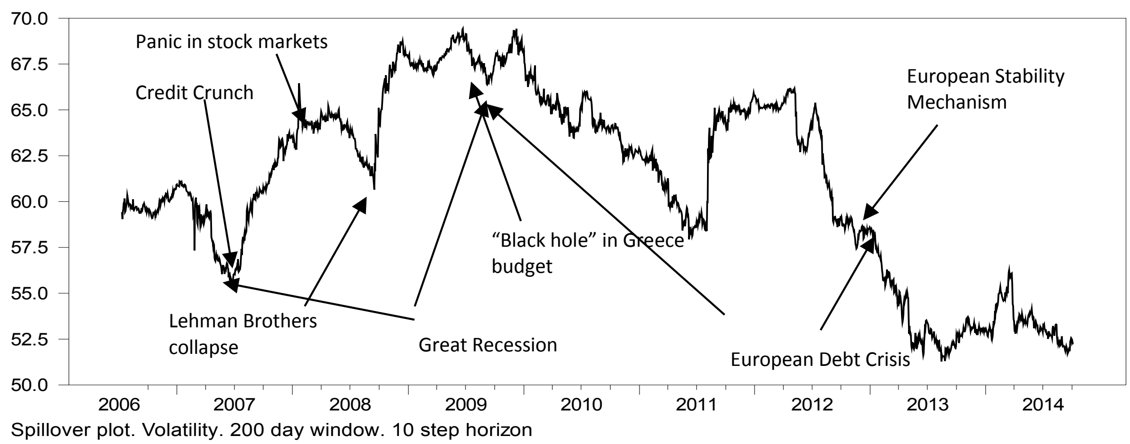


Figure 5.2 and Figure 5.3 graphically illustrate cyclical movements and bursts in spillovers during recent crisis episodes, such as the Global Financial Crisis and the European Debt Crisis. These results are consistent with opinions articulated in contagion literature which supports the position that crisis episodes impact not only on the volatility of financial markets but also impacts on the transmission of volatility across them. The Credit Crunch started in July 2007 caused a burst in total volatility spillovers from 55% to 63% at the end of 2007 (from 67% to 75% for returns spillovers). The financial panic in stock markets during the first quarter 2008 which followed pushed further total spillovers to 67% for volatility and to 79% for returns. The Lehman Brothers collapse on 15 September 2008 became a starting point for the world-wide spread of the Great Recession and raised values of total volatility spillovers to its maximum level, 72% (82% for return spillovers). These values remained high until the economic recovery. Consequently, total spillovers began to decrease from the beginning of 2010 and by the middle of 2011 had reached their pre-crisis values. However, the plot of intra-region volatility spillovers across the Eurozone shows that there was no decline in spillovers

from the beginning of 2010 as evidenced in the global trend. This was because the European Debt Crisis, which started in October 2009 in Greece, spread to several Eurozone state members, causing an increase in spillovers.

Figure 5.4 graphically illustrates volatility spillovers across the Eurozone for the period from 2005 to 2014. The spread of the crisis throughout the Eurozone in 2010 caused further increases in spillovers. Actions by Eurozone leaders to stabilize the situation through the European Financial Stability Facility (EFSF) and the European Financial Stabilization Mechanism (EFSM), for example the bailouts of Ireland and Portugal, initiated the recovery from the crisis. In September 2011 the IMF pronounced that the global economy had entered a 'dangerous new phase' of sharply lower growth as a result of the European debt crisis.

Figure 5.4 Volatility spillover plot, Eurozone, stock indices, full-sample.

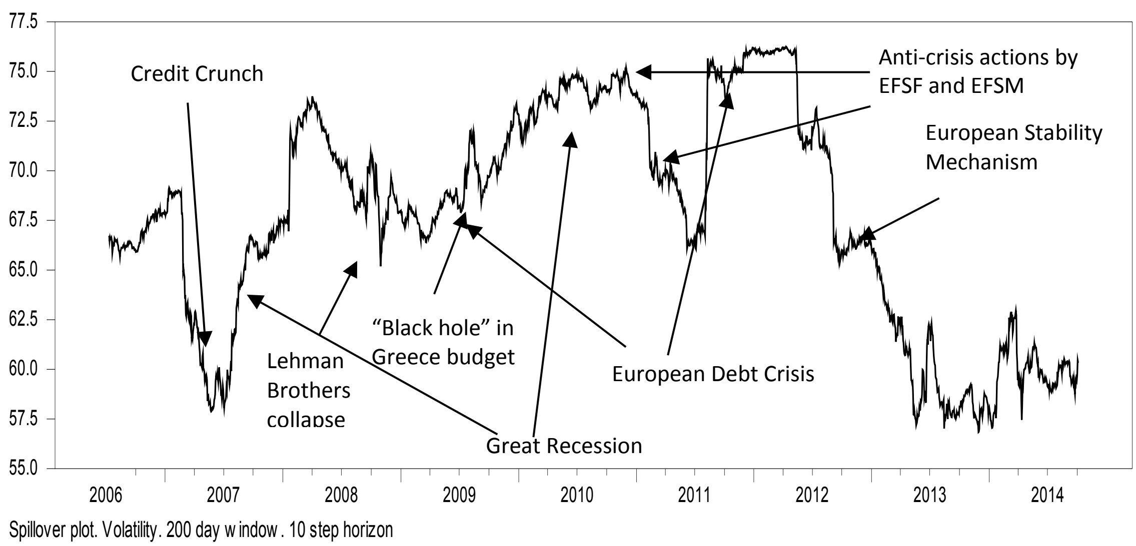


Figure 5.5 and Figure 5.6 plot intra-regional return and volatility spillovers for the full-sample period for all regions separately. The highest magnitude of total spillovers is still in the Eurozone, and total spillovers in the Americas follow the same trend as in Europe and Africa. A different situation pertains in the Asian region, where the magnitude of total intra-region spillovers across Asian countries is much lower than the Americas and Europe for both returns and volatility. As indicated previously, Asian countries are more isolated from external shocks, and Figures 5.5 and 5.6 confirm these findings.

Figure 5.5 Intra-regional return spillovers plot.

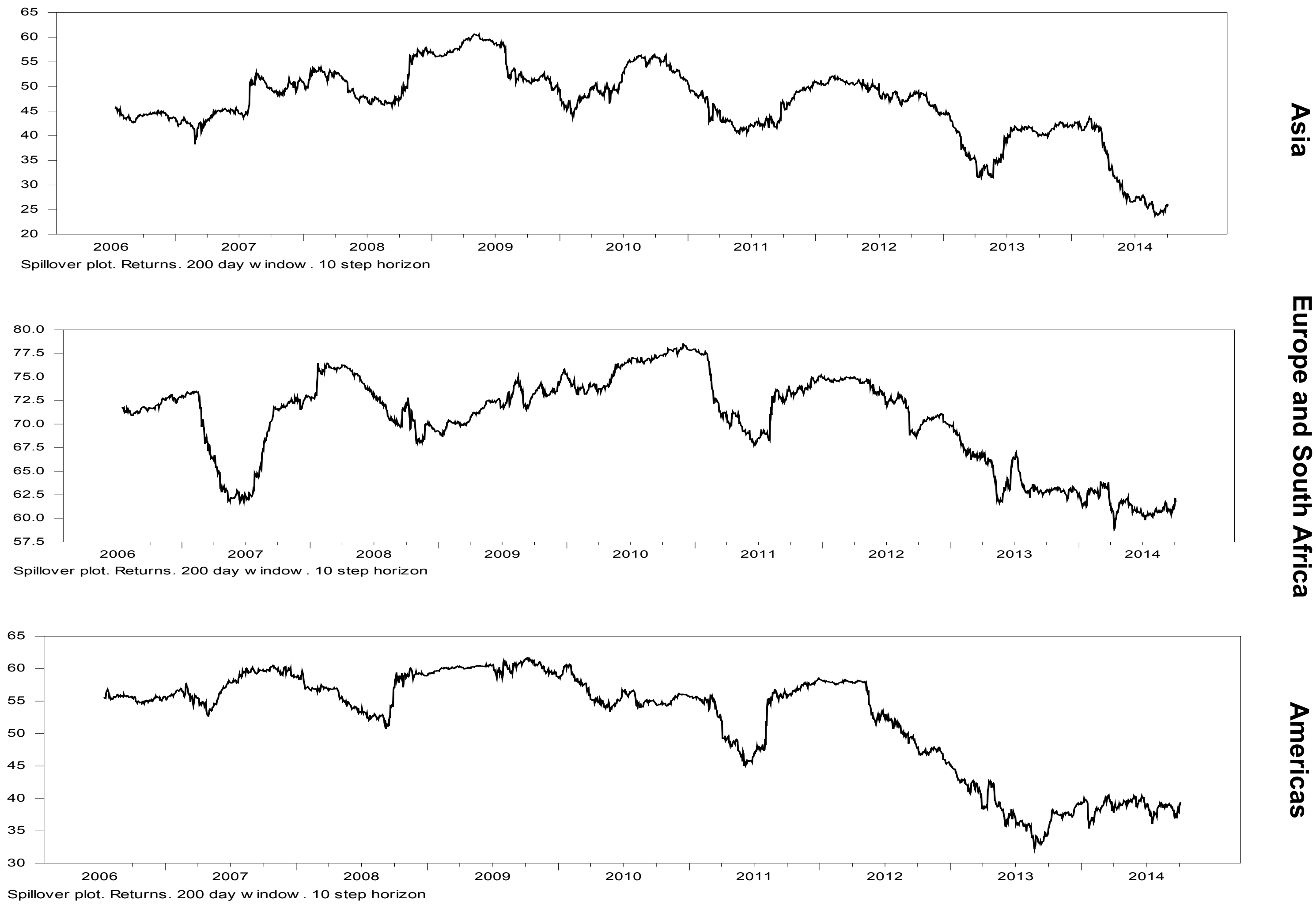
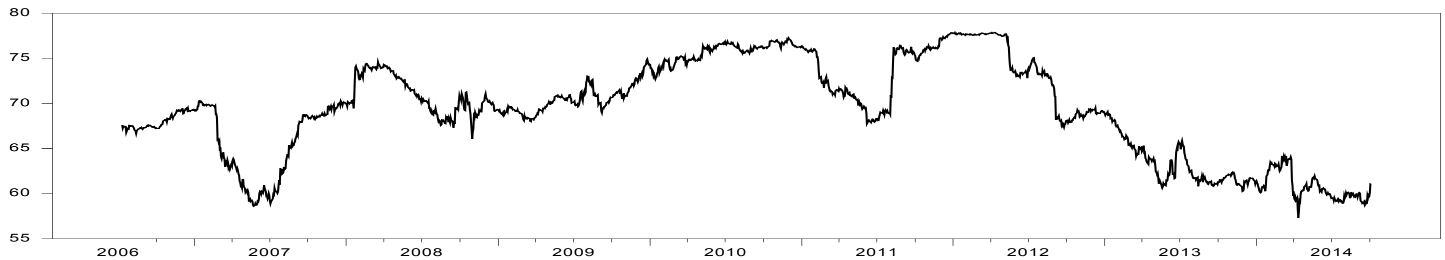


Figure 5.6 Intra-regional volatility spillovers plot.

Spillover plot. Volatility. 200 day w indow . 10 step horizon



Spillover plot. Volatility. 200 day window. 10 step horizon

Europe and South Africa

Spillover plot. Volatility. 200 day w indow . 10 step horizon

Americas

5.5 Structural breaks

In this section the issue of whether there is evidence of structural breaks in the dynamics of stock indices and futures returns volatility is examined. The existence of structural breaks is a classical statistical problem which affects volatility and long-range dependence in stock returns (Andreou & Ghysels, 2002). Omitting structural breaks in an analysis of volatility spillovers may lead to a significant overestimation of volatility transmission because jumps in volatility can influence information flow in relation to intensity, direction, origin, and the scheme of transmission (Huang, 2012). The iterated cumulative sum of squares (ICSS) algorithm introduced by Inclan and Tiao (1994) has been employed to test for multiple breaks in the volatility of spot and futures markets for each country separately.

The test on structural shifts is used by many scholars to identify the crisis period (Dimitriou et al., 2013; Karanasos et al., 2014). In this section the identified structural breaks are linked to the major shocks during the Great Recession and the European Debt Crisis. These results are consistent with the timeline of the Global Financial Crisis provided by BIS (2009) which is used in this Chapter. The structural changes in variance do not occur exactly simultaneously in futures and spot markets, though certain similarities in breaks across markets are found, especially, between markets within the same geographical region around crisis episodes. This provides additional evidence of strong intra-region market dependencies.

Tables 5.7 and 5.8 summarize the results of the IT test and indicate the existence of multiple structural breaks in the dynamics of volatility over both the full-sample and the subsample periods. All the return series have at least 10 structural breaks in their variance over the full-sample period and at least one structural break over the subsample period, but the number of jumps in variance varies from year to year as demonstrated in Tables 5.7 and 5.8

Table 5.7 Structural breaks, full-sample.

	Market	HKG	JPN	SGP	CHN	KOR	MYS	TWN	IND	GBR	GER	FRA	ESP	SUI	RUS	HUN	ZAF	TUR	CAN	USA	MEX	BRA
2005	**Futures**			11:18																11:02		
2006	**Spot**		08:14	05:05 07:27	05:05 07:19	07:10	05:17 07:26 11:06	05:08 06:20 09:18	05:12 06:16 07:27 12:07	05:11 08:07	05:10 08:15	05:11 05:31 08:15	05:11 05:31	05:02 05:31 08:15	05:11 07:13	05:16 07:17	05:12 06:15 09:11	05:11 07:20		05:10 07:28	05:16 07:20	07:24
2007	**Futures**	01:01 03:12 07:31	04:19 08:14 09:19	01:19 04:19 07:06 08:14 08:22	01:05 08:03	07:25	02:23 03:08 05:24 07:30 08:23	07:25	02:22 04:16 07:26	07:23	02:26	07:09 09:18	04:19 09:19	07:18		11:16	07:24	07:11	10:17	02:26 03:21 07:23	02:23 03:21 11:02	07:23
2008	**Spot**	01:08 03:28 09:16 11:07	01:03 03:17 10:03 10:30 12:15	01:11 03:25 09:10 11:07	01:18 12:12	02:04 07:01 10:15 12:10	01:03 03:03 04:03 09:10 11:03	06:19 10:27 12:24	01:17 03:31 10:02 11:21	09:02 11:24	01:14 02:18 09:26 12:02	01:14 02:15 09:16 12:09	01:14 02:06 05:30 09:16 12:02	01:03 02:15 09:15 12:01	01:15 02:12 07:16 09:15 11:25	02:18 09:16 11:14	09:04 12:10	09:10 12:03	09:05 12:01	09:12 12:05	03:14 09:16 12:01	09:08 11:24
2009	**Futures**	05:06 12:17	05:07	05:11 08:31	07:28 09:28	04:29 12:04	08:24	07:13	08:24	04:03 12:01	04:02 12:01	07:02	05:18	05:18	08:03	07:15	07:15	05:20	03:02 06:25 12:04	04:21 11:09	05:08 12:02	05:18
2010	**Spot**		10:12	01:25 07:07		10:08		07:06		04:26 05:27 09:01	04:26 05:20 09:24	04:26 10:05	01:18 05:03 05:14 07:07	09:24	05:03 07:06	06:10	04:27 05:27 09:01	05:06 05:26 11:19	05:14 07:21	04:26 09:01	04:26 09:01	07:07
2011	**Futures**	08:09 11:16	03:11 04:08	08:01 11:02	02:22	08:01 10:05	08:05 10:18	08:03 11:25		08:02 10:06 12:14	07:29 12:21	07:29 08:18 12:21	01:18 06:09 07:29 08:12 12:12	08:01 09:06 12:20	08:02 12:12	07:28 12:01	01:10 08:03 11:30	08:03 12:12	01:25 07:25 10:07	05:30 08:03 08:23 12:20	08:01 09:26	08:01 10:27
2012	**Spot**	07:24	12:17	08:03		01:06	01:05	07:31	03:26	08:03	09:11	04:02 08:07	04:12 09:06		05:03 10:01	06:25	10:01	08:03	06:21		01:18	09:13
2013	**Futures**		05:22 06:17 08:08	04:22 07:25	07:23	07:11	01:18 09:10	11:21	02:25 08:15 10:18	05:22 07:09		07:08	07:18	04:01 07:05			04:02 07:11	01:24 02:11 05:31 07:15 12:16		06:24	03:12 10:15	05:28
2014	**Spot**		04:16					04:24						01:23 03:25	02:12 03:18		02:17	02:06			03:21	

Notes: The date of structural break in volatility is displayed as month: day.

Table 5.8 Structural breaks, subsample.

Y	Market	HKG	JPN	SGP	CHN	KOR	MYS	TWN	IND	GBR	GER	FRA	ESP	SUI	RUS	HUN	ZAF	TUR	CAN	USA	MEX	BRA

2010	**Futures**					12:09																
	Spot		11:19													11:09 12:07						
2011	**Futures**	08:08 11:17	03:09 03:23 07:29 12:19	07:29 12:09	02:22 08:05	02:08 08:01 12:21	04:14 08:05 12:06	08:03 11:25		08:03 08:18 12:14	07:29 12:12	07:29 12:14	01:27 07:29 12:12	08:01 09:06	08:02 12:12	07:29 10:10	08:03 11:30	07:21 08:19	07:25 12:14	07:29 11:30	07:28 10:19	07:29 12:20
	Spot	08:09 11:16	03:11 04:08	08:01 11:02	02:22	08:01 11:29	08:05	08:03 11:25		08:02 10:06 12:14	07:29 12:12	07:29 08:18 12:21	01:18 07:29 12:12	08:01 09:06 12:20	08:02 12:12	07:28 12:01	08:01 11:30	07:21 12:12	03:04 08:01 10:07 12:30	05:30 08:01 08:23 12:20	08:01 09:26	08:01 10:27
2012	**Futures**	07:23		07:24	02:08 12:04	05:15 09:14		07:12	06:19	03:30 08:03	08:03	04:12 08:07	04:12 09:06	02:03	10:01	01:26 09:14	08:03	02:01 08:03	08:07	05:16 08:03	07:31	
	Spot	07:24	12:17	08:03			01:05	07:31	06:19	03:30 08:03	08:06	04:02 08:07	04:12 09:06		05:03 10:01	06:25	10:01	08:03	05:02 07:10		01:18	09:13
2013	**Futures**	03:01 09:05	01:03 05:22 06:13 08:20	04:22 09:30	07:23		01:18 09:12	10:08	02:20 08:05 10:03	04:01 09:03		07:08	07:18	04:01 07:04	04:08 07:18	06:06 08:28	04:02 09:02	01:24 02:07 05:28 07:08	03:20 08:30	06:26	05:22 10:03	
	Spot		05:22 06:17 08:08	04:22 07:25	07:23	07:11	01:18 09:10	11:21	02:25 08:15 10:18	05:22 07:09	07:08	07:08 12:02	07:18	04:01 07:05	04:08 07:12		04:02 07:11	01:24 02:11 05:31 07:15 12:16		06:24	03:12 10:15	05:28
2014	**Futures**		01:03 04:16		04:15 07:21	02:04		04:24				07:04		01:02 03:25	02:26 05:07			03:28			03:21	
	Spot		04:16					04:24			01:01	03:25 07:02		01:23 03:25	02:25 03:18		02:17	02:06			03:21	

Notes: The date of structural break in volatility is displayed as month: day.

5.6 Chapter Summary

This Chapter provides a new insight into global financial interconnectedness through the analysis of intra- and inter-regional return and volatility transmission across 21 developed and emerging markets from Asia, the Americas, Europe and Africa. It also contributes to the discussion about the applicability of different types of data in analyses of cross-markets financial dependencies by providing the evidence from both stock index futures and stock indices. The results demonstrate that futures markets provide more efficient channels of inter-regional information transmission than stock markets, because the magnitude of return and volatility spillovers is larger using stock index futures. It is suggested that the analysis of spillovers across stock index futures has important practical implications for the development of trading strategies. Therefore, the findings are particularly relevant not only to academics, but also to a broad range of practitioners.

The results presented in this Chapter have implications for asset allocation strategy and international portfolio diversification. The findings show that Asian markets are less susceptible to external shocks and could provide better opportunities for international portfolio diversification. The research provides significant evidence of intra-region information transmission for both futures and spot markets, but evidence of inter-regional spillovers is more limited. The spillovers between emerging and developed markets are weaker than between developed markets, consequently the benefits of international portfolio diversification are best achievable by investing in emerging markets in different geographical zones.

Finally, this Chapter contributes to contagion literature evaluating global and regional spillover trends. The burst in spillovers during crisis episodes is verified, which is important for investors as during periods of turmoil diversification benefits are limited. These findings are important for policy makers and financial regulators due to the fact that contagion during crisis episodes affect macroeconomic stability. Linkages of economic cycles with intensity of global return and volatility spillovers provide the opportunity to use the intensity of spillovers as an indicator of recession and recovery. In this Chapter a decrease in both return and volatility spillovers from 2012 to 2014 has been identified, which can be interpreted as an indication of global economic recovery.

An investigation of spillovers across futures markets, with non-overlapping trading hours, with the purpose of analysing the meteor shower effect, identified by Engle et al. (1990), across stock index futures within one trading day, is a key area for future research. Furthermore, as trading hours on stock index futures differ from their underlying stock indices due to the additional electronic trading hours for futures, such analysis will help to provide new evidence of inter-regional information transmission and contribute to stock market predictability literature.

Chapter 6 Asymmetric return and volatility spillovers

6.1 Introduction

This chapter investigates the asymmetry in causal linkages between markets with non-overlapping trading hours. The evidence of inter-regional return and volatility spillovers has important implications for international portfolio diversification and predictability. The findings presented by Chapter 5 show limited evidence of inter-regional spillover across markets. Therefore, the question of whether investing in stock index futures from different geographical regions can offer higher diversification opportunities requires further attention. This chapter focuses on pairwise spillovers in investigating the causal linkages between positive innovations and negative innovations across futures' returns and volatilities.

This Chapter is organised as follows:

Section 6.2 discusses methodology employed and explains the process of selection of market pairs with non-overlapping trading hours utilised in this Chapter. Due to the fact that we have found the analysis of futures data to have more realistic practical implications, this chapter focuses on futures data only to enrich empirical evidence and fill the gap in the literature. The investigation of the interconnectedness across markets with non-overlapping trading hours is important, not only to enhance understanding of meteor-shower effect but also to provide further evidence of contagion and predictability that can be useful for diversification strategy.

Section 6.3 presents the empirical results obtained for the first geographical time-zone, i.e. the Asian region. Therefore, this section demonstrates causal linkages between stock index futures in the market pairs where Asian markets are acting as recipients of information and markets from Europe and Africa and the Americas are contributors. Section 6.3 divided in two subsections. The former presents results for return spillovers, while the latter demonstrates results for volatility spillovers.

Section 6.4 and Section 6.5 discuss the empirical results for Europe and Africa, and the Americas region respectively. Similar to Section 6.3, the findings for return and volatility spillovers are presented in separate subsections.

Section 6.6 summarises the findings and concludes this study.

6.2 Methodology

6.2.1 Test on causalities

In order to test the asymmetry in return and volatility spillovers, this thesis employs the asymmetric causality test proposed by Hatemi-J (2012). The idea of transforming the data into both cumulative positive and negative innovations was originated by Granger and Yoon (2002), who used this approach to test time-series for cointegration. Later, Hatemi-J (2012) adopted this idea to investigate the causal linkages between positive and negative innovations between two variables. Following Hatemi-J (2012), the approach employed is discussed below.

Assume that two integrated variables y_{1t} and y_{2t} are described by the following random walk processes:

$$y_{1t} = y_{1t-1} + \theta_{1t} = y_{1,0} + \sum_{i=1}^{t} \theta_{1i}^{+} + \sum_{i=1}^{t} \theta_{1i}^{-}, \quad (6.2.1)$$

and similarly

$$y_{2t} = y_{2t-1} + \theta_{2t} = y_{2,0} + \sum_{i=1}^{t} \theta_{2i}^{+} + \sum_{i=1}^{t} \theta_{2i}^{-}, \quad (6.2.2)$$

The cumulative sums of positive and negative shocks of each underlying variables can be defined as follows:

$$y_{1t}^{+} = \sum_{i=1}^{t} \Delta\theta_{1i}^{+}, y_{1t}^{-} = \sum_{i=1}^{t} \Delta\theta_{1i}^{-}, \quad y_{2t}^{+} = \sum_{i=1}^{t} \Delta\theta_{2i}^{+}, \quad y_{2t}^{-} = \sum_{i=1}^{t} \Delta\theta_{2i}^{-}, \quad (6.2.3)$$

where positive and negative shocks are defined as: $\theta_{1t}^{+} = \max(\Delta\theta_{1i}, 0)$; $\theta_{2t}^{+} = \max(\Delta\theta_{2i}, 0)$; $\theta_{1t}^{-} = \min(\Delta\theta_{1i}, 0)$, and $\theta_{2t}^{-} = \min(\Delta\theta_{2i}, 0)$.

To test the causalities between these components vector autoregressive model of order *p,* VAR (p) is used:

$$y_{t}^{+} = v + A_1 y_{t-1}^{+} + \cdots + A_p y_{t-1}^{+} + u_{t}^{+}, \quad (6.2.4)$$

where $y_{t}^{+} = (y_{1t}^{+}, y_{2t}^{+})$ is the 2×1 vector of the variables, v is the 2×1 vector of intercepts, and u_{t}^{+} is a 2×1 vector of error terms (corresponding to each of the variables representing the cumulative sum of positive shocks); A_j is a 2×1 matrix of parameters for lag order γ ($\gamma = 1, \dots, p$). The information criterion suggested by Hatemi-J (2003) is used to select the optimal lag order (p):

$$HJC = \ln\left(\left|\hat{\Omega}_j\right|\right) + j\left(\frac{n^2 lnT + 2n^2 \ln(lnT)}{2T}\right), \tag{6.2.5}$$

where $j = 0, \dots, p$; $\left|\hat{\Omega}_j\right|$ is the determinant of the estimated variance-covariance matrix of the error terms in the VAR model based on the lag order j, n is the number of equations in the VAR model and T is the number of observations.

This information criterion was tested by Hatemi-J (2008). The simulation experiments confirmed the robustness of this criterion to ARCH effect, which is important for this thesis due to the existence of heteroskedasticity in the data.

The next step of the analysis is to test the Null Hypothesis that *k*th element of y_t^+ does not Granger-cause the ωth element of y_t^+ using the Wald test methodology. Furthermore, Hatemi-J (2012) has employed a bootstrap algorithm with leverage correction to calculate the critical values for the asymmetric causality test in order to remedy the heteroskedasticity problem. The Wald test methodology and the bootstrap procedure are discussed in detail by Hacker and Hatemi-J (2012), Hatemi-J (2012). The thesis used GAUSS coding provided by Hatemi-J (2012) to conduct the asymmetric causality test presented in this chapter.

6.2.2 Data filtering

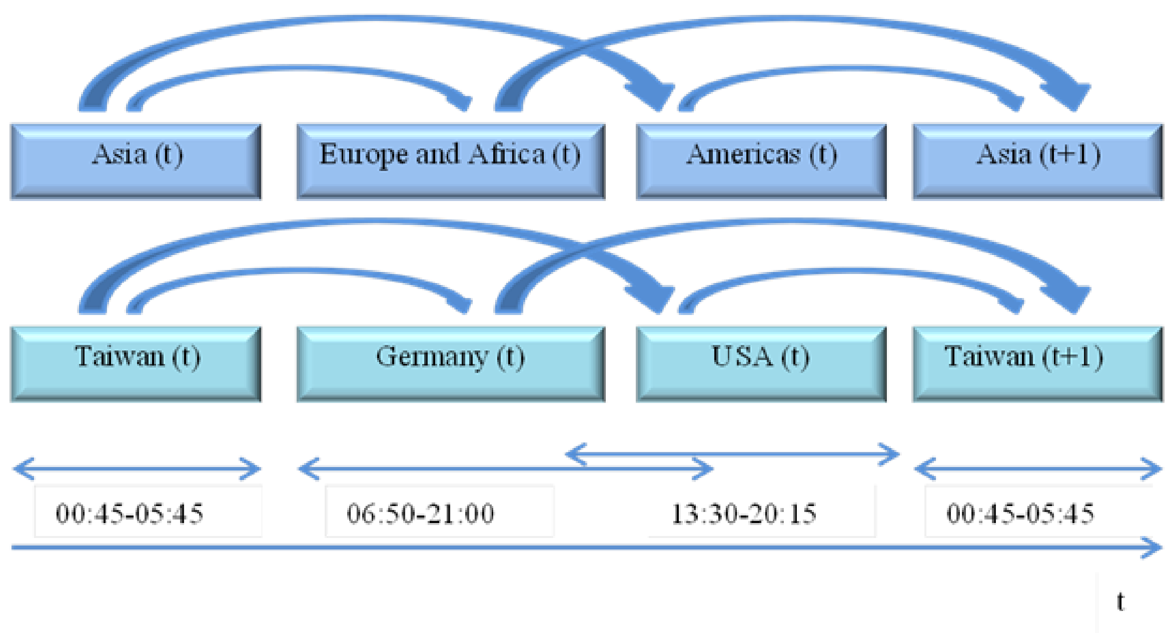
Since this chapter focuses on stock index futures data only to fill the gap in literature, the trading hours of futures are considered to identify market pairs with non-overlapping trading hours, taking into account differences in time-zone and DST policies. Table 6.1 demonstrates that, from the data set of 10 developed and 11 emerging markets, it is possible to analyse 104 channels of return and volatility transmission, avoiding an overlap in trading hours.

Table 6.1 Markets pairs with non-overlapping trading hours.

Country	Futures trading hours (GMT)	Futures trading hours during DST	Combined with	Number of combinations
Asia				
Hong Kong	01:15-04:00; 05:00-08:15	01:15-04:00; 05:00-08:15	TUR, CAN, USA, MEX, BRA	5
Japan	00:00-6:15	00:00-06:15	ESP, RUS, HUN, TUR, ZAF, CAN, USA, MEX, BRA	9
Singapore	00:30-09:15	00:30-09:15	TUR, CAN, USA, MEX, BRA	5
China	01:15-03:30; 05:00-07:15	01:15-03:30; 05:00-07:15	TUR, CAN, USA, MEX, BRA	5
South Korea	00:00-06:15	00:00-06:15	ESP, RUS, HUN, TUR, ZAF, CAN, USA, MEX, BRA	9
Malaysia	00:45-03:45; 06:30-08:15	00:45-03:45; 06:30-08:15	TUR, CAN, USA, MEX, BRA	5
Taiwan	00:45-05:45	00:45-05:45	GER, FRA, ESP, SUI, RUS, HUN, TUR, ZAF, CAN, USA, MEX, BRA	12
India	03:30-12:45	03:30-12:45	CAN BRA	2
Europe and South Africa				
UK	06:00-20:00	05:00-19:00	N/A	0
Germany	06:50-21:00	05:50-20:00	TWN (t+1)	1
France	07:00-21:00	06:00-20:00	TWN (t+1)	1
Spain	08:00-19:00	07:00-18:00	JPN (t+1), KOR (t+1), TWN (t+1)	3
Switzerland	06:50-21:00	05:50-20:00	TWN (t+1)	1
Russia	07:00-15:45; 16:00-20:50	07:00-15:45; 16:00-20:50	JPN (t+1), KOR (t+1), TWN (t+1)	3
Hungary	08:02-16:00	07:02-15:00	JPN (t+1), KOR (t+1), TWN (t+1)	3
Turkey	11:55-15:45	10:55-14:45	HKG(t+1), JPN(t+1), SGP(t+1), CHN(t+1), KOR(t+1), MYS(t+1), TWN(t+1)	7
South Africa	06:30-15:30	06:30-15:30	JPN, KOR, TWN	3
Americas				
Canada	11:00-21:15	10:00-20:15	HKG(t+1), JPN(t+1), SGP(t+1), CHN(t+1), KOR(t+1),MYS(t+1), TWN(t+1), IND(t+1)	8
USA	13:30-20:15	12:30-19:15	HKG(t+1), JPN(t+1), SGP(t+1), CHN(t+1), KOR(t+1),MYS(t+1), TWN(t+1)	7
Mexico	13:30-21:00	12:30-20:00	HKG(t+1), JPN(t+1), SGP(t+1), CHN(t+1), KOR(t+1),MYS(t+1), TWN(t+1)	7
Brazil	11:00-19:55	10:00-18:55	HKG(t+1), JPN(t+1), SGP(t+1), CHN(t+1), KOR(t+1),MYS(t+1), TWN(t+1), IND(t+1)	8
Total:				104

For example, the stock market of Germany opens when stock market of Taiwan is closed. Therefore the pair Germany–Taiwan provides two routes of information transmission for analysis; that is, from Taiwan to Germany and the reverse direction from Germany to Taiwan, as is demonstrated by Figure 6.1 below.

Figure 6.1 Inter-regional information transmission.



Therefore, as is clearly illustrated by Figure 6.1 the channels of inter-regional return and volatility spillovers across sequentially opening and closing markets are between Europe and Asia and between Asia and Americas. This is because European and Americans markets have an overlap in trading times.

Thus, from the total sample of 21 markets, 20 markets were selected for investigation of asymmetry in inter-regional return and volatility transmission across futures markets, with non-overlapped trading times for the period from 03 October 2010 until 03 October 2014. Table 6.2 shows that 104 potential channels of information transmission are under investigation with specification of the intensity of net-pairwise spillover indices for the target market combinations discussed in the previous chapter.

Table 6.2 Channels of inter-regional return and volatility transmission.

Market recipient of information	Acronyms	Contributors/ (net-pairwise spillovers for returns/net-pairwise spillovers for volatility)	Number of combinations
Asia			
Hong Kong	HKG	TUR (0.66/0.21), CAN (1.62/1.07), USA (2.85/0.96), MEX (2.72/0.66), BRA (3.17/0.77)	5
Japan	JPN	ESP (4.28/2.25), RUS (3.28/2.01), HUN (1.84/1.45), TUR (1.15/0.60), ZAF (1.19/1.37), CAN (1.09/2.50), USA (1.48/5.17), MEX (1.73/0.40), BRA (1.40/1.88)	9
Singapore	SGP	TUR (1.51/0.42), CAN (2.59/2.71), USA (2.82/5.34), MEX (2.23/1.64), BRA (2.45/2.79)	5
China	CHN	TUR (0.30/0.19), CAN (0.47/0.14), USA (0.31/0.29), MEX (0.40/0.25), BRA (0.65/0.04)	5
South Korea	KOR	ESP (3.39/1.67), RUS (4.19/2.62), HUN (2.62/1.62), TUR (1.59/0.70), ZAF (2.31/1.10), CAN (0.14/3.22), USA (0.06/4.73), MEX (0.06/1.72), BRA (0.05/2.25)	9
Malaysia	MYS	TUR (0.61/0.16), CAN (1.60/0.22), USA (1.44/1.26), MEX (1.78/1.28), BRA (2.14/0.58)	5
Taiwan	TWN	GER (0.05/0.15), FRA (0.27/0.32), ESP (0.09/0.38), SUI (0.08/0.43), RUS (2.09/0.93), HUN (1.22/0.27), TUR (0.12/0.14), ZAF (0.35/0.51), CAN (0.07/0.91), USA (0.09/2.01), MEX (0.19/0.34), BRA (0.19/0.42)	12
India	IND	CAN (0.06/1.25) BRA (0.21/1.09)	2
Europe and Africa			
UK	GBR	N/A	0
Germany	GER	TWN (0.02/0.02)	1
France	FRA	TWN (0.06/0.03)	1
Spain	ESP	JPN (0.05/0.04), KOR (0.03/0.07), TWN (0.14/0.06)	3
Switzerland	SUI	TWN (0.06/0.03)	1
Russia	RUS	JPN (1.16/0.63), KOR (2.75/1.30), TWN (1.11/0.40)	3
Hungary	HUN	JPN (0.21/0.06), KOR (1.50/0.34), TWN (0.82/0.17)	3
Turkey	TUR	HKG (0.90/0.16), JPN (0.15/0.14), SGP (1.50/0.24), CHN (0.12/0.18), KOR (0.51/0.16), MYS (0.58/0.10), TWN (0.41/0.14)	7
South Africa	ZAF	JPN (0.04/0.07), KOR (0.49/0.29), TWN (0.17/0.08)	3
Americas			
Canada	CAN	HKG (0.50/0.43), JPN (0.02/0.23), SGP (0.76/0.49), CHN (0.10/0.04), KOR (0.46/0.38), MYS (0.11/0.14), TWN (0.31/0.54), IND (0.71/0.37)	8
USA	USA	HKG (0.93/0.30), JPN (0.33/0.20), SGP (1.67/0.72), CHN (0.14/0.11), KOR (1.41/0.84), MYS (0.89/0.40), TWN (1.07/0.49)	7
Mexico	MEX	HKG (0.65/0.35), JPN (0.15/0.07), SGP (0.67/0.17), CHN (0.40/0.16), KOR (1.23/0.68), MYS (0.69/0.41), TWN (0.65/0.19)	7
Brazil	BRA	HKG (0.32/0.47), JPN (0.21/0.20), SGP (0.39/0.31), CHN (0.15/0.17), KOR (0.69/0.72), MYS (0.22/0.23), TWN (0.33/0.24), IND (0.59/0.47)	8
Total number of combinations			104

Due to the fact that an asymmetric causality test allows investigation of the impact of positive and negative shocks separately, the test has been employed twice for each combination of markets, giving 208 total estimations. Furthermore, the asymmetry in causal linkages has been analysed for both return and volatilities; therefore, the test was conducted on 416 cases overall. In order to structure the analysis and to present empirical results in a clear way, each country in the region has been considered as a recipient of information, as is presented by Table 6.2.

6.3 Asian markets as recipients of positive and negative shocks

The increasing role of Asian financial markets in the world economy has recently attracted much attention to the problem of transmission of volatility shocks within the Asian region and beyond (e.g., Sin, 2013; He et al., 2015; Rughoo & You, 2015). The existing literature has increasingly focused on this issue after the Asian financial crisis of 1997 (e.g., Caporale et al., 2006; Yilmaz, 2010). Parallel to this, the introduction of the stock index futures in Asian markets stimulated a debate about the intensity, speed and directions of international information transmission across futures markets (see e.g., Li, 2015). The application of the Diebold and Yilmaz (2012) methodology presented in previous chapter of this thesis reveals that Asian markets are less susceptible to external shocks and could provide better opportunities for international portfolio diversification. This section further explores the causal linkages of Asian markets with the main contributors of inter-regional information transmission.

6.3.1 Asymmetry in return spillovers across futures markets

Eight markets from Asia region are under investigation as recipients of the information flows originated from positive and negative innovations in return on relative foreign markets, i.e. from Europe and Africa and the Americas regions. The asymmetric causality test has therefore been conducted on 52 pairs of markets for both positive and negative type of shocks, giving the104 Null Hypotheses of absence of causal linkages between markets analysed in this section. Table 6.3 presents the empirical results for each country and the channel of information conveyance: the first column represents the Null Hypothesis which is under consideration; the second column indicates test value; the three subsequent columns present critical values for 1%, 5% and 10% significance levers respectively; and the final column provides the conclusion of rejection or acceptance of the Null hypothesis.

Overall, the Null Hypothesis was rejected for 49 cases (i.e. 47%) indicating the presence of inter-regional causal linkages at different levels of significance. Hence, the evidence of causality was found for 23 out of 49 cases (i.e. 46.9%) at the 1% significance level, 13 cases (i.e. 26.5%) at the 5% significance level, and for 13 cases (i.e. 26.5%) at the 10% significance level. However, the evidence of causality varies across markets, which indicates that some Asian markets are more susceptible to foreign shocks than others.

Table 6.3 The asymmetric causality test results for returns, Asia.

Null Hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%	Conclusion
Hong Kong as a recipient					
TUR + ⇏ HKG +	0.872	9.275	5.743	4.486	TUR + ⇏ HKG +
TUR - ⇏ HKG -	2.106	8.865	5.884	4.455	TUR - ⇏ HKG -
CAN + ⇏ HKG +	3.999	8.739	5.765	4.312	CAN + ⇏ HKG +
CAN - ⇏ HKG -	2.584	9.041	6.169	4.861	CAN - ⇏ HKG -
USA + ⇏ HKG +	4.110	11.432	8.154	6.407	USA + ⇏ HKG +
USA - ⇏ HKG -	4.862	12.401	7.993	6.256	USA - ⇏ HKG -
MEX + ⇏ HKG +	1.628	9.623	6.238	4.571	MEX + ⇏ HKG +
MEX - ⇏ HKG -	3.994	9.224	6.062	4.607	MEX - ⇏ HKG -
BRA + ⇏ HKG +	1.954	9.001	6.089	4.540	BRA + ⇏ HKG +
BRA - ⇏ HKG -	**5.715***	9.071	5.689	4.433	**BRA - => HKG -**
Japan as a recipient					
ESP + ⇏ JPN +	0.935	10.957	6.488	4.673	ESP + ⇏ JPN +
ESP - ⇏ JPN-	**5.559***	8.946	6.034	4.899	**ESP - => JPN-**
RUS + ⇏ JPN +	3.186	9.862	5.472	4.394	RUS + ⇏ JPN +
RUS - ⇏ JPN -	2.820	9.023	5.711	4.318	RUS - ⇏ JPN -
HUN + ⇏ JPN +	0.007	9.047	6.088	4.717	HUN + ⇏ JPN +
HUN - ⇏ JPN -	1.351	8.935	6.090	4.575	HUN - ⇏ JPN -
TUR + ⇏ JPN +	2.098	10.282	6.412	4.797	TUR + ⇏ JPN +
TUR - ⇏ JPN -	**5.630***	9.094	6.115	4.751	**TUR - => JPN -**
ZAF + ⇏ JPN +	0.633	9.355	5.807	4.440	ZAF + ⇏ JPN +
ZAF - ⇏ JPN -	0.981	8.906	6.213	4.426	ZAF - ⇏ JPN -
CAN + ⇏ JPN +	0.066	10.346	6.343	4.590	CAN + ⇏ JPN +
CAN - ⇏ JPN -	**8.851****	10.548	5.886	4.384	**CAN - => JPN -**
USA + ⇏ JPN +	4.427	12.736	7.864	6.579	USA + ⇏ JPN +
USA - ⇏ JPN -	4.555	13.856	9.296	7.658	USA - ⇏ JPN -
MEX + ⇏ JPN +	2.456	11.792	6.109	4.710	MEX + ⇏ JPN +
MEX - ⇏ JPN -	**9.545****	10.567	6.742	5.001	**MEX - => JPN -**
BRA + ⇏ JPN +	3.543	9.453	6.263	4.719	BRA + ⇏ JPN +
BRA - ⇏ JPN -	**7.375****	10.196	6.434	4.991	**BRA - => JPN -**
Singapore as a recipient					
TUR + ⇏ SGP +	**5.759***	8.183	5.897	4.666	**TUR + => SGP +**
TUR - ⇏ SGP -	**5.466***	8.947	5.550	4.247	**TUR - => SGP -**
CAN + ⇏ SGP +	1.000	8.733	5.783	4.505	CAN + ⇏ SGP +
CAN - ⇏ SGP -	0.852	9.586	6.361	4.766	CAN - ⇏ SGP -
USA + ⇏ SGP +	**8.234****	12.837	7.582	6.010	**USA + => SGP +**
USA - ⇏ SGP -	**12.566*****	10.329	7.661	6.160	**USA - => SGP -**
MEX + ⇏ SGP +	**8.981*****	8.508	5.476	4.243	**MEX + => SGP +**
MEX - ⇏ SGP -	**26.351*****	11.478	8.082	6.559	**MEX - => SGP -**
BRA + ⇏ SGP +	**8.298****	9.977	5.947	4.484	**BRA + => SGP +**
BRA - ⇏ SGP -	**19.735*****	11.223	7.621	6.066	**BRA - => SGP -**
China as a recipient					
TUR + ⇏ CHN +	1.223	10.003	6.235	4.486	TUR + ⇏ CHN +
TUR - ⇏ CHN -	0.422	10.704	6.306	4.829	TUR - ⇏ CHN -
CAN + ⇏ CHN +	0.957	9.680	5.673	4.275	CAN + ⇏ CHN +
CAN - ⇏ CHN -	0.201	8.106	5.492	4.334	CAN - ⇏ CHN -
USA + ⇏ CHN +	1.708	11.788	7.739	6.217	USA + ⇏ CHN +
USA - ⇏ CHN -	5.638	11.333	7.648	6.002	USA - ⇏ CHN -
MEX + ⇏ CHN +	2.919	9.547	6.449	4.720	MEX + ⇏ CHN +
MEX - ⇏ CHN -	2.471	10.169	5.880	4.397	MEX - ⇏ CHN -
BRA + ⇏ CHN +	2.167	9.338	6.039	4.340	BRA + ⇏ CHN +
BRA - ⇏ CHN -	1.313	10.336	5.937	4.689	BRA - ⇏ CHN -

Table 6.3 continued

South Korea as a recipient					
ESP + ≠> KOR +	**9.247*****	8.283	5.594	4.439	**ESP + => KOR +**
ESP - ≠> KOR -	**13.016*****	10.404	6.661	4.953	**ESP - => KOR -**
RUS + ≠> KOR +	1.536	10.191	6.098	4.614	RUS + ≠> KOR +
RUS - ≠> KOR -	0.476	8.302	6.001	4.562	RUS - ≠> KOR -
HUN + ≠> KOR +	2.827	9.315	5.887	4.630	HUN + ≠> KOR +
HUN - ≠> KOR -	**10.078*****	8.542	5.933	4.746	**HUN - => KOR -**
TUR + ≠> KOR +	0.232	9.215	6.083	4.715	TUR + ≠> KOR +
TUR - ≠> KOR -	1.889	9.169	5.730	4.434	TUR - ≠> KOR -
ZAF + ≠> KOR +	**6.569****	9.655	5.997	4.648	**ZAF + => KOR +**
ZAF - ≠> KOR -	**22.430*****	8.780	5.768	4.576	**ZAF - ≠> KOR -**
CAN + ≠> KOR +	**5.671***	10.363	6.463	4.779	**CAN + => KOR +**
CAN - ≠> KOR -	2.165	10.146	5.964	4.512	CAN - ≠> KOR -
USA + ≠> KOR +	**6.717***	12.249	7.747	6.096	**USA + => KOR +**
USA - ≠> KOR -	5.837	12.488	9.769	8.073	USA - ≠> KOR -
MEX + ≠> KOR +	1.047	9.968	6.339	4.911	MEX + ≠> KOR +
MEX - ≠> KOR -	**5.983***	8.959	5.749	4.390	**MEX - => KOR -**
BRA + ≠> KOR +	2.604	10.851	6.550	5.057	BRA + ≠> KOR +
BRA - ≠> KOR -	3.431	10.663	5.777	4.633	BRA - ≠> KOR -
Malaysia as a recipient					
TUR + ≠> MYS +	3.756	9.057	6.086	4.603	TUR + ≠> MYS +
TUR - ≠> MYS -	**7.664****	8.694	5.853	4.333	**TUR - => MYS -**
CAN + ≠> MYS +	**12.888*****	9.359	6.311	4.557	**CAN + => MYS +**
CAN - ≠> MYS -	**24.027*****	10.979	7.414	6.015	**CAN - => MYS -**
USA + ≠> MYS +	**7.518***	12.007	8.392	6.388	**USA + => MYS +**
USA - ≠> MYS -	**17.649*****	11.854	7.815	6.244	**USA - => MYS -**
MEX + ≠> MYS +	5.067	12.845	8.544	6.420	MEX + ≠> MYS +
MEX - ≠> MYS -	**11.040*****	10.896	7.340	5.724	**MEX - => MYS -**
BRA + ≠> MYS +	1.845	9.148	5.914	4.810	BRA + ≠> MYS +
BRA - ≠> MYS -	3.906	7.728	5.409	4.230	BRA - ≠> MYS -
Taiwan as a recipient					
GER + ≠> TWN +	**23.883*****	12.809	8.061	6.344	**GER + => TWN +**
GER - ≠> TWN -	**42.466*****	15.140	10.077	8.215	**GER - => TWN -**
FRA + ≠> TWN +	**15.639*****	11.709	7.500	6.438	**FRA + => TWN +**
FRA - ≠> TWN -	**25.158*****	15.381	10.208	8.194	FRA - ≠> TWN -
ESP + ≠> TWN +	**13.784*****	10.150	6.318	5.013	**ESP + => TWN +**
ESP - ≠> TWN -	**8.089****	8.776	5.826	4.470	**ESP - => TWN -**
SUI + ≠> TWN +	**25.578*****	11.792	8.003	6.472	**SUI + => TWN +**
SUI - ≠> TWN -	**28.845*****	15.129	10.200	8.140	**SUI - => TWN -**
RUS + ≠> TWN +	**6.130***	10.385	6.316	4.651	**RUS + => TWN +**
RUS – ≠> TWN -	**5.091***	10.567	6.346	4.817	**RUS – => TWN -**
HUN + ≠> TWN +	**7.672****	9.765	6.128	4.736	**HUN + =>TWN +**
HUN – ≠> TWN -	4.141	10.156	6.270	4.642	HUN – ≠> TWN -
TUR + ≠> TWN +	**5.653***	10.169	5.953	4.523	**TUR + => TWN +**
TUR - ≠> TWN -	**8.918****	9.230	5.764	4.564	**TUR - => TWN -**
ZAF + ≠> TWN +	**10.536****	11.776	7.711	6.183	**ZAF + => TWN +**
ZAF - ≠> TWN -	**10.839*****	9.921	6.174	4.670	**ZAF - => TWN -**
CAN + ≠> TWN +	**8.949****	10.270	5.672	4.258	**CAN + => TWN +**
CAN - ≠> TWN -	**17.895*****	8.330	5.578	4.374	**CAN - => TWN -**
USA + ≠> TWN +	**9.069****	11.584	8.486	6.618	**USA + => TWN +**
USA - ≠> TWN -	**30.448*****	13.141	9.682	8.090	**USA - => TWN -**
MEX + ≠> TWN +	1.959	10.180	5.723	4.323	MEX + ≠> TWN +
MEX - ≠> TWN -	**23.797*****	12.354	7.957	6.251	**MEX - =>TWN -**
BRA + ≠> TWN +	0.467	9.514	6.276	4.817	BRA + ≠> TWN +
BRA - ≠> TWN -	**5.298***	10.008	6.105	4.641	**BRA - => TWN -**
India as a recipient					
CAN + ≠> IND +	0.563	9.831	6.310	4.792	CAN + ≠> IND +
CAN - ≠> IND -	3.065	8.857	6.059	4.369	CAN - ≠> IND -
BRA + ≠> IND +	4.117	9.461	6.052	4.870	BRA + ≠> IND +
BRA - ≠> IND -	1.430	10.465	5.943	4.715	BRA - ≠> IND -

Notes: The critical values for the asymmetric causality test are calculated using a bootstrap algorithm with leverage correction.*The rejection of the Null Hypothesis of no causality at the 10% significance level. **The rejection of the Null Hypothesis of no causality at the 5% significance level; ***The rejection of the Null Hypothesis of no causality at the 5% significance level.

For example, the evidence for China demonstrates that futures returns are not affected by negative or positive shocks transmitted from the futures markets of Turkey, Canada, USA, Mexico and Brazil. The relative independence of the Chinese markets from foreign shocks can be explained from two perspectives. First, due to the fact that stock index futures are comparatively new financial instrument for this market and, as has been mentioned before, stock index futures were introduced in April 2010, and the degree of development and financial integration of this asset may be lower than in the Asian markets. Thus, the first stock index futures contracts traded in China was IFBK10 (04/16/10-05/21/10), in Hong Kong it was HIJ92 (04/01/92-04/29/92), in Taiwan it was FTU98 (07/21/98-09/17/98), in Singapore it was QZV98 (09/07/98-10/30/98), in South Korea it was KMM96 (05/03/96-06/13/96) and in Japan it was NKZ88 (09/05/88-12/08/88). Second, the restricted access to this market for foreign investors, due to its unique institutional arrangement, can cause the isolation of financial futures' markets. In regard to this stance, the Chinese market is potentially attractive from the perspective of international diversification. However, these diversification benefits are not fully available to foreign investors due to the lack of market openness in China. These results also support the position held by Aityan et al. (2010), who indicate that China plays one of the leading roles in the global economy and is relatively isolated from external shocks.

Similar results obtained for India demonstrate that futures returns are not susceptible in terms either of positive nor negative innovations in returns on Canada and Brazil. Furthermore, as is clearly presented in Table 6.3, Hong Kong is also relatively independent from target markets with non-overlapping trading hours. In only 1 out of 10 cases (i.e. 10%) the results show the presence of causal linkages of Brazil and Hong Kong for the negative shock at 10% significance level. Thus, for China, India and Hong Kong the results are consistent with those provided in previous Chapter (See Table 6.2). For instance, the intensity of return transmission from selected foreign markets to China and India is below 1%. For Hong Kong, the highest value of net-pairwise spillover is with Brazil (3.17); overall, therefore, the conclusion could be reached that the decline in returns on Brazil futures market can cause a decline in Hong Kong stock markets.

The evidence from Japan also shows that futures returns are more susceptible from negative rather than positive shocks on foreign markets. The Null Hypothesis has been rejected for 5 out of 18 cases (i.e. 27%) only for the negative innovation i.e. Spain-Japan and Turkey-Japan at 10% significance level, and for Canada-Japan, Mexico-Japan and Brazil-Japan at 5% significance level. Combining the results of the asymmetric causality test with the intensity of return spillovers obtained through a generalized VAR framework, the intensity of spillovers from Spain to Japan is 4.28, i.e. the highest among target markets. Thus, it is evident that the decline in returns on Spanish financial futures causes a decline in returns on Japanese futures markets. Similarly negative shocks occur in Turkey, Canada, Mexico and Brazil can affect Japan, although the net-pairwise return spillovers are much lower and equal 1.15, 1.09, 1.73 and 1.40 respectively. Alternatively, the intensity of spillovers displayed in the previous chapter is higher for the Russia-Japan channel (i.e. 3.28). However, an asymmetric causality test does not reveal any particular causal linkages between negative or positive innovations in returns on these markets.

Meanwhile, for Japan and Hong Kong the results demonstrate clear evidence of asymmetry in causalities between returns, but for Singapore we can say that the returns are susceptible from transmission of both positive and negative type of shocks. The Null Hypothesis has been rejected for 8 out of 10 cases (i.e. 80%), only for Canada-Singapore does the channel asymmetric causality test not reveal any evidence of information transmission. Similar to the Russia-Japan case discussed above, the intensity of spillovers estimated in previous chapter for Canada-Singapore channel (i.e. 2.59) is higher than, for example, for Turkey-Singapore (i.e. 1.51).

However the linkages between positive and negative shocks are not identified. The evidence for the Korean market also does not reflect asymmetric response on information transmission because causalities of both types of innovations have been found. Thus, the Null Hypothesis has been rejected for 8 out of 18 cases (i.e. 44%), which indicates an equal amount of conveyance channels for positive (4 out of 8, 50%) and negative (4 out of 8, 50%) shocks. In particular, for the Spain-Korea and South Africa–Korea cases, the transmission of both types of shocks is evident, yet for other market pairs the results are vary for developed and emerging markets. The results show that Korea is not susceptible to the shocks transmitted from the emerging markets of Russia, Turkey and Brazil. Furthermore, the findings demonstrate that a decline in the futures returns in the markets of Hungary, Mexico and South

Africa can cause a decline in returns on the Korean market, while positive innovations on these markets do not affect Korean markets. Alternatively, futures returns are susceptible to the positive shocks transmitted from Canada and USA, which means that an increase in return on American and Canadian futures can cause the growth of futures returns in Korea.

Taking into account the fact that the Korean markets constitute an emerging market, the conclusion can be reached that Asian emerging markets are more susceptible to negative shocks originating in emerging markets. This evidence is supported by the results obtained for Malaysia. The Null Hypothesis has been rejected for 6 out of 10 cases (i.e. 60%), while the conveyance of negative shocks from emerging markets of Turkey and Mexico is verified at 5% and 1% significance level respectively. Although positive innovations of neither emerging markets can cause a growth in returns on Malaysian market, for the developed markets of Canada and USA the empirical results show evidence of the transmission of both types of shock to the Malaysian market. For the final emerging market in the sample, i.e. Taiwan, the findings indicate numerous causalities with markets with non-overlapping trading hours. The Null Hypothesis has been rejected for 21 out of 24 cases (i.e. 87.5 %). Therefore, among the Asian markets, Taiwan is the main recipient of the shock transmitted from other regions. However, according to results presented in previous chapter, the intensity of return spillovers from other markets to Taiwan is close to zero, with the exception of Russia-Taiwan case (2.09) and Hungary-Taiwan (1.22) channels. These results demonstrated that the asymmetric causality test reveals further channels of inter-regional information transmission, which was not captured by generalised VAR.

In summary, in considering the results presented by Table 6.3 from the perspective of contributors and recipients of return transmission, the following patterns can be identified. Among the 104 total channels of transmission analysed for the Asian region, causal linkages between markets are verified for 49 cases (i.e. 47%), while in 14 cases the recipient is a developed market, and in 35 cases the recipient is an emerging market. For the pairs where the developed market is acting as recipient of information, the Null Hypothesis has been rejected for 14 out of 38 cases (i.e. 36.8%), where 10 cases indicated the transmission of negative shocks and 4 positive shocks. Furthermore, in 7 cases the emerging market is the contributor of shock, while in 7 cases the developed market acts as contributor giving an equal 50-50 distribution. For the pairs where emerging market is acting as recipient of information, the Null Hypothesis has been rejected for 35 out of 66 cases (i.e. 53%), where 19 cases have indicated the transmission of negative shocks and 16 positive shocks. The distribution of cases when emerging or developed markets are acting as contributors is 40-60, i.e. in 14 cases, the emerging market is the contributor of shock and in 21 cases, and the developed market is acting as the contributor of shocks. However, as has been mentioned above, emerging markets are more susceptible to the negative shocks transmitted from emerging markets, which is evident for Korea and Malaysia.

6.3.2 Asymmetry in volatility spillovers across futures markets

In a similar way, the asymmetric causality test has been employed to volatility data in order to investigate the impact of the transmission of information flows originating from positive and negative innovations on the volatility of Asian markets. However, in regard to asymmetry in returns, the results of asymmetric test for volatility spillovers have to be interpreted differently. While a positive shock on return is the identification of bullish market, a positive shock in volatility demonstrates an increase of volatility, which can occur during both a bullish and bearish market. Moreover, a negative shock on return is a sign of decline in the market's returns - i.e. a bearish market - while a decline in volatility can be interpreted as stabilisation of the market. Therefore transmission of the negative volatility shocks from one market to another indicates the stabilising role of spillovers between those markets, i.e. stabilisation of the market-contributor can promote stabilisation of the market-recipient. Thus, it is particularly interesting to compare the evidence obtained for returns with the evidence received for volatility. To ensure clarity of comparison, this section analyses the findings for volatility estimations following the same order suggested by the previous section.

Table 6.4 presents the results for 52 pairs of markets for both positive and negative type of shocks in the volatility of the market-contributor. It is structured in the same way as Table 6.3. Amongst the 104 Null Hypotheses tested in this section the evidence of causality was found for 36 cases (i.e. 34.6%), which is significantly lower than evidence obtained for returns (47%). This supports the results provided by previous chapter, demonstrating that the intensity of volatility spillovers is lower than return spillovers. More specifically, the Null Hypothesis was rejected for 13 out of 36 cases (i.e. 36.1%) at the 1% significance level, for 16 cases (i.e. 44.4 %) at the 5% significance level, and for 7 cases (i.e. 19.4 %) at the 10% significance level.

While the results obtained for returns show that China is not susceptible to any type of shocks originating in foreign market, Table 6.4 demonstrates causality between negative innovation on Mexican market volatility and negative innovations on Chinese market volatility, owing to the fact that the Null Hypothesis is rejected at 10% significance level. However, there is lack of causality among other combinations of the markets, which demonstrates that China is relatively isolated from the foreign shocks. Similar evidence provided for India indicates that the volatility of the Indian market is not affected by either positive or negative volatility shocks transmitted from markets with non-overlapping trading hours, i.e. Canada and Mexico. Comparing the results provided by applications of the generalised VAR methodology outlined in chapter 5, the magnitude of volatility spillovers from target markets is even lower than the magnitude of return spillovers, which makes the results obtained through both methodologies consistent with each other.

Table 6.4 The asymmetric causality test results for volatility, Asia.

Null Hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%	Conclusion
Hong Kong as a recipient					
TUR + ≠> HKG +	1.133	9.258	5.614	4.444	TUR + ≠> HKG +
TUR - ≠> HKG -	0.525	9.389	6.138	4.967	TUR - ≠> HKG -
CAN + ≠> HKG +	3.447	10.571	5.816	4.498	CAN + ≠> HKG +
CAN - ≠> HKG -	2.766	9.751	6.317	4.839	CAN - ≠> HKG -
USA + ≠> HKG +	4.112	11.588	7.853	6.290	USA + ≠> HKG +
USA - ≠> HKG -	1.507	11.842	8.336	6.642	USA - ≠> HKG -
MEX + ≠> HKG +	0.944	10.475	6.306	4.672	MEX + ≠> HKG +
MEX - ≠> HKG -	5.138*	10.390	6.787	4.825	MEX - ≠> HKG -
BRA + ≠> HKG +	**4.748***	9.252	5.860	4.551	**BRA + => HKG +**
BRA - ≠> HKG -	2.365	10.598	6.251	4.699	BRA - ≠> HKG -
Japan as a recipient					
ESP + ≠> JPN +	0.658	9.217	6.152	4.633	ESP + ≠> JPN +
ESP - ≠> JPN-	1.912	8.769	5.712	4.198	ESP - ≠> JPN-
RUS + ≠> JPN +	0.986	9.835	5.954	4.503	RUS + ≠> JPN +
RUS - ≠> JPN -	0.714	9.239	5.683	4.439	RUS - ≠> JPN -
HUN + ≠> JPN +	0.365	8.959	5.933	4.548	HUN + ≠> JPN +
HUN - ≠> JPN -	1.246	9.432	6.162	4.615	HUN - ≠> JPN -
TUR + ≠> JPN +	3.995	10.425	6.144	4.714	TUR + ≠> JPN +
TUR - ≠> JPN -	2.864	9.897	5.975	4.616	TUR - ≠> JPN -
ZAF + ≠> JPN +	**18.407*** **	14.503	9.791	8.070	**ZAF + => JPN +**
ZAF - ≠> JPN -	**9.955*** *	11.278	8.013	6.582	**ZAF - => JPN -**

Table 6.4 continued

CAN + ≠> JPN +	9.108**	9.851	6.234	4.708	CAN + => JPN +
CAN - ≠> JPN -	0.600	10.021	6.075	4.708	CAN - ≠> JPN -
USA + ≠> JPN +	1.451	13.534	9.573	8.050	USA + ≠> JPN +
USA - ≠> JPN -	5.358	13.711	8.239	6.470	USA - ≠> JPN -
MEX + ≠> JPN +	10.161**	11.211	7.391	5.976	MEX += > JPN +
MEX - ≠> JPN -	0.908	9.469	5.943	4.432	MEX - ≠> JPN -
BRA + ≠> JPN +	3.717	9.093	5.946	4.545	BRA + ≠> JPN +
BRA - ≠> JPN -	6.836*	10.861	7.790	6.286	BRA - => JPN -
Singapore as a recipient					
TUR + ≠> SGP +	2.008	10.181	6.065	4.753	TUR + ≠> SGP +
TUR - ≠> SGP -	0.886	9.836	6.340	4.776	TUR - ≠> SGP -
CAN + ≠> SGP +	1.276	12.827	6.391	4.819	CAN + ≠> SGP +
CAN - ≠> SGP -	0.077	13.317	6.419	4.650	CAN - ≠> SGP -
USA + ≠> SGP +	5.485	11.511	8.056	6.466	USA + ≠> SGP +
USA - ≠> SGP -	5.752	13.395	7.969	6.270	USA - ≠> SGP -
MEX + ≠> SGP +	5.088*	10.875	6.058	4.623	MEX + => SGP +
MEX - ≠> SGP -	2.254	9.713	5.655	4.215	MEX - ≠> SGP -
BRA + ≠> SGP +	4.224	9.879	6.188	4.726	BRA + ≠> SGP +
BRA - ≠> SGP -	4.645	11.854	6.462	4.659	BRA - ≠> SGP -
China as a recipient					
TUR + ≠> CHN +	3.939	10.008	6.135	4.521	TUR + ≠> CHN +
TUR - ≠> CHN -	4.462	10.168	6.136	4.574	TUR - ≠> CHN -
CAN + ≠> CHN +	1.535	9.236	6.123	4.802	CAN + ≠> CHN +
CAN - ≠> CHN -	0.260	9.617	6.079	4.725	CAN - ≠> CHN -
USA + ≠> CHN +	5.442	10.994	7.384	5.768	USA + ≠> CHN +
USA - ≠> CHN -	1.814	12.512	7.334	6.234	USA - ≠> CHN -
MEX + ≠> CHN +	0.626	9.795	5.951	4.509	MEX + ≠> CHN +
MEX - ≠> CHN -	4.423*	8.860	5.943	4.256	MEX - => CHN -
BRA + ≠> CHN +	0.570	9.821	6.332	4.869	BRA + ≠> CHN +
BRA - ≠> CHN -	1.534	10.488	6.259	5.007	BRA - ≠> CHN -
South Korea as a recipient					
ESP + ≠> KOR +	13.550***	11.110	6.708	4.917	ESP + => KOR +
ESP - ≠> KOR -	1.910	10.222	6.629	4.595	ESP - ≠> KOR -
RUS + ≠> KOR +	11.251***	9.330	5.508	4.287	RUS + => KOR +
RUS - ≠> KOR -	3.043	12.017	8.448	6.461	RUS - ≠> KOR -
HUN + ≠> KOR +	8.855**	10.739	6.084	4.664	HUN + => KOR +
HUN - ≠> KOR -	2.516	9.050	5.872	4.597	HUN - ≠> KOR -
TUR + ≠> KOR +	4.635	9.113	5.778	4.713	TUR + ≠> KOR +
TUR - ≠> KOR -	1.102	9.074	5.966	4.709	TUR - ≠> KOR -
ZAF + ≠> KOR +	27.548***	9.145	5.626	4.535	ZAF + => KOR +
ZAF - ≠> KOR -	11.892**	12.449	8.596	6.411	ZAF - => KOR -
CAN + ≠> KOR +	1.129	10.385	6.635	4.894	CAN + ≠> KOR +
CAN - ≠> KOR -	4.769*	10.202	5.978	4.597	CAN - => KOR -
USA + ≠> KOR +	3.780	13.066	9.222	7.522	USA + ≠> KOR +
USA - ≠> KOR -	5.853	12.093	8.546	6.304	USA - ≠> KOR -
MEX + ≠> KOR +	7.654**	9.357	6.165	4.643	MEX + =>KOR +
MEX - ≠> KOR -	0.648	10.154	6.755	4.846	MEX - ≠> KOR -
BRA + ≠> KOR +	2.272	11.271	5.941	4.580	BRA + ≠> KOR +
BRA - ≠> KOR -	4.061	10.114	6.213	4.742	BRA - ≠> KOR -
Malaysia as a recipient					
TUR + ≠> MYS +	2.245	8.671	5.900	4.464	TUR + ≠> MYS +
TUR - ≠> MYS -	1.509	9.421	5.706	4.650	TUR - ≠> MYS -
CAN + ≠> MYS +	6.322**	9.896	5.992	4.545	CAN + => MYS +
CAN - ≠> MYS -	8.966**	9.122	5.881	4.684	CAN - => MYS -
USA + ≠> MYS +	9.480**	11.363	7.811	6.340	USA + => MYS +
USA - ≠> MYS -	1.532	12.854	8.705	6.616	USA - ≠> MYS -
MEX + ≠> MYS +	0.407	9.563	6.099	4.443	MEX + ≠> MYS +
MEX - ≠> MYS -	1.081	9.483	5.528	4.575	MEX - ≠> MYS -
BRA + ≠> MYS +	0.018	9.640	6.177	4.533	BRA + ≠> MYS +
BRA - ≠> MYS -	2.990	8.976	5.966	4.545	BRA - ≠> MYS -
Taiwan as a recipient					
GER + ≠> TWN +	34.854***	15.030	9.623	7.573	GER + => TWN +
GER - ≠> TWN -	23.357***	12.577	7.716	6.365	GER - => TWN -
FRA + ≠> TWN +	9.821**	13.373	7.655	6.308	FRA + => TWN +
FRA - ≠> TWN -	17.806***	12.047	8.158	6.563	FRA - => TWN -
ESP + ≠> TWN +	7.048**	8.819	5.606	4.421	ESP + => TWN +
ESP - ≠> TWN -	12.079**	13.907	7.663	6.043	ESP - => TWN -

Table 6.4 continued

SUI + ≠> TWN + SUI - ≠> TWN -	**31.766***** **28.232*****	14.458 13.448	10.028 9.607	8.121 8.176	**SUI + => TWN +** **SUI - => TWN -**
RUS + ≠> TWN + RUS – ≠> TWN -	**8.644**** **5.642***	8.991 10.145	5.863 5.883	4.784 4.444	**RUS + => TWN +** **RUS – => TWN -**
HUN + ≠> TWN + HUN – ≠> TWN -	**7.143**** **5.383***	9.690 9.553	6.318 5.695	4.875 4.590	**HUN + =>TWN +** **HUN – => TWN -**
TUR + ≠> TWN + TUR - ≠> TWN -	0.626 2.562	8.834 10.483	5.854 5.530	4.601 4.383	TUR + ≠> TWN + TUR - ≠> TWN -
ZAF + ≠> TWN + ZAF - ≠> TWN -	**22.471***** **12.140*****	12.523 11.227	8.623 8.081	6.998 6.221	**ZAF + => TWN +** **ZAF - => TWN -**
CAN + ≠> TWN + CAN - ≠> TWN -	2.841 2.628	9.965 9.470	5.763 5.726	4.327 4.353	CAN + ≠> TWN + CAN - ≠> TWN -
USA + ≠> TWN + USA - ≠> TWN -	**22.191***** **9.436****	13.414 11.820	9.698 8.142	8.323 6.460	**USA + => TWN +** **USA - => TWN -**
MEX + ≠> TWN + MEX - ≠> TWN -	**20.325***** 2.287	12.591 8.784	8.168 5.670	6.239 4.520	**MEX + =>TWN +** MEX - ≠> TWN -
BRA + ≠> TWN + BRA - ≠> TWN -	**6.905**** 0.740	8.626 10.364	5.681 5.835	4.566 4.485	**BRA + => TWN +** BRA - ≠> TWN -
India as a recipient					
CAN + ≠> IND + CAN - ≠> IND -	1.817 0.179	8.233 9.653	5.650 6.222	4.378 4.816	CAN + ≠> IND + CAN - ≠> IND -
BRA + ≠> IND + BRA - ≠> IND -	0.346 3.522	9.228 9.704	5.654 6.450	4.467 4.529	BRA + ≠> IND + BRA - ≠> IND -

Notes: The critical values for the asymmetric causality test are calculated using a bootstrap algorithm with leverage correction.*The rejection of the Null Hypothesis of no causality at the 10% significance level. **The rejection of the Null Hypothesis of no causality at the 5% significance level; ***The rejection of the Null Hypothesis of no causality at the 5% significance level.

Besides China and India, the application of the asymmetric causality test to volatility reveals that the Hong Kong stock market is another market in the Asian region which is not susceptible to foreign shocks. The Null hypothesis is rejected for only 1 out of 10 cases (i.e. 10%), showing the existence of causal linkages between Brazil and Hong Kong for the positive shock at 10% significance level. While for returns, evidence of the transmission of the negative shocks can now be provided, indicating that decline in returns in Brazil can cause decline in the returns of stock index futures in Hong Kong market, while the transmission of positive volatility shock shows that increase of volatility on Brazilian markets causes an increase in volatility on the Hong Kong market. Thus, we can draw the conclusion that the transmission of positive volatility shock is associated with bearish markets in this case i.e. decline of return and increase of volatility. These results provide additional evidence supporting the contagion hypothesis, so indicating that the crisis shock originating in Brazil can potentially spread to the Hong Kong market.

As has been mentioned above, there are two alternative interpretations of the transmission of positive and negative volatility shocks, which can be demonstrated using the evidence provided for Japan as a market recipient. Asymmetry in causal linkages across returns was found in the previous section, indicating the conveyance of negative shock only.

However, according to the results presented in Table 6.4, both positive and negative types of shocks may affect volatility of Japanese futures. The Null Hypothesis has been rejected for 5 out of 18 cases (i.e. 27%), where 3 channels of transmission of positive volatility shocks are identified, i.e. South Africa-Japan at 1% significance level, Canada-Japan and Mexico-Japan at 5% significance level; and 2 channels of transmission of negative innovations, i.e. South Africa-Japan at 5% significance level and Brazil-Japan at 10% significance level. Thus, while volatility transmission from South Africa to Japan can be associated with both bearish and bullish market, transmission of the positive volatility shock from Canada and Mexico to Japan will cause an increase in volatility of Japanese futures market. Alternatively, for the Brazil-Japan channel volatility, spillovers can potentially play a stabilising role because the decline in volatility of Brazil may cause a decline in the volatility of Japan.

The evidence for Singapore reveals another important difference in results for returns and volatility. While for returns, the Null Hypothesis has been rejected in 80% of cases, indicating numerous channels of inter-regional return transmission, for volatility the Null Hypothesis has been rejected only for 1 out of 10 cases (i.e. 10%) for positive innovations transmitted from Mexico at 10% significance level. Therefore, results suggest that increases in the volatility of Mexican markets may cause an increase in the volatility of Singapore. These results are especially surprising taking into account the magnitude of volatility spillovers for such markets as the US (i.e. the pairwise return spillover index equals 2.82, while the pairwise volatility spillover index equals 5.34) and Brazil (i.e. the pairwise return spillover index equals 2.45, while pairwise volatility spillover index equals 2.79) are higher than magnitude of return spillovers. Therefore, the empirical results demonstrate that asymmetry in causal linkages across return and volatility may have not only different interpretation from the sign of shocks perspective, but also can reveal different patterns in financial market linkages.

Although the evidence for Korean market also does not reflect asymmetric response on information transmission among return, volatility is more susceptible to positive than negative shocks. The Null Hypothesis has been rejected for 7 out of 18 cases (i.e. 38.9%), which indicates conveyance channels of positive shocks for 5 out of 8 cases (62.5%), and negative shocks for 3 out of 8 cases (37.5%). More specifically, for the South Africa–Korea cases, the transmission of both types of shocks is evident, which is similar for the return transmission, which indicates strong causal linkages between these markets, i.e. Korea is susceptible from changes in both the returns and volatility of South African market. However, for other market pairs the results vary for developed and emerging markets. Similar to the results obtained for returns, the volatility of the Korean futures market is not influenced by changes in volatility of Turkey and Brazil. However, the transmission of positive volatility shocks from the Russian market has been established to support the evidence from Chapter 6; namely, that strong linkages between Russia and South Korea exist (i.e. pairwise the return spillover index equals 4.19 and pairwise volatility spillover index equals 2.62). The transmission of positive volatility shocks from one emerging market to another supports the contagion hypothesis.

The empirical results for Malaysia suggest the rejection of the Null Hypothesis for 3 out of 10 cases (i.e. 30%). Thus, Malaysia is susceptible to both positive and negative volatility shock originating on the Canadian markets. Furthermore, the findings reveal that an increase in the volatility of the futures market of the USA may cause an increase in volatility of the Malaysian futures market, providing further evidence on contagion. Regarding the Taiwan cases, multiple channels of transmission are identified for both types of shocks. The Null Hypothesis has been rejected for 18 out of 24 cases (i.e. 75%). Although the lower number of rejections for returns (i.e. 87.5 %) the evidence suggests that Taiwan is still main recipient of inter-regional information in the Asian region. The findings demonstrate the absence of causal linkages for Canada-Taiwan and the Turkey-Taiwan channels.

Finally, similar to the previous section the results presented in Table 6.4 are to be considered from the perspective of the contributors and recipients of volatility transmission. Among the 104 total channels of transmission analysed for the Asian region, causalities between markets are identifies for 36 cases (i.e. 34.6%), whereas for 7 cases the recipient is a developed market, and for 29 cases the recipient is an emerging market. Thus, for the pairs where the developed market is acting as the recipient of information, the Null Hypothesis has been rejected for 7 out of 36 cases (i.e. 19.4%), where 2 out of 7 cases suggest transmission of negative shocks (i.e. 28.5%) and 5 positive shocks (i.e. 71.4%). From the contributors' perspective, for 6 cases (i.e. 85.7%) the emerging market is the contributor of shock and only in 1 case (i.e. 14.3%) does the developed market act as contributor. For the pairs where emerging market is acting as a recipient of information, the Null Hypothesis has been rejected for 29 out of 36 cases (i.e. 80.6%), where 12 out of 29 cases (i.e. 41.3%) indicate the transmission of negative shocks and 17 cases (i.e. 58.6) positive shocks. Furthermore, in 1 of the 4 cases the emerging market is the contributor of shock and in 15 cases the developed market is acting as contributor of shocks, giving almost an equal (i.e. 48.2%-51.7%) distribution of results.

6.4 European and South African markets as recipients of positive and negative shocks

The results of chapter 5 indicate that the main channels of inter-regional information transmission are from the Americas to Europe and from Europe to the Americas. However, the existence of overlap in trading hours can directly affect the magnitude of the transmission. For example, the strongest magnitude of volatility spillovers was found between developed European countries, i.e. the UK, Germany, France, Spain and Switzerland, where trading hours are fully overlapped. Hence, the intensity of the inter-regional spillover tends to be much lower than intra-regional spillovers. Therefore, investigation of channels of inter-regional return and volatility transmission is relevant for European region; in particular, asymmetric causalities between Asian and European markets require further attention. Besides, the South African market is found to be the third most influential emerging market in the sample, after Mexico and Brazil, according to the results presented by chapter 5. However, in this section South Africa is analysed as the recipient of positive and negative shocks transmitted from Asian markets, enhancing empirical evidence for this market.

6.4.1 Asymmetry in return spillovers across futures markets

There are 8 markets from the Europe and Africa time-zone which are considered as a recipient of the information flows originating from positive and negative innovations in the return on relative markets from the Asian region. The asymmetric causality test was conducted on 22 pairs of markets for both positive and negative types of shocks; thus, the 44 Null Hypotheses of the absence of causal linkages between markets analysed in this section. Table 6.5 presents the empirical results for each county for positive and negative shocks, providing the conclusion of whether the Null hypothesis has to be rejected and at what level of significance 1%, 5% or 10%. Table 6.5 is structured in a similar way to Tables 6.3 and 6.4. In terms of clarity of interpretation of the results, this section follows the logic of Section 6.3.

Table 6.5 The asymmetric causality test results for returns, Europe and Africa.

Null Hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%	Conclusion
Germany as a recipient					
TWN + ≠> GER +	**24.892*** **	11.701	7.390	6.082	**TWN + => GER +**
TWN - ≠> GER -	**31.616*** **	12.655	9.619	7.851	**TWN - => GER -**
France as a recipient					
TWN + ≠> FRA +	**11.106*** **	10.811	7.561	5.999	**TWN + => FRA +**
TWN - ≠> FRA -	**18.448*** **	12.556	9.369	7.755	**TWN - => FRA -**
Spain as a recipient					
JPN + ≠> ESP +	**84.248*** **	10.243	5.963	4.246	**JPN + => ESP +**
JPN - ≠> ESP -	**56.475*** **	8.791	5.816	4.393	**JPN - => ESP -**
KOR + ≠> ESP +	**74.718*** **	9.074	5.820	4.475	**KOR + => ESP +**
KOR - ≠> ESP -	**84.482*** **	8.574	5.875	4.436	**KOR - => ESP -**
TWN + ≠> ESP +	**6.479** **	9.050	6.093	4.714	**TWN + => ESP +**
TWN - ≠> ESP -	1.311	9.962	6.386	4.675	TWN - ≠> ESP -
Switzerland as a recipient					
TWN + ≠> SUI +	**19.068*** **	12.746	8.046	6.257	**TWN + => SUI +**
TWN - ≠> SUI -	**38.717*** **	15.054	9.736	8.165	**TWN - => SUI -**
Russia as a recipient					
JPN + ≠> RUS +	**12.458*** **	8.813	5.963	4.538	**JPN + => RUS +**
JPN - ≠> RUS -	**5.390* **	9.066	5.552	4.370	JPN - ≠> RUS -
KOR + ≠> RUS +	**24.169*** **	10.385	6.480	4.749	**KOR + => RUS +**
KOR - ≠> RUS -	**8.471** **	9.156	6.399	4.967	**KOR - => RUS -**
TWN + ≠> RUS +	2.977	8.230	5.970	4.547	TWN + ≠> RUS +
TWN - ≠> RUS -	4.687	8.737	6.220	4.719	TWN - ≠> RUS -
Hungary as a recipient					
JPN + ≠> HUN +	**25.613*** **	9.075	6.599	4.748	**JPN + => HUN +**
JPN - ≠> HUN -	**11.951*** **	9.822	6.040	4.384	**JPN - => HUN -**
KOR + ≠> HUN +	**28.610*** **	8.358	5.855	4.604	**KOR + => HUN +**
KOR - ≠> HUN -	**21.609*** **	10.547	6.562	4.899	**KOR - => HUN -**
TWN + ≠> HUN +	1.126	10.764	6.048	4.665	TWN + ≠> HUN +
TWN - ≠> HUN -	3.171	9.386	6.225	4.841	TWN - ≠> HUN -
Turkey as a recipient					
HKG + ≠> TUR +	0.815	11.574	6.582	4.952	HKG + ≠> TUR +
HKG - ≠> TUR -	**4.869* **	8.647	5.753	4.498	**HKG - => TUR -**
JPN + ≠> TUR +	**37.940*** **	10.140	6.358	4.996	**JPN + => TUR +**
JPN - ≠> TUR -	**18.454*** **	8.988	5.998	4.623	**JPN - => TUR -**
SGP + ≠> TUR +	**43.955*** **	9.657	6.117	4.617	**SGP + => TUR +**
SGP - ≠> TUR -	**23.844*** **	9.807	6.442	5.022	**SGP - => TUR -**
CHN + ≠> TUR +	3.959	10.729	6.148	4.449	CHN + ≠> TUR +
CHN - ≠> TUR -	3.668	9.076	6.165	4.852	CHN - ≠> TUR -
KOR + ≠> TUR +	**41.910*** **	9.352	6.345	4.832	**KOR + => TUR +**
KOR - ≠> TUR -	**14.251*** **	9.897	5.749	4.550	**KOR - => TUR -**
MYS + ≠> TUR +	0.052	10.229	5.904	4.735	MYS + ≠> TUR +
MYS - ≠> TUR -	3.837	8.766	5.673	4.482	MYS - ≠> TUR -
TWN + ≠> TUR +	2.810	9.015	5.982	4.643	TWN + ≠> TUR +
TWN - ≠> TUR -	4.372	9.633	6.422	4.944	TWN - ≠> TUR -
South Africa as a recipient					
JPN + ≠> ZAF +	**53.523*** **	11.790	6.798	5.044	**JPN + => ZAF +**
JPN - ≠> ZAF -	**38.956*** **	9.328	5.917	4.501	**JPN - => ZAF -**
KOR + ≠> ZAF +	**52.113*** **	10.496	6.481	5.207	**KOR + => ZAF +**
KOR - ≠> ZAF -	**42.238*** **	8.717	5.529	4.521	**KOR - => ZAF -**
TWN + ≠> ZAF +	**23.725*** **	12.639	8.122	6.265	**TWN + => ZAF +**
TWN - ≠> ZAF -	**12.092*** **	8.983	6.204	4.737	**TWN - => ZAF -**

Notes: The critical values for the asymmetric causality test are calculated using a bootstrap algorithm with leverage correction.*The rejection of the Null Hypothesis of no causality at the 10% significance level. **The rejection of the Null Hypothesis of no causality at the 5% significance level; ***The rejection of the Null Hypothesis of no causality at the 5% significance level.

For the European and South African futures returns, the Null Hypothesis has been rejected for 32 out of 44 cases (i.e. 72.7%), which is higher than for the Asian region (i.e. 47%). The evidence of causality was found for 28 out of 32 cases (i.e. 87.5%) at the 1%

significance level, 2 cases (i.e. 6.25%) at the 5% significance level, and also for 2 cases (i.e. 6.25%) at the 10% significance level. Therefore the significance of the results is also higher for this region rather than for Asia. Furthermore, in contrast to Asian markets, none of the target markets from Europe and Africa are fully independent from external shocks.

For the developed European markets of Germany, France and Switzerland, only one contributor of external shocks with non-overlapping trading hours has been considered, i.e. Taiwan. The empirical results show that all markets are susceptible from both positive and negative shocks transmitted from Taiwan. The Null hypotheses have been rejected at 1% significance level. This evidence also highlights that the futures market of Taiwan are not only the main recipient of information, as we found in Sections 6.2 and 6.3, but also the main contributor of inter-regional information. Thus, the evidence for Germany, France and Switzerland supports the same day effect discussed in the literature review, while the markets that opened and closed prior to the target market can influence the returns on this market. Besides, Taiwan has had a strong impact on South African market.

The results for South Africa suggest the rejection of the Null Hypothesis at a 1% significance level for both positive and negative type of shocks. Furthermore, the futures market of Spain is also susceptible from information transmitted from Taiwan. However, the evidence has been found only for causalities of positive innovations, while the Null Hypothesis has been rejected at 5% significance level. This indicates that an increase in the returns in futures market of Taiwan can potentially cause an increase of returns on the Spanish futures market. Alternatively, negative shocks in the Taiwanese market do not affect Spanish stock index futures returns. Furthermore, Table 6.5 shows strong causalities between Spain and Japan and Korea regarding both positive and negative shocks, whether the Null Hypothesis has been rejected at 1% significance level for all cases.

For the emerging European markets of Russia and Hungary, the identified causal linkages are similar to those established for Spain, despite both Russia and Hungary not being susceptible to either positive or negative innovations of Taiwanese futures returns. While for the Japan-Hungary and Korea-Hungary channels, the Null Hypothesis has been rejected for all 4 cases at 1% significance level and for Japan-Russia and Korea-Russia channels the Null Hypothesis for positive innovations has been rejected at 1% level, but for negative at 5% and

10% significance level respectively. Taking into account evidence from other emerging markets in the sample - i.e. Turkey and South Africa - that both of these countries are also susceptible from Japan and Korea, the conclusion may be reached that Japan and Korea have a strong influence on emerging markets in Europe and Africa regions. The African region is represented in this study only by the South African market, while the results indicate that changes in returns on the futures markets of Japan, Korea and Taiwan cause changes in returns on South African futures regarding both directions of changes - i.e. decrease or increase - because the Null Hypothesis has been rejected for 6 out of 6 cases at 1% significance level.

Trading hours on the stock index futures of the Turkish market allow investigation into the largest number of channels of inter-regional spillovers among Europe and Africa markets. Thus, 14 channels of transmission have been investigated for Turkey as a recipient of return shocks, while the Null Hypothesis has been rejected for 7 out of 14 cases (i.e. 50%). The strongest linkages identified for the Japan-Turkey, Singapore-Turkey and Korea-Turkey pairs suggest the presence of causalities for both positive and negative shocks at 1% significance level. For the Hong Kong-Turkey channels, there is evidence of return transmission found only for negative shocks with rejection of the Null Hypothesis at a 10% level of significance. Furthermore, the findings demonstrate that neither China nor Malaysia nor Taiwan impact upon Turkish futures returns. Therefore, from the emerging Asian markets only Korea can affect the dynamic of returns on stock index futures in Turkey.

In summary, similar to Section 6.3 the empirical results of asymmetric causality test are considered from the perspective of contributors and recipients of return transmission. Among the 44 total channels of information conveyance analysed for Europe and Africa, causalities between markets are identified for 32 cases (i.e. 72.7%), whereas for 11 cases (i.e. 34.3%) the recipient is a developed market, and for 21 cases (i.e. 65.60%) the recipient is an emerging market. Thus, for the pairs where the developed market is acting as the recipient of information, the Null Hypothesis has been rejected for 5 out of 11 cases suggesting the transmission of negative shocks (i.e. 45.5%) and 5 positive shocks (i.e. 54.5%). Regarding the results statistics for markets-contributors, for 19 out of 32 cases (i.e. 59.4%) the emerging market is acting as a contributor of shock and in 13 cases (i.e. 40.6%) it is the developed market that is acting as contributor. More specifically, with pairs where the emerging market is acting as the contributor of information, the causal linkages have been verified in 10 out of 19 cases (i.e. 52.6 %), with evidence provided of negative shocks and in 9 cases (i.e. 47.3) of positive shocks.

6.4.2 Asymmetry in volatility spillovers across futures markets

In view of the different interpretations of the asymmetry of volatility transmission, it is important to investigate which markets can potentially be viewed as sources of contagion or, alternatively, stabilising forces for markets in Europe and Africa. As in previous subsections, we have selected similar market combinations to investigate the channels of information transmission between Asia, Europe and Africa. However, the asymmetric test has been employed to volatility data, enhancing the understanding of inter-regional causal linkages between selected futures markets. The results provided by Chapter 5 show that application of a generalised VAR methodology does not reveal volatility transmission between Asia, Europe and Africa for markets with non-overlapping trading hours. The magnitudes of volatility spillovers for all market combinations are close to zero (see Table 6.2), and even lower than relative magnitudes of return spillovers. However, the application of an asymmetric causality test to the stock index futures returns presented in previous subsection shows numerous channels of transmission of both types of shocks, negative and positive. Therefore, it is essential to further investigate these channels of transmission, this time using volatility data to understand the extent to which markets are dependent upon each other.

The transmission of positive and negative volatility shock has been analysed for 22 pairs of markets with non-overlapping trading time, giving 44 channels of information conveyance. Table 6.6 summarises the empirical results in a similar way as Tables 6.3-6.5 above, presenting the results for each market-recipient of the foreign shocks. The Null Hypothesis for each type of shocks - i.e. positive and negative shocks - are tested separately using a bootstrap algorithm with leverage correction to identify critical values at 1%, 5% or 10% significance level. To ensure the clarity of discussion of the results, a similar logic of interpretation of the results is used as in previous sections. For the European and South African futures volatility, the Null Hypothesis has been rejected for 35 out of 44 cases (i.e.

79.5%), which is higher than for returns (i.e. 72.7%), and higher than for volatilities in the Asian region (34.6%). Therefore, while evidence from Asia supports the hypothesis that the intensity of return spillovers is higher than volatility spillovers, the results for Europe and Africa show the reverse pattern.

Table 6.6 demonstrates that evidence of causality was found for 27 out of 35 cases (i.e. 77%) at the 1% significance level, and for 8 cases (i.e. 22.9 %) at the 5% significance level, which indicates high significance of the results from this region. Furthermore, similar to the evidence provided for returns, none of the target markets from Europe and Africa are fully independent from external volatility shocks.

Table 6.6 The asymmetric causality test results for volatility, Europe and Africa.

Null Hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%	Conclusion
Panel A. Asian Region					
Germany as a recipient					
TWN + ≠> GER +	**41.319*** **	13.910	9.870	7.738	**TWN + => GER +**
TWN - ≠> GER -	**15.030*** **	11.652	7.413	5.788	**TWN - => GER -**
France as a recipient					
TWN + ≠> FRA +	**20.007*** **	12.665	8.298	6.394	**TWN + => FRA +**
TWN - ≠> FRA -	**13.788*** **	11.670	7.592	6.100	**TWN - => FRA -**
Spain as a recipient					
JPN + ≠> ESP +	**18.007*** **	9.688	6.597	4.739	**JPN + => ESP +**
JPN - ≠> ESP -	**26.846*** **	10.909	6.268	4.720	**JPN - => ESP -**
KOR + ≠> ESP +	**33.074*** **	9.318	6.290	5.030	**KOR + => ESP +**
KOR - ≠> ESP -	**31.155*** **	9.158	5.867	4.632	**KOR - => ESP -**
TWN + ≠> ESP +	**6.448** **	9.410	5.885	4.378	**TWN + => ESP +**
TWN - ≠> ESP -	**10.454** **	11.953	7.882	6.336	**TWN - => ESP -**
Switzerland as a recipient					
TWN + ≠> SUI +	**45.318*** **	14.585	9.925	7.877	**TWN + => SUI +**
TWN - ≠> SUI -	**25.762*** **	14.134	9.583	7.690	**TWN - => SUI -**
Russia as a recipient					
JPN + ≠> RUS +	3.363	9.427	6.094	4.601	JPN + ≠> RUS +
JPN - ≠> RUS -	**7.588** **	10.006	5.871	4.588	**JPN - => RUS -**
KOR + ≠> RUS +	**8.935*** **	10.132	6.397	4.774	**KOR + => RUS +**
KOR - ≠> RUS -	**37.453*** **	10.872	8.003	6.364	**KOR - => RUS -**
TWN + ≠> RUS +	**9.141** **	9.508	6.209	4.781	**TWN + => RUS +**
TWN - ≠> RUS -	**6.515** **	9.660	6.388	4.982	**TWN - => RUS -**
Hungary as a recipient					
JPN + ≠> HUN +	**13.688*** **	10.943	5.924	4.626	**JPN + => HUN +**
JPN - ≠> HUN -	**18.890*** **	8.938	5.945	4.999	**JPN - => HUN -**
KOR + ≠> HUN +	**24.749*** **	9.888	6.356	4.801	**KOR + => HUN +**
KOR - ≠> HUN -	**35.489*** **	9.814	6.381	4.607	**KOR - => HUN -**
TWN + ≠> HUN +	**10.178*** **	8.982	5.825	4.403	**TWN + =>HUN +**
TWN - ≠> HUN -	**5.845** **	10.233	5.736	4.551	**TWN - => HUN -**
Turkey as a recipient					
HKG + ≠> TUR +	4.291	9.203	6.129	4.945	HKG + ≠> TUR +
HKG - ≠> TUR -	1.266	10.771	6.553	4.644	HKG - ≠> TUR -
JPN + ≠> TUR +	**13.552*** **	11.109	6.202	4.664	**JPN + => TUR +**
JPN - ≠> TUR -	**20.389*** **	9.520	6.577	5.005	**JPN - => TUR -**
SGP + ≠> TUR +	2.136	9.939	6.022	4.573	SGP + ≠> TUR +
SGP - ≠> TUR -	**11.679*** **	9.717	5.780	4.403	**SGP - => TUR -**

Table 6.6 continued

CHN + ≠> TUR + CHN - ≠> TUR -	2.889 2.852	9.625 9.793	6.475 6.133	4.720 4.605	CHN + ≠> TUR + CHN - ≠> TUR -
KOR + ≠> TUR + KOR - ≠> TUR -	**7.159**** **26.605*****	9.806 10.216	6.320 6.076	4.672 4.506	**KOR + => TUR +** **KOR - => TUR -**
MYS + ≠> TUR + MYS - ≠> TUR -	0.858 2.522	8.874 9.915	5.849 6.305	4.472 4.802	MYS + ≠> TUR + MYS - ≠> TUR -
TWN + ≠> TUR + TWN - ≠> TUR -	**7.754**** 2.395	8.668 9.585	5.547 5.970	4.315 4.559	**TWN + => TUR +** TWN - ≠> TUR -
South Africa as a recipient					
JPN + ≠> ZAF + JPN - ≠> ZAF -	**40.322***** **45.923*****	12.791 11.785	9.632 8.175	7.827 6.435	**JPN + => ZAF +** **JPN - => ZAF -**
KOR + ≠> ZAF + KOR - ≠> ZAF -	**23.070***** **46.793*****	8.666 12.443	6.469 7.938	4.893 6.053	**KOR + => ZAF +** **KOR - => ZAF -**
TWN + ≠> ZAF + TWN - ≠> ZAF -	**27.100***** **20.008*****	12.640 13.346	8.006 8.118	6.418 6.440	**TWN + => ZAF** + **TWN - => ZAF -**

Notes: The critical values for the asymmetric causality test are calculated using a bootstrap algorithm with leverage correction.*The rejection of the Null Hypothesis of no causality at the 10% significance level. **The rejection of the Null Hypothesis of no causality at the 5% significance level; ***The rejection of the Null Hypothesis of no causality at the 5% significance level.

The evidence of volatility transmission for developed European markets confirms that Germany, France, Spain and Switzerland are susceptible to both negative and positive volatility shocks originating in the market of Taiwan. In particular, for the Taiwan-Germany, Taiwan-France and Taiwan-Switzerland channels the Null Hypotheses are rejected at 1% significance level, similar to the results obtained for returns transmission. However, the Taiwan-Spain channel analysis of volatility data reveals both the negative and positive volatility shock on Taiwanese markets can affect the volatility of the stock index futures of Spanish markets, while the results for return suggest transmission of negative shocks only. These findings further expand upon the evidence of causalities between Taiwan and Spain.

Furthermore, the application of asymmetric causality for return data did not indicate causal linkages between Taiwan and the emerging markets of Russia, Hungary and Turkey. However, those linkages are verified by utilising the volatility data. Thus, the evidence of transmission of both types of shocks has been established for the Taiwan-Russia and Taiwan-Hungary pairs, while the conveyance of positive volatility innovations is confirmed for the Taiwan-Turkey pair (the Null is rejected at 5% significance level). Therefore, the influential role of Taiwan in inter-regional information transmission is evident for the European market. Another main contributor of volatility shocks is Korea, being that positive and negative innovations of volatility can cause increase and decrease volatility in the futures market of Spain, Russia, Hungary, Turkey and South Africa. Therefore both Korea and Taiwan can play destabilising and stabilising roles in these markets. Similarly, the volatility of the futures markets of Japan can cause changes in the volatility of these markets. More specifically, the no causality hypothesis has been rejected for both types of shocks for Japan-Spain, Japan-Hungary, Japan-Turkey and Japan-South Africa at 1% significance level, while for the Japan-Russia channel of volatility transmission the Null Hypothesis rejected for negative shocks only at 5% significance level. Therefore, it is evident for Russia that stabilising of Japanese futures market, i.e. a decrease in volatility, can promote the stabilising of the Russian market.

The stabilising role of the transmission of negative volatility shocks is also evident for the Singapore-Turkey channel, where the hypothesis of no causalities is rejected at 1% level for the negative innovations, but cannot be rejected for positives. Overall, for the Turkish market, the Null Hypothesis has been rejected for 6 out of 14 cases (i.e. 42.8%). Similar to the return transmission, the strongest linkages between the volatility of futures markets have been identified for the Japan-Turkey (the Null Hypothesis is rejected at 1% significance level for both types of shocks) and Korea-Turkey pairs (the Null Hypothesis is rejected for positive shocks at 5% significance level and for negative at 1% significance level). While the transmission of negative shock in return from Hong Kong to Turkey is found in previous subsection, in regard to volatility transmission Turkey is not susceptible to Hong Kong. Similarly, the results show that China and Malaysia have not impacted on the volatility of the stock index futures of Turkish markets.

Finally, the empirical results of the asymmetric causality test have been considered from the perspective of contributors and recipients of volatility spillovers. There are 44 total channels of transmission analysed for Europe and Africa. Amongst them, for 35 cases (i.e. 79.5%), the hypothesis of no causalities between markets has been rejected, whereas for 12 cases (i.e. 34.2%) the recipient is a developed market, and for 23 cases (i.e. 65.7%) the recipient is an emerging market. Furthermore, the transmission of positive and negative volatility shocks for the pairs where developed market has been verified for equal number of cases (i.e. 6 out of 12). For the market pairs where the emerging market is the recipient of information, the transmission of negative shocks is evident for 12 out of 23 cases (i.e. 52.1%), while the transmission of positive volatility shocks is evident for 11 cases (48.9%). Summarising the results from the perspective of the contributors of volatility, for 25 out of 35 cases (i.e. 71.4%) the emerging market is acting as the contributor of shocks while in 10 cases (i.e. 28.6%) the developed market is acting as contributor. More specifically, for emerging market-contributor pairs the causal linkages of positive innovations has been identified for 13 out of 25 cases (i.e. 52%) and 12 cases (i.e. 48%) for negative innovations. For the developed market-contributor pairs, the Null Hypothesis has been rejected for 4 out of 10 cases (i.e. 40%), indicating causalities between positive innovations, while for 6 cases (i.e. 60%) indicating causalities between negative innovations.

6.5 American markets as recipients of positive and negative shocks

This section provides evidence of inter-regional return and volatility transmission for the markets of North and South America using an asymmetric causality test to investigate the impact of positive and negative shocks separately. The influential role of the US market has been widely analysed in the contagion literature, especially in the context of the Global Financial Crisis (e.g. Aloui et al., 2011; Dimitriou et al., 2013; Bekiros, 2014; Syriopoulos et al., 2015). The contagion from other large developed and emerging markets has been also investigated (e.g. by, Bekaert et al., 2011; Ahmad et al., 2013; Li & Giles, 2014). This section presents the results for the stock index futures markets of Canada, USA, Mexico and Brazil acting as recipients of inter-regional return and volatility shocks transmitted from markets with non-overlapping trading hours. Due to the fact that markets in the Americas region have no overlap in trading hours with Asian markets, it has been possible to investigate multiple channels of return and volatility transmission across the majority of market pairs.

6.5.1 Asymmetry in return spillovers across futures markets

There are 4 markets from the Americas region which are considered as a recipient of the positive and negative shocks in futures returns transmitted by the 8 selected Asian markets, both developed (Hong Kong, Japan, Singapore) and emerging (China, Korea, Malaysia, Taiwan and India). This country selection allows the conducting of an asymmetric causality test on 30 pairs of giving 60 channels of transmission of both positive and negative types of shocks to be analysed. Table 6.7 demonstrates the empirical results for each county for positive and negative shocks, providing a conclusion as to whether causal linkages between markets exist or not. Therefore, critical values at 1%, 5% and 10% have been considered to reject the hypothesis of no causalities.

For the return of stock index futures from the Americas region, the Null Hypothesis has been rejected for 50 out of 60 cases (i.e. 83.3%), which is higher than for Asian (i.e. 47%) and the European and Africa (i.e. 72.7%) regions. The evidence of causality was found for 38 out of 50 cases (i.e. 76%) at the 1% significance level, 7 cases (i.e. 14%) at the 5%

significance level, and for 5 cases (i.e. 10%) at the 10% significance level. Similar to Europe and Africa, and contrary to Asia, none of the markets of Canada, USA, Mexico and Brazil are isolated from external shocks and susceptible to the majority of Asian markets in the sample.

Table 6.7 The asymmetric causality test results for returns, the Americas.

Null Hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%	Conclusion
Canada as a recipient					
HKG + ⇏ CAN +	**12.428*****	8.773	5.937	4.457	**HKG + => CAN +**
HKG - ⇏ CAN -	1.991	10.322	6.679	4.924	HKG - ⇏ CAN -
JPN + ⇏ CAN +	**66.091*****	10.133	6.345	4.809	**JPN + => CAN +**
JPN - ⇏ CAN -	**31.800*****	9.205	6.256	4.677	**JPN - => CAN -**
SGP + ⇏ CAN +	**137.978*****	10.366	6.398	4.729	**SGP + => CAN +**
SGP - ⇏ CAN -	**89.158*****	9.761	6.201	4.626	**SGP - => CAN -**
CHN + ⇏ CAN +	0.820	9.560	6.166	4.704	CHN + ⇏ CAN +
CHN - ⇏ CAN -	2.738	9.216	6.195	4.655	CHN - ⇏ CAN -
KOR + ⇏ CAN +	**103.583*****	9.608	6.051	4.593	**KOR + => CAN +**
KOR - ⇏ CAN -	**89.253*****	9.011	5.604	4.535	**KOR - => CAN -**
MYS + ⇏ CAN +	3.430	9.809	6.059	4.571	MYS + ⇏ CAN +
MYS - ⇏ CAN -	**21.125*****	11.610	8.651	6.631	**MYS - => CAN -**
TWN + ⇏ CAN +	0.166	9.238	5.999	4.707	TWN + ⇏ CAN +
TWN - ⇏ CAN -	**8.068****	9.579	6.103	4.748	**TWN - => CAN -**
IND + ⇏ CAN +	**14.799*****	9.439	6.009	4.533	**IND + => CAN +**
IND - ⇏ CAN -	**6.887****	10.200	6.258	4.610	**IND - => CAN -**
USA as a recipient					
HKG + ⇏ USA +	**22.522*****	11.165	7.989	6.617	**HKG + => USA +**
HKG - ⇏ USA -	5.225	12.180	8.273	6.618	HKG - ⇏ USA -
JPN + ⇏ USA +	**104.125*****	12.840	8.279	6.418	**JPN + => USA +**
JPN - ⇏ USA -	**110.052*****	13.315	9.952	7.863	**JPN - => USA -**
SGP + ⇏ USA +	**178.320*****	10.757	7.639	6.477	**SGP + => USA +**
SGP - ⇏ USA -	**137.842*****	12.002	8.273	6.438	**SGP - => USA -**
CHN + ⇏ USA +	3.980	12.396	7.924	6.093	CHN + ⇏ USA +
CHN - ⇏ USA -	4.600	12.658	8.133	6.554	CHN - ⇏ USA -
KOR + ⇏ USA +	**120.354*****	12.381	7.744	6.096	**KOR + => USA +**
KOR - ⇏ USA -	**121.720*****	14.597	9.768	7.888	**KOR - => USA -**
MYS + ⇏ USA +	**6.805***	12.328	8.099	6.633	**MYS + => USA +**
MYS - ⇏ USA -	**22.874*****	11.300	8.004	6.463	**MYS - => USA -**
TWN + ⇏ USA +	**17.115*****	12.504	7.484	6.079	**TWN + => USA +**
TWN - ⇏ USA +	**47.911*****	14.710	10.086	8.005	**TWN - => USA +**
Mexico as a recipient					
HKG + ⇏ MEX +	**28.187*****	9.148	6.252	4.873	**HKG + =>MEX +**
HKG - ⇏ MEX -	**8.538****	9.376	6.814	5.035	**HKG - => MEX -**
JPN + ⇏ MEX +	**34.769*****	9.638	6.259	4.830	**JPN + => MEX +**
JPN - ⇏ MEX -	**19.203*****	8.561	5.735	4.390	**JPN - => MEX -**
SGP + ⇏ MEX +	**110.157*****	9.103	6.346	4.864	**SGP + => MEX +**
SGP - ⇏ MEX -	**73.439*****	11.251	7.929	6.174	**SGP - => MEX -**
CHN + ⇏ MEX +	**8.134****	9.159	6.167	4.519	**CHN + => MEX +**
CHN - ⇏ MEX -	**5.454***	9.561	5.965	4.637	**CHN - => MEX -**
KOR + ⇏ MEX +	**54.564*****	8.859	6.161	4.692	**KOR + =>MEX +**
KOR - ⇏ MEX -	**26.865*****	10.521	6.061	4.670	**KOR - => MEX -**
MYS + ⇏ MEX +	**12.832*****	10.844	7.994	6.263	**MYS + => MEX +**
MYS - ⇏ MEX -	**17.524*****	11.903	8.031	6.522	**MYS - => MEX -**
TWN + ⇏ MEX +	**5.526***	10.248	6.133	4.670	**TWN + =>MEX +**
TWN - ⇏ MEX -	**11.497*****	10.707	7.861	6.074	**TWN - => MEX -**
Brazil as a recipient					
HKG + ⇏ BRA +	**21.549*****	9.039	5.644	4.602	**HKG + => BRA +**
HKG - ⇏ BRA -	**8.835****	10.009	6.473	4.560	HKG - => BRA -
JPN + ⇏ BRA +	**37.637*****	9.236	6.139	4.819	**JPN + => BRA +**
JPN - ⇏ BRA -	**23.751*****	10.231	6.578	4.739	**JPN - => BRA -**
SGP + ⇏ BRA +	**101.751*****	10.385	5.847	4.500	**SGP + => BRA +**
SGP - ⇏ BRA -	**92.114*****	10.361	7.367	6.000	**SGP - => BRA -**

Table 6.7 continued

CHN + ≠> BRA + CHN - ≠> BRA -	4.473 1.853	9.543 9.895	5.974 6.399	4.516 4.983	CHN + ≠> BRA + CHN - ≠> BRA -
KOR + ≠> BRA + KOR - ≠> BRA -	**57.088***** **35.212*****	9.191 8.962	5.852 6.625	4.731 5.115	**KOR + => BRA +** **KOR - => BRA -**
MYS + ≠> BRA + MYS - ≠> BRA -	**5.655**** **6.434****	9.542 9.348	5.627 6.201	4.498 4.749	**MYS + => BRA +** **MYS - => BRA -**
TWN + ≠> BRA + TWN - ≠> BRA -	**4.834*** **11.715*****	9.630 9.272	6.297 6.253	4.812 4.937	**TWN + => BRA +** **TWN - => BRA -**
IND + ≠> BRA + IND - ≠> BRA -	**9.443***** **6.070***	9.064 9.820	6.087 6.122	4.638 4.807	**IND + => BRA +** **IND - => BRA -**

Notes: The critical values for the asymmetric causality test are calculated using a bootstrap algorithm with leverage correction.*The rejection of the Null Hypothesis of no causality at the 10% significance level. **The rejection of the Null Hypothesis of no causality at the 5% significance level; ***The rejection of the Null Hypothesis of no causality at the 5% significance level.

For Canada, the results suggest the rejection of the Null Hypothesis for 11 out of 16 cases, i.e. for 9 cases at 1% significance level and for 2 cases at 5% significance level. The evidence shows that China futures returns do not affect Canadian markets, US markets and Brazilian markets, which once again justifies the lack of inter-regional linkages of Chinese futures market with other markets. Furthermore, Canada is not susceptible to the transmission of negative shocks from Hong Kong. However, the increase in return on the futures market of Hong Kong can cause an increase in returns on Canadian stock index futures. Alternative evidence found for the Malaysia-Canada and Taiwan-Canada channels, i.e. the causalities of negative innovations are verified at 1% and 5% significance level respectively, while for positive innovations the Null Hypothesis could not be rejected. Amongst developed markets, the main contributors of both positive and negative shocks are the markets of Japan and Singapore, whose causal linkages with Canada are evident (the Null Hypothesis has rejected at 1% significance). Amongst emerging markets, the main contributors are South Korea and India, being that the transmission of both types of shocks from those markets to Canada has been confirmed.

Similar patterns have been identified for the US stock index futures returns. However, 14 channels of return transmission have been considered due to the overlap in trading times between USA and India markets. Thus, the hypothesis of no causalities has been rejected for 11 out of 14 cases (i.e. 78.6%); particularly, for 10 cases at 1% significance level and for 1 case at 10% significance level. Similar to evidence obtained for Canada, the US futures markets are susceptible to both types of shock transmitted from Japan, Singapore and Korea. However, amongst emerging markets the main contributors are also Malaysia and Taiwan.

Overall, the US market does receive information from China, as has been mentioned above, and does not depend on negative shocks in Hong Kong futures markets.

For Mexico, the empirical results indicate that stock index futures returns have causalities with all the selected markets from the Asian region because the Null Hypothesis has been rejected for 14 out of 14 cases (100%), which makes Mexico the main recipient of foreign shocks in the region. The significance level for the majority of cases is 1% (for 10 out of 14 cases, i.e. 71.4%), with lower significance for China-Mexico channels (5% for positive innovations and 10 % for negative innovation), as well as for Hong Kong-Mexico (5% for negative innovations) and Taiwan-Mexico (10% for positive innovations). The evidence for final emerging market-recipient in this region, i.e. Brazil, suggests the rejection of the Null Hypothesis for 14 out of 16 cases (87.5). The asymmetric causality test failed to reject the Null only for China-Brazil channels, indicating the lack of causalities between both positive and negative innovations.

In summary, the results for the Americas region do not reveal any asymmetry in return spillovers because the intensity of transmission of both types of shocks are equally high. In order to provide some statistics for results, Table 6.7 has been considered from the perspective of contributors and recipients of return transmission, following the logic used in the previous section in this Chapter. Therefore, 60 channels of return transmission have been analysed for the Americas region and for 50 cases (i.e. 83.3%), causal linkages between stock index futures markets are verified, whereas in 22 cases (44%) the recipient is the developed market, and in 28 cases (i.e. 56%) the recipient is the emerging market. For the pairs where developed market is acting as a recipient of information, the Null Hypothesis has been rejected in 11 out of 22 cases (i.e. 50%) for negative innovations and in 11 cases (i.e. 50%) for positive innovation, which once again justifies the absence of asymmetry in inter-regional return spillovers. Furthermore, in 10 cases the emerging market is the contributor of shock and in 12 cases the developed market is acting as contributor, giving almost an equal 45.5-54.5 distribution of results and indicating that the identified channels of transmission are not related to the level of market development. For the pairs where the emerging market is acting as recipient of information, the Null Hypothesis has been rejected for 14 out of 28 cases for negative shocks and for 14 cases for positive shocks, again providing equal 50-50 distribution and demonstrating the absence of asymmetry. Furthermore, there are 16 cases where the emerging market is the contributor of shocks and 12 cases where the developed market is acting as a contributor of shocks. Due to the fact that the majority of markets taken into consideration from the Asian region are emerging markets, these findings do not allow us to conclude that the level of development of the market has affected causal linkages across returns on stock index futures.

6.5.2 Asymmetry in volatility spillovers across futures markets

In order to further enhance the understanding of information transmission mechanism between markets with non-overlapping trading times, and particularly how Asian markets may impact markets from the Americas region, volatility data has been utilised for investigation of asymmetric causal linkages. This test has this been conducted for 60 combination of volatility transmission, while the hypothesis of no causalities has been rejected for 49 cases (i.e. 81.6%) as it clearly demonstrated by Table 6.8. The evidence of causality among futures volatility was found for 32 out of 49 cases (i.e. 65.3%) at the 1% significance level, 11 cases (i.e. 22.4%) at the 5% significance level, and also for 6 cases (i.e. 12.2%) at the 10% significance level, which shows that the significance of the results is generally lower for volatility than for returns.

Table 6.8 The asymmetric causality test results for volatility, the Americas

Null Hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%	Conclusion
Canada as a recipient					
HKG + ⇏ CAN +	**10.325****	10.533	6.536	4.800	**HKG + => CAN +**
HKG - ⇏ CAN -	**18.713*****	9.048	5.997	4.336	**HKG - => CAN -**
JPN + ⇏ CAN +	**9.956****	10.143	5.875	4.676	**JPN + => CAN +**
JPN - ⇏ CAN -	**28.292*****	8.818	5.523	4.476	**JPN - => CAN -**
SGP + ⇏ CAN +	**22.384*****	11.136	5.854	4.601	**SGP + => CAN +**
SGP - ⇏ CAN -	**52.514*****	10.878	5.928	4.513	**SGP - => CAN -**
CHN + ⇏ CAN +	3.879	10.952	6.047	4.568	CHN + ⇏ CAN +
CHN - ⇏ CAN -	1.022	8.581	5.597	4.373	CHN - ⇏ CAN -
KOR + ⇏ CAN +	**70.204*****	8.886	6.330	4.608	**KOR + => CAN +**
KOR - ⇏ CAN -	**40.623*****	9.626	5.951	4.306	**KOR - => CAN -**
MYS + ⇏ CAN +	**7.137****	9.949	6.279	5.040	**MYS + => CAN +**
MYS - ⇏ CAN -	1.893	9.053	5.805	4.417	MYS - ⇏ CAN -
TWN + ⇏ CAN +	**5.747***	10.431	6.330	4.727	**TWN + => CAN +**
TWN - ⇏ CAN -	0.109	8.914	5.883	4.524	TWN - ⇏ CAN -
IND + ⇏ CAN +	**9.402*****	8.629	6.051	4.907	**IND + => CAN +**
IND - ⇏ CAN -	**7.174****	10.745	6.215	4.666	**IND - => CAN -**

Table 6.8 continued

USA as a recipient					
HKG + ≠> USA +	**7.830***	13.407	7.912	6.235	**HKG + => USA +**
HKG - ≠> USA -	**25.625*****	11.812	8.030	6.168	**HKG - => USA -**
JPN + ≠> USA +	**48.213*****	17.653	10.610	8.280	**JPN + => USA +**
JPN - ≠> USA -	**52.316*****	12.998	8.210	6.530	**JPN - => USA -**
SGP + ≠> USA +	**31.414*****	12.919	7.955	6.196	**SGP + => USA +**
SGP - ≠> USA -	**60.598*****	13.450	8.541	6.452	**SGP - => USA -**
CHN + ≠> USA +	4.179	12.202	8.240	6.308	CHN + ≠> USA +
CHN - ≠> USA -	**6.536***	11.871	7.902	6.367	**CHN - => USA -**
KOR + ≠> USA +	**87.550*****	14.473	10.284	7.980	**KOR + => USA +**
KOR - ≠> USA -	**73.956*****	13.125	7.913	6.395	**KOR - => USA -**
MYS + ≠> USA +	**13.385*****	11.742	7.874	6.216	**MYS + => USA +**
MYS - ≠> USA -	1.412	12.870	7.910	6.339	MYS - ≠> USA -
TWN + ≠> USA +	**56.733*****	12.316	9.278	7.516	**TWN + => USA +**
TWN - ≠> USA +	**21.105*****	11.349	7.691	6.424	**TWN - => USA +**
Mexico as a recipient					
HKG + ≠> MEX +	**6.180****	9.727	5.965	4.809	**HKG + =>MEX +**
HKG - ≠> MEX -	**28.587*****	9.839	6.332	4.968	**HKG - => MEX -**
JPN + ≠> MEX +	**10.607****	11.334	7.662	5.871	**JPN + => MEX +**
JPN - ≠> MEX -	**22.603*****	9.130	5.782	4.427	**JPN - => MEX -**
SGP + ≠> MEX +	**29.238*****	10.643	5.646	4.463	**SGP + => MEX +**
SGP - ≠> MEX -	**35.952*****	9.911	6.220	4.723	**SGP - => MEX -**
CHN + ≠> MEX +	**5.196***	10.591	6.025	4.411	**CHN + => MEX +**
CHN - ≠> MEX -	**9.722****	10.104	6.413	4.546	**CHN - => MEX -**
KOR + ≠> MEX +	**25.881*****	9.824	6.152	4.729	**KOR + =>MEX +**
KOR - ≠> MEX -	**28.260*****	9.489	6.016	4.691	**KOR - => MEX -**
MYS + ≠> MEX +	**18.667*****	8.811	6.055	4.509	**MYS + => MEX +**
MYS - ≠> MEX -	**6.095****	8.544	5.862	4.386	**MYS - => MEX -**
TWN + ≠> MEX +	**10.091****	11.695	7.985	6.184	**TWN + =>MEX +**
TWN - ≠> MEX -	**8.222****	9.632	5.883	4.557	**TWN - => MEX -**
Brazil as a recipient					
HKG + ≠> BRA +	**11.063*****	9.725	6.016	4.851	**HKG + => BRA +**
HKG - ≠> BRA -	**19.275*****	9.125	6.085	4.578	**HKG - => BRA -**
JPN + ≠> BRA +	**31.912*****	9.420	6.098	4.576	**JPN + => BRA +**
JPN - ≠> BRA -	**45.949*****	13.572	7.404	6.198	**JPN - => BRA -**
SGP + ≠> BRA +	**31.541*****	11.360	6.690	5.112	**SGP + => BRA +**
SGP - ≠> BRA -	**31.012*****	9.212	6.171	4.587	**SGP - => BRA -**
CHN + ≠> BRA +	3.282	9.906	6.267	4.805	**CHN + => BRA +**
CHN - ≠> BRA -	3.256	8.591	5.718	4.602	CHN - ≠> BRA -
KOR + ≠> BRA +	**23.332*****	9.224	6.353	5.065	**KOR + => BRA +**
KOR - ≠> BRA -	**16.739*****	10.246	6.108	4.576	KOR - ≠> BRA -
MYS + ≠> BRA +	**5.393***	9.318	6.340	4.712	**MYS + => BRA +**
MYS - ≠> BRA -	2.767	9.499	5.838	4.491	MYS - ≠> BRA -
TWN + ≠> BRA +	**8.958****	10.516	6.412	4.786	**TWN + => BRA +**
TWN - ≠> BRA -	4.007	10.263	6.128	4.492	TWN - ≠> BRA -
IND + ≠> BRA +	**5.236***	10.132	6.303	4.491	**IND + => BRA +**
IND - ≠> BRA -	4.492	9.869	5.963	4.806	IND - ≠> BRA -

Notes: The critical values for the asymmetric causality test are calculated using a bootstrap algorithm with leverage correction.*The rejection of the Null Hypothesis of no causality at the 10% significance level. **The rejection of the Null Hypothesis of no causality at the 5% significance level; ***The rejection of the Null Hypothesis of no causality at the 5% significance level.

The results for the Canadian market indicate the rejection of the Null Hypothesis for 12 out of 16 cases (i.e. 75%), more specifically, for 7 cases at 1% significance level, for 4 cases at 5% significance level and for 1 case at 10% significance level. The asymmetric causality test for volatility further supports the absence of linkages between China and Canada. Alternatively, similar to the results obtained for the returns causalities, both positive and negative innovations are verified for the Japan-Canada, Singapore-Canada and Korea-Canada volatility transmission channels. Analysis of volatility transmission further justifies the proposition that crisis shocks occurring in Malaysia and Taiwan can be transmitted to Canada leading to decreasing returns and the increasing volatility of Canadian market (the Null Hypothesis has rejected for positive volatility shocks and negative return shocks). Besides, while the results for returns suggest that Canada is not susceptible to the transmission of negative shocks from Hong Kong, but susceptible to positive shocks, the evidence for volatility shows causalities of both types of shocks.

For the US markets the Null Hypothesis has been rejected for 12 out of 14 cases (i.e. 85.7%). Thus, causalities of both types of volatility shocks have been verified for the channels Hong Kong-USA, Japan-USA, Singapore-USA, Korea-USA and Taiwan-USA. The empirical findings also indicate that the positive volatility shocks transmitted from Malaysia can increase volatility on the US markets. Alternatively, for the China-USA channels the results suggest a rejection of the Null for positive innovations, indicating that the decrease in volatility of the Chinese futures can cause a decrease of the volatility of the US stock index futures. However, the Null Hypothesis has been rejected at just 10% significance level. For Mexico, the results obtained for volatility are similar to those were for returns; here, the Null Hypothesis has rejected for 14 out of 14 cases (i.e. 100%) supporting that conclusion that Mexico is the main recipient of foreign information in the region. The findings for Brazil suggest the rejection of the Null Hypothesis for 11 out of 16 cases (i.e. 68.7%). While the asymmetry in return spillovers had not been identified in the previous subsection, the results for the Malaysia-Brazil, Taiwan-Brazil, and India-Brazil shows evidence of the asymmetry in causal linkages between volatilities due to the fact that Brazilian market is susceptible from transmission of only positive volatility shocks. Therefore, the stabilising role of the Asian emerging markets on the Brazilian markets may be identified. Amongst all the markets only China does not impact upon the volatility of stock index futures in Brazil.

Finally, Table 6.8 represents the perspective of contributors and recipients of volatility shock. The causal linkages between stock index futures volatility of markets from Asia and the Americas region have been identified for 49 out of 60 cases (i.e. 81.6), where in 24 cases (48.9%) the recipient is the developed market, and in 25 cases (i.e. 51%) the recipient is the emerging market. In particular, the Null Hypothesis has been rejected in 11 out of 24 cases (i.e. 45.8%) for negative innovations and in 13 cases (i.e. 54.1%) for positive innovation for the pairs where the developed market is acting as a recipient of information. Furthermore, among 24 cases when the recipient is a developed market, 12 cases indicate that the emerging market is the contributor of shocks, while 12 cases indicate the developed market is acting as a contributor, giving an equal 50-50 distribution of results. This shows that the results are not influenced by the level of development of the market contributor. For the pairs where the emerging market is acting as the recipient of information, the Null Hypothesis has been rejected for 11 out of 25 cases for negative shocks and for 13 cases for positive shocks, again providing a 44-52 distribution of the results. Amongst these 25 channels of volatility transmission, in 16 cases the emerging market acts as contributor of shocks and in 12 cases the developed market acts as contributor of volatility shocks.

6.6 Chapter summary

This chapter has analysed the transmission of positive and negative shocks in returns and volatility across markets with non-overlapped trading hours. A total of 104 combinations of markets were analysed, in which the Null Hypothesis of no causality has been tested 416 times - i.e. 208 times for returns and 208 times for volatilities - in order to investigate the transmission of both positive and negative shocks.

Whilst the results from the previous chapter demonstrated limited evidence of inter-regional return and volatility spillover, this chapter has shown numerous rejections of the Null Hypothesis of no causality. Thus, 47% of rejection for returns and 34.6% for volatilities in Asia; 72.7% for returns and 79.5% for volatilities in Europe and Africa; 83.3% for returns and 75% for volatilities in American region. Being that the analysed markets pairs do not have an overlap in trading hours, the main channels of inter-regional information transmission are from Asia to the Americas, from Asia to Europe, from the Americas to Asia (t+1) and from Europe to Asia (t+1). Therefore, the findings obtained from this chapter demonstrate that the strongest intensity of intra-day information transmission is from Asia to the Americas and Europe and Africa, while the intensity of the reverse channels of transmission is rather weak.

This can be explained by different time span when market participants are processing foreign information (Maderitch, 2015). For the channels, i.e. from Asia to Europe and Africa and the Americas, the time span is relatively short, while for reverse channels the time span is longer. Thus, the evidence for Germany, France and Switzerland - which are susceptible from information transmitted from Taiwan - supports the same day effect, i.e. the markets which opened and closed prior to the target market can influence the returns on this market. Alternatively, the results indicate that markets from the Asian region (i.e. China, India and Hong Kong) are not susceptible to foreign shocks. In particular, the findings obtained for China suggests the isolation of this market from the foreign shocks, a proposition supporting the results of Aityan et al. (2010), Aloui et al. (2011), among others.

The results provide evidence of both the destabilising and stabilising volatility spillovers across financial markets, suggesting that the transmission of the positive volatility shocks from one market to another may cause an increase in volatility on the market-recipient, with subsequent contagion of the crisis from the foreign market. Alternatively, the transmission of negative volatility shocks plays a stabilising role in relation to the foreign market, i.e. the decline in volatility in one market causes the decline in volatility of another market.

The spillover effect is therefore found to be asymmetric, with evidence of asymmetry in spillovers for different combination of markets, i.e. developed-developed, emerging-emerging, emerging-developed and developed-emerging (former market is recipient of information). The results suggest that the strongest asymmetry is for market pairs where the recipient is the emerging market, while there is no evidence of asymmetry for developed-developed and developed-emerging market combinations. Furthermore, the empirical results demonstrate that asymmetry in causal linkages across return and volatility may not only have different interpretations from the sign of shocks perspective, but may also reveal different patterns in financial market linkages, being that the results obtained for return spillovers are often different for volatility spillovers.

Chapter 7 International information transmission mechanism and forecasting

7.1 Introduction

The forecasting of returns on financial markets is crucial for asset allocation decision making and investment strategy. Forecasting of future returns is a particularly challenging task due to the variety of factors that can potentially impact on the dynamic of future returns. The previous chapters of this thesis identified numerous channels of intra- and inter-regional information transmission, demonstrating that domestic returns on stock index futures can be susceptible to positive and negative shocks conveyed from foreign markets. However, the question whether information transmission mechanisms can be used in practice to predict domestic returns is still open. This question is critical in order to further investigate the presence of the meteor-shower effect among selected markets. This chapter analyses the ability of information contained on returns from international markets to forecast the performance of domestic returns, i.e. the meteor-shower-like effect, comparing the forecasting performance with a simple AR-model forecast.

The chapter is organized as follows:

Section 7.2 explains the methodology employed to estimate the forecasting ability for returns from foreign markets.

Section 7.3 discusses the empirical results of individual ARDL model forecasts conducted for all 21 markets in the sample. This section is further divided into three subsections; each of these summarizes the results for markets from Asia, Europe and Africa, and the Americas regions.

Section 7.4 presents the results of the forecasting encompass test for bagging and combination forecasts.

Section 7.5 summarises and concludes.

7.2 Methodology

7.2.1 ARDL Model

In order to test research hypotheses H13-H15, this chapter employs the autoregressive distributed lag (ARDL) models to generate the out-of-sample forecast for domestic market returns on stock index futures y_{t+h}^{h} at time *t* for a given predictor $x_{i,t-j}$, denoted by $\hat{y}_{i,t+h|t}^{h}$. Twenty individual ADRL forecasts have been generated for each of the 21 markets (i.e. 420 models overall) in order to compare the significance of each predictor, i.e. information contained in foreign market returns on stock index futures, for forecasting of dependent variable, i.e. domestic market return. The ARDL model can be described using following equation:

$$y_{t+h}^{h} = \propto + \sum_{j=0}^{q_1-1} \beta_j \Delta y_{t-j} + \sum_{j=0}^{q_2-1} \gamma_j x_{i,t-j} + \epsilon_{t+h}^{h}, \qquad (7.1)$$

where ϵ_{t+h}^{h} is an error term; the recursive simulated out-of-sample forecast $\hat{y}_{i,t+h|t}^{h}$ is computed by plugging Δy_{t-j} $(j = 0 \ldots, q_1 - 1)$ and $x_{i,t-j}$ $(j = 0 \ldots, q_2 - 1)$ into equation. 7.1 with the parameters set equal to their OLS estimates based on the data available from the start of the sample through period t, and setting the error term equal to its expected value of zero. The lag lengths in 7.1 are selected using the Schwarz information criterion (SIC) following Rapach and Strauss (2010), where the minimum lag length of 0 for q_1, and 1 for q_2 to ensure that $x_{i,t}$ appears in the model, while the maximum lag length equals 6 for q_1 and 9 for q_2. Due to the fact that the values of q_1 and q_2 vary for each forecast, the lag length may also vary. By conducting this procedure throughout the whole sample *t,* till the end of the out-of-sample period, a series of $P - (h - 1)$ out-of-sample forecast $\{\hat{y}_{BA,t+h|t}^{h}\}_{t=R}^{T-h}$ is generated for the ARDL model containing the predictor $x_{i,t-j}$.

In order to evaluate the predicting ability of foreign information, the recursive simulated out-of-sample forecast is constructed for an AR model using the equation 7.1 with restriction $\gamma_j = 0$ $(j = 0 \ldots, q_2 - 1)$, and the same lag length identification procedure mentioned above, i.e. max lag =6, and min lag = 0. The AR model is the common benchmark for forecasting performance of financial time-series.

7.2.2 The bootstrap aggregating methodology

The bootstrap aggregating methodology was introduced by Breiman (1996) and, in general terms, can be explained as a procedure of reducing the number of predictors by sequentially re-estimating the forecasting model and removing insignificant predictors to improve the forecasting performance. The bootstrap aggregating (bagging) methodology was used by Inoue and Kilian (2008) to forecast US inflation and by Rapach and Strauss (2010) to forecast US employment growth. Both studies highlighted the fact that that the bagging procedure improves the forecasting accuracy of macroeconomic variables. The bagging methodology is particularly useful for forecasting tasks where the dependent variable has a wide range of potential predictors, and whose predictive ability may vary over time. However, this methodology has not yet been employed to stock index futures data. In this chapter, the bagging methodology is employed to forecast returns on stock index futures for each of the 21 markets in the sample, using the returns on other markets as predictors, i.e. 20 predictors for each case.

The bagging methodology starts from the bagging-augmented pretesting procedure developed by Inoue and Kilian (2008). Following Rapach and Strauss (2010), this thesis adopts this procedure to forecast the logarithmic return on futures market y_t at horizon h. For this reason the approximate growth from time t to t+h, can be defined as: $y_{t+h}^{h} = (\frac{1}{h})\sum_{j=1}^{h}\Delta y_{t+j}$, and the pretesting procedure can be described in the following way:

$$y_{t+h}^{h} = \mu + \sum_{j=0}^{q_1-1}\theta\Delta y_{t-j} + \sum_{i=1}^{n}\delta_i x_{i,t} + \varepsilon_{t+h}^{h}, \quad (7.2)$$

where $x_{i,t}$ is n potential predictors (i.e. 20 for each market selected for this thesis), ε_{t+h}^{h} is an error term characterized by autocorrelation of degree $h-1$.

The pretesting procedure estimates equation 7.2 via ordinary least squares computing t-statistics for each of the potential predictors $x_{i,t}$, where q_1 is selected using the Schwarz information criterion (SIC) following Rapach and Strauss (2010). If t-statistics for one of the predictors is less than 1.645 in absolute value, it has to be removed from the model, and equation 7.2 is re-estimated. The forecast of y_{t+h}^{h} is generated by plugging the included $x_{i,t}$ values along with the Δy_{t-j} (j = 0,…, $q_1 - 1$) values into the re-estimated version of (7.2) and setting the error term equal to its expected value of zero. The pretesting procedure uses pseudo-data and OLS to determine which predictors can be included in the model to achieve the best forecasting performance, and then a forecast for actual data is generated. By dividing the complete estimation sample available forΔy_t, and for each of the predictors into in-sample period (i.e. the first *R* observations), and out-of-sample period (i.e. the last *P* observations), the series of $P-(h-1)$ out-of-sample forecasts is generated by using the bagging procedure, which is denoted by $\{\hat{y}_{BA,t+h|t}^{h}\}_{t=R}^{T-h}$.

7.2.3 Forecast combining methodology

Due to the fact that there are many predictors that may affect the behaviour of time-series, the forecast based on a single predictor or a small number of predictors may face substantial model uncertainty and structural instability problems (Rapach & Strauss, 2010). Several studies (e.g., Inoue & Kilian, 2008; Stock & Watson, 1999, 2003, 2004; Rapach & Strauss, 2008, 2010) employed combination forecasts, formed by taking a weighted average of individual ARDL forecasts, to improve the forecasting accuracy and consistently outperform the AR benchmark in terms of a mean square forecast error (MSFE) metric. The calculation of the weights used to combine individual ARDL models requires a holdout period, which is taken from the first P_0 observations from the out-of-sample period. For each market a combination forecast $\{\hat{y}_{CB,t+h|t}^{h}\}_{t=R+P_0}^{T-h}$ is conducted for the post-holdout out-of-sample period $P_h = P-(h-1)-P_o$.

In this chapter, six combining methods are used: the mean, median, trimmed mean, discount MSFE, cluster combining method and principal component. Generally, all the combining methods take the form of a linear combination of the individual forecasts specified by equation. 7.3:

$$\hat{y}^h_{CB,t+h|t} = w_{0,t} + \sum_{i=1}^{n} w_{i,t}\hat{y}^h_{i,t+h|t}, \tag{7.3}$$

where the weights $w_{i,t}$ are estimated for each combining method differently. The mean combining method sets weights for equation 7.3 as $w_{0,t} = 0$ and $w_{i,t} = (1/n)$; the median combining method sets the sample median of $\{\hat{y}^h_{i,t+h|t}\}_{i=1}^{n}$; and the trimmed mean combining methods produces the smallest and the largest forecasts at time *t* setting the weights as $w_{0,t} = 0$ and $w_{i,t} = 0$ for the individual models. Stock and Watson (2003, 2004) indicated that these three simple combining forecast methods work well for forecasting inflation using many predictors. Stock and Watson (2004) also considered the discount MSFE (DMSFE) combining method, where the weights for equation 7.3 sets $w_{0,t} = 0$ and $w_{i,t}$ are estimated as the function of the recent historical forecasting performance of the individual ARDL models. According to the DMSFE method, weights are calculated as:

$$w_{i,t} = m_{i,t}^{-1} / \sum_{j=1}^{n} m_{j,t}^{-1}, \tag{7.4}$$

where

$$m_{i,t} = \sum_{s=R}^{t-h} \varphi^{t-h-s}(y^h_{s+h} - \hat{y}^h_{i,s+h|s})^2, \tag{7.5}$$

and φ is a discount factor. For example, if $\varphi = 1$, there is no discounting, if $\varphi < 1$ greater importance is given to the recent forecasting accuracy of the individual ARDL models. Based on Rapach and Strass (2010), this chapter analyses both situations taking values of $\varphi = 1$ and $\varphi = 0.9$into consideration.

The next combining method, proposed by Aiolfi and Timmermann (2006), is a cluster combining method, which is conditional on combining methods that incorporate persistence in forecasting performance. Their algorithm $C(K, PB)$ starts with grouping the individual ARDL model forecasts over the initial holdout out-of-sample period, $\{\hat{y}^h_{i,s+h|s}\}_{s=R}^{R+(P_0-1)-(h-1)}$, (where $i = 1, \ldots, n$) into K equal-sized clustered based on MSFE. The first cluster contains the individual ARDL models with the lowest MSFE values. The second cluster contains ARDL models with the next lowest MSFE values, and so on. The first combination forecast is the average of the individual ARDL model forecasts of $y^h_{(R+P_0)+h}$ in the first cluster. In forming the second combination forecast, the MSFE for the individual ARDL model forecasts is computed, $\{\hat{y}^h_{i,s+h|h}\}_{i=1}^{R+(P_0-1)-(h-1)+1}$ (where $i = 1,..,n$), and again the individual forecasts are grouped into K clusters. The second combination forecast is the average of the individual ARDL model forecasts of $y^h_{(R+P_0+1)+h}$ included in the first cluster. This procedure is repeated until the end of the available out-of-sample period, where the clusters are formed by computing MSFE using a rolling window. Following Aiolfi and Timmermann (2006), as well as, Rapach and Strauss (2010), K = 2 and K = 3 is employed.

Finally, the principal component combining method is employed, which generates a combination forecast using the first *m* principal components of the individual ARDL model forecasts (Chan, Stock & Watson, 1999; Stock & Watson, 2004, Rapach & Strauss, 2008, 2010). The principal component combining method can be explained in following way:

$$y^h_{s+h} = \theta_1 \hat{F}^h_{1,s+h|s} + \cdots + \theta_m \hat{F}^h_{m,s+h|s} + v^h_{s+h}, \tag{7.6}$$

where $\hat{F}^h_{m,s+h|s}$ is the first *m* principal components of the uncentered second-moment matrix of the individual ARDL model forecast; $s = R, \ldots, t-h$. The combination forecast is given by $\hat{\theta}_1 \hat{F}^h_{1,s+h|s} + \cdots + \hat{\theta}_m \hat{F}^h_{m,s+h|s}$, where $\hat{\theta}_1, \ldots, \hat{\theta}_m$ are the OLS estimates of $\theta_1, \ldots, \theta_m$ respectively in equation 7.6. The value of *m* is selected by using the IC_{p3} information criterion developed by Bai and Ng (2002).

7.2.4 Forecast encompassing tests

In line with methodology suggested by Rapach and Strauss (2010), at the final stage of the analysis the forecast encompassing test is performed to compare the bagging (BA) forecast and combination forecasts (CB). The optimal forecast of y^h_{t+h} as convex combination of CB and BA forecasts is specified by the following equation:

$$\hat{y}^h_{OPT,t+h|t} = \lambda_{CB} \hat{y}^h_{CB,t+h|t} + \lambda_{BA} \hat{y}^h_{BA,t+h|t}, \tag{7.7}$$

where $\lambda_{CB} + \lambda_{BA} = 1$. If $\lambda_{CB} = 0$, then the BA forecasts encompass the CB forecasts, as CB forecasts do not contribute any useful information apart from that already contributed by BA forecasts. If $\lambda_{CB} > 0$, then the BA forecast do not encompass the CB, which represents an opposite situation when BA forecasts do not contain any useful information apart from that already contributed by CB forecasts.

There are two approaches used to test the Null Hypothesis that $\lambda_{CB} = 0$ against the one-sided (upper-tail) alternative hypothesis that $\lambda_{CB} > 0$. First, the approach is suggested by Harvey et al. (1998), who adopted the Diebold and Mariano (1995) procedure to test the Null Hypothesis (i.e. $\lambda_{CB} = 0$). This approach can be explained in the following way. Let $\hat{u}^h_{k,t+h|t} = y^h_{t+h} - \hat{y}^h_{k,t+h|t}$ $(k = BA, CB)$ denote the forecast error associated with $\hat{y}^h_{k,t+h|t}$ and define:

$$\hat{d}^h_{t+h|t} = (\hat{u}^h_{BA,t+h|t} - \hat{u}^h_{CB,t+h|t})\hat{u}^h_{BA,t+h|t}, \tag{7.8}$$

More specifically, the modified version of HLN_h statistics, i.e. suggested by Harvey et al. (1998), the $MHLN_h$ statistics is employed, following Rapach and Strauss (2010):

$$MHLN_h = \left[\frac{P_h+1-2h+P_h^{-1}h(h-1)}{P_h}\right] HLN_h, \tag{7.9}$$

where HLN_h is asymptotically distributed as a standard normal variate under the Null Hypothesis that $\lambda_{CB} = 0$, and denote $[\hat{V}(\bar{d}^h)]^{-1/2}\bar{d}^h$, where $\bar{d}^h = P_h^{-1}\sum_{t=R+P_0}^{T-h} \hat{d}^h_{t+h|t}$; $\hat{V}(\bar{d}^h) = P_h^{-1}(\hat{\omega}_0 + 2\sum_{j=1}^{h-1}\hat{\omega}_j)$, and $\hat{\omega}_j = P_h^{-1}\sum_{t=R+P_0+j}^{T-h}(\hat{d}^h_{t+h|t} - \bar{d}^h)(\hat{d}^h_{(t-j)+h|(t-j)} - \bar{d}^h)$.

A second approach is the Student's *t* distribution with $P_h - 1$ degrees of freedom to test the null hypothesis that $\lambda_{CB} = 0$.

In a similar way, $MHLN_h$ statistics are used to test whether the CB encompasses the BA forecast, i.e. $\lambda_{BA} = 0$ against the alternative hypothesis that the CB does not encompass BA, i.e. $\lambda_{BA} > 0$, hence the Eq. 7.8 can be rewritten as followed:

$$\hat{d}^h_{t+h|t} = (\hat{u}^h_{CB,t+h|t} - \hat{u}^h_{BA,t+h|t})\hat{u}^h_{CB,t+h|t}, \tag{7.10}$$

7.2.5 Data and model specification

This chapter adapts methodology provided by Rapach and Strauss (2010) to test the ability of foreign information to predict returns on the domestic market. The GAUSS codes provided by Rapach and Strauss (2010) are followed to conduct empirical analysis and the daily logarithmic returns on 21 markets from 03 October, 2010 to 02 October, 2015 are utilized, giving 1305 observations in total. The estimation period was divided into an in-sample period from 03 October, 2010 to 03 October, 2014, i.e. 1087 observations, and one year of an out-of-sample period, from 04 October, 2014 to 02 October, 2015, i.e. 261 observations. The combining forecast test requires a holdout of a certain amount of observations from the out-of-sample period. Using the same ratio (holdout observations/out-of-sample observations) as in Rapach and Strauss (2010), the first 181 observations of the out-of-sample period were taken as the holdout period, giving 80 observations for the post-holdout out-of-sample period. The min. and max. lags remain the same, at 0 and 6 respectively.

Finally, the presentation of results in this chapter, obtained for forecasting horizon $h = 1$, instead of 1, 3, and 6, are as suggested by Rapach and Strauss (2010). Due to the specifics of the investigated phenomenon, i.e. meteor-shower effect, only a one-step-ahead forecast can provide evidence of the predictive ability of daily returns on markets that open and close sequentially. A study by Jordan et al. (2014) used a similar methodology and reports that out-of-sample predictability of stock market returns has, by its nature, a short horizon.

7.3 Individual ARDL model forecasts

This section includes the empirical results of individual ARDL model forecasts for each of the 21 markets in the sample. Domestic market returns on stock index futures are taken as dependent variables, while foreign market returns on stock index futures are considered as predictors. For each country, the individual ARDL model forecast is generated for 20 predictors. The performance of an individual ARDL is model compared with the AR benchmark using MSFE criterion, i.e. MSFE ratio (Theil's U statistics= $\frac{MSFE_1}{MSFE_0}$). If the MSFE ratio is equal above unity the individual ARDL forecasts failed to outperform the benchmark. Alternatively, if the MSFE ratio is below unity it means that the individual ARDL forecasts outperform the AR benchmark. In this thesis the decline in MSFE error is assumed to be sizable if it is higher than 5%. The comparison of forecasting performance leads to an enhanced understanding of markets linkages across the globe. The results obtained by this chapter are compared with findings presented in Chapters 5 and 6 of this thesis in order to provide a comprehensive picture of futures markets interconnectedness.

7.3.1 The Asian region

This section discusses the results obtained for the Asian region. There are 20 predictors considered to generate an out-of-sample forecast for each of the returns for eight markets. Table 7.1 records the MSFE for the benchmark AR model forecast and the ratio of the MSFE for the individual ARDL model forecasts to the MSFE for the AR benchmark. Table 7.1 shows that the performance of individual ARDL models varies between markets and predictors. The cases where the market-predictor is situated in different time zones and traded sequentially with target markets are also highlighted in Table 7.1.

Table 7.1 Individual ARDL model forecasting results for 2014:10:03-2015:10:02 out-of-sample period, forecasting horizon =1, Asia.

Hong Kong		Japan		Singapore		China	
Predictor	**Ratio**	**Predictor**	**Ratio**	**Predictor**	**Ratio**	**Predictor**	**Ratio**
AR-model MSFE = 0.0001611		**AR-model MSFE** = 0.0001722		**AR-model MSFE** = 0.0001085		**AR-model MSFE** = 0.0001632	
JPN	1.01	**HKG**	1.00	**HKG**	1.01	**HKG**	1.00
SGP	1.00	**SGP**	1.00	**JPN**	1.00	**JPN**	1.00
CHN	1.00	**CHN**	1.00	**CHN**	1.00	**SGP**	1.00
KOR	1.01	**KOR**	0.99	**KOR**	1.00	**KOR**	1.00
MYS	1.00	**MYS**	1.00	**MYS**	1.00	**MYS**	1.00
TWN	1.00	**TWN**	1.00	**TWN**	1.00	**TWN**	1.00
IND	1.01	**IND**	1.00	**IND**	1.00	**IND**	0.99
GBR	1.01	**GBR**	1.00	**GBR**	0.99	**GBR**	0.99
GER	1.00	**GER**	1.00	**GER**	1.00	**GER**	1.01
FRA	0.99	**FRA**	1.00	**FRA**	0.98	**FRA**	1.00
ESP	0.98	**ESP**	0.98	**ESP**	0.99	**ESP**	0.97
SUI	1.03	**SUI**	1.02	**SUI**	0.96	**SUI**	0.99
RUS	0.99	**RUS**	1.00	**RUS**	1.00	**RUS**	1.00
HUN	0.98	**HUN**	0.94	**HUN**	1.00	**HUN**	0.98
TUR	0.98	**TUR**	1.00	**TUR**	0.99	**TUR**	0.99
ZAF	0.94	**ZAF**	0.94	**ZAF**	0.96	**ZAF**	0.93
CAN	0.98	**CAN**	0.97	**CAN**	0.96	**CAN**	1.01
USA	0.98	**USA**	0.97	**USA**	0.97	**USA**	0.96
MEX	1.01	**MEX**	0.84	**MEX**	0.95	**MEX**	0.86
BRA	1.00	**BRA**	0.92	**BRA**	0.93	**BRA**	0.96
Korea		**Malaysia**		**Taiwan**		**India**	
Predictor	**Ratio**	**Predictor**	**Ratio**	**Predictor**	**Ratio**	**Predictor**	**Ratio**
AR-model MSFE = 0.0001661		**AR-model MSFE** =0.0001708		**AR-model MSFE** = 0.0001661		**AR-model MSFE** =0.0001615	
HKG	1.01	**HKG**	1.00	**HKG**	1.00	**HKG**	1.00
JPN	1.00	**JPN**	1.00	**JPN**	1.00	**JPN**	1.00
SGP	1.00	**SGP**	1.00	**SGP**	1.00	**SGP**	1.00
CHN	1.00	**CHN**	1.00	**CHN**	1.00	**CHN**	0.99
MYS	1.00	**KOR**	1.01	**KOR**	1.00	**KOR**	1.00
TWN	1.00	**TWN**	1.00	**MYS**	1.00	**MYS**	0.99
IND	1.00	**IND**	1.01	**IND**	1.00	**TWN**	1.00
GBR	1.01	**GBR**	1.01	**GBR**	1.01	**GBR**	1.01
GER	1.01	**GER**	1.01	**GER**	1.00	**GER**	0.99
FRA	1.01	**FRA**	1.01	**FRA**	1.01	**FRA**	1.01
ESP	0.99	**ESP**	0.98	**ESP**	0.98	**ESP**	0.98
SUI	1.01	**SUI**	1.01	**SUI**	1.01	**SUI**	1.01
RUS	1.03	**RUS**	1.03	**RUS**	1.02	**RUS**	1.03
HUN	1.02	**HUN**	1.02	**HUN**	1.01	**HUN**	1.01
TUR	0.99	**TUR**	1.00	**TUR**	1.00	**TUR**	1.00
ZAF	1.00	**ZAF**	1.00	**ZAF**	1.00	**ZAF**	0.98
CAN	0.96	**CAN**	0.96	**CAN**	0.95	**CAN**	0.95
USA	0.96	**USA**	0.96	**USA**	0.97	**USA**	0.96
MEX	0.92	**MEX**	0.95	**MEX**	0.93	**MEX**	0.92
BRA	0.93	**BRA**	0.92	**BRA**	0.93	**BRA**	0.92

Notes: The entries for the AR benchmark model report the MSFE; the other entries report the MSFE Ratio (MSFE of Individual ADRL/MSFE of AR benchmark); the highlighted entries indicate the markets with non-overlapping trading hours.

The number of entries with an MSFE ratio below unity is 61 out of 160 (i.e. 38%). For the majority of cases, the individual ARDL forecasts failed to outperform AR benchmark forecasts. More specifically, for the developed markets, such as Hong Kong, 8 out of 20 variables are significant for the forecasting of domestic market returns, and for Japan and

Singapore the figures are 8 and 10, respectively. However, the number of predictors that demonstrated relative forecasting accuracy varies significantly between emerging markets; while 10 and 9 are identified for China and India, for other markets, i.e. Korea, Malaysia and Taiwan, the number of important predictors are 6, 5 and 5 respectively. For developed Asian markets, the average is 41% with, from 40% to 50%)of cases outperforming the AR benchmark, while for emerging markets the average figure is 35% (i.e. from 25% to 50%).

The predictive power of individual ARDL models also varies. For the emerging markets of Korea, Malaysia, Taiwan, India, and China the ARDL models produce average declines in MSFE of 4.2%, 4.6%, 4.8%, 3.6% and 3.8% respectively, while for the developed Asian markets of Hong-Kong and Singapore the average declines in MSFE are 2.2%, 5.6% and 3.2% respectively. The results presented in Table 7.1 allow a range identifying the significance of predictors for each market. The following patterns are identified for the Asian region.

According to the results, the markets with non-overlapping trading hours have higher forecasting power than markets with an overlap in trading hours. For each country, the most influential foreign predictors are situated in different geographical time-zones. For example, Table 7.1 shows that South Africa has the highest predicting power on the stock index futures of Hong Kong, producing an MSFE decline of 6 %, while other predictors generate declines in MSFE between 1-2%. For Japan, several markets demonstrated the most sizable decline in MSFE, where all the market-predictors are from other time-zones, i.e. Europe and Africa (Hungary, 6%; South Africa, 6%), and the Americas (Mexico, 16%; Brazil, 8%). Among ARDL model forecasts, constructed for the Singapore market, the strongest predictors are the emerging markets from the American region (Mexico, 5% and Brazil 7%). These results indicate that returns on developed Asian markets can be predicted by emerging markets from other regions.

Similar patterns are identified for emerging Asian markets. For China (the market which was found to be comparatively isolated from foreign shocks, as evidenced by the results presented in both Chapters 5 and 6, the sizable reduction of MSFE error, i.e. 14%, achieved by the ARDL model, used Mexico as a predictive variable. This corresponds to established causality between negative innovation on Mexican market volatility and negative innovations on Chinese market volatility (see Chapter 6, Table 6.4), indicating that decline in volatility and stabilization of the Mexican market can cause a decline in volatility in China. Although the results of asymmetric causality tests for returns have not revealed causal linkages of China with any other market, the ability of the Mexican market to predict Chinese stock index futures returns is still the strongest in the sample. For the rest, the emerging Asian markets display similar patterns. There is significant predicting power on Chinese markets, demonstrated by South Africa (7%), although their stock markets have an overlap in trading times. One of the possible explanations is that both South Africa and China are from the BRICS grouping and interlinked by several economic and political agreements.

The overall influential role of Mexico and South Africa is supported by the findings from Chapter 6 of this thesis and illustrates that among emerging markets, the highest return spillover was detected from Mexico, Brazil and South Africa. The performance of individual ARDL models further proves these findings. Mexico and Brazil have also demonstrated the best relative forecasting performance for Korea (Mexico, 8%; Brazil, 7%), Malaysia (Mexico, 5%; Brazil 8%), Taiwan (Mexico, 7%; Brazil, 7%) and India (Mexico, 8%; Brazil, 8%). With only one exception, the India-Brazil pair, all the market-predictors have non-overlapping trading hours with Asian markets. Among market combinations with overlapping trading hours, the ARDL model used Brazil to predict India futures returns and demonstrated the best relative forecasting performance, because for other predictors, the average declines in MSFE between 1-2%, which shows the absence of the predictive power of return transmission across markets with overlapping trading hours.

Based on the results obtained for the Asian region, the conclusion can be reached that the predictive power of meteor-shower-like effect of return transmissions across markets with non-overlapping trading hours is stronger than the predictive power of return transmissions across markets with overlapping trading hours. This provides supporting evidence for same day effect and meteor shower hypotheses. While existing literature suggests the predictive power of the US (e.g., Pan & Hsueh, 1998; Rapach et al., 2013), the results show that although the ARDL forecasts models employed the US futures return as predictor were able to outperform the AR benchmark for all Asian markets in the sample, the declines in MSFE were not sizable and between 2-4%.

7.3.2 Europe and Africa

The relative forecasting performance of the individual ARDL models over the AR benchmark is analysed for stock index futures in the regions of Europe and Africa. This section tabulates the empirical results. First, the statistics on results summarized by Table 7.2 are discussed. The total number of models that demonstrated an MSFE ratio below unity (Theil's U statistics) is 60 out of 180 (i.e. 33%), therefore, for the majority of cases the individual ARDL forecasts failed to outperform the AR benchmark forecasts. This percentage is lower than for the Asian region (38%). In contrast to the Asian region, where the number of models that demonstrated relative forecasting accuracy, varied significantly among markets (especially emerging), the evidence for Europe and Africa shows that the number of ARDL forecasts that outperform the AR benchmark is almost equal for each market, and ranged between 6-7 for each.

Table 7.2 Individual ARDL model forecasting results for 2014:10:03-2015:10:02 out-of-sample period, forecasting horizon =1, Europe and Africa.

UK		Germany		France	
Predictor	**Ratio**	**Predictor**	**Ratio**	**Predictor**	**Ratio**
AR-model MSFE = 0.0001636		**AR-model MSFE** = 0.0001724		**AR-model MSFE** = 0.0001661	
HKG	1.01	**HKG**	1.00	**HKG**	1.00
JPN	1.00	**JPN**	1.00	**JPN**	1.00
SGP	1.00	**SGP**	1.00	**SGP**	1.01
CHN	1.00	**CHN**	1.00	**CHN**	1.00
KOR	1.01	**KOR**	1.01	**KOR**	1.01
MYS	1.00	**MYS**	1.01	**MYS**	1.00
TWN	1.00	**TWN**	1.00	**TWN**	0.99
IND	1.01	**IND**	1.01	**IND**	1.01
GER	1.01	**GBR**	1.01	**GBR**	1.00
FRA	1.01	**FRA**	1.01	**GER**	1.01
ESP	0.98	**ESP**	0.98	**ESP**	0.98
SUI	1.01	**SUI**	1.01	**SUI**	1.01
RUS	1.04	**RUS**	1.04	**RUS**	1.03
HUN	1.01	**HUN**	1.02	**HUN**	1.02
TUR	1.00	**TUR**	1.00	**TUR**	1.00
ZAF	0.98	**ZAF**	0.98	**ZAF**	0.98
CAN	0.95	**CAN**	0.96	**CAN**	0.96
USA	0.97	**USA**	0.98	**USA**	0.98
MEX	0.94	**MEX**	0.96	**MEX**	0.96
BRA	0.94	**BRA**	0.95	**BRA**	0.95
Spain		**Switzerland**		**Russia**	
Predictor	**Ratio**	**Predictor**	**Ratio**	**Predictor**	**Ratio**
AR-model MSFE = 0.000166		**AR-model MSFE** = 0.0001691		**AR-model MSFE** = 0.0001786	
HKG	1.00	**HKG**	1.01	**HKG**	1.02
JPN	1.00	**JPN**	1.00	**JPN**	1.00
SGP	1.01	**SGP**	1.00	**SGP**	1.01
CHN	1.00	**CHN**	1.00	**CHN**	1.01
KOR	1.01	**KOR**	1.01	**KOR**	1.01

Table 7.2 continued

MYS	1.00	**MYS**	1.00	**MYS**	1.00
TWN	0.99	**TWN**	0.99	**TWN**	0.99
IND	1.01	**IND**	1.01	**IND**	1.02
GBR	1.01	**GBR**	1.00	**GBR**	1.00
GER	1.01	**GER**	1.01	**GER**	1.00
FRA	0.98	**FRA**	0.98	**FRA**	0.99
SUI	1.01	**ESP**	1.01	**ESP**	1.02
RUS	1.04	**RUS**	1.04	**SUI**	1.03
HUN	1.02	**HUN**	1.01	**HUN**	1.01
TUR	1.00	**TUR**	1.00	**TUR**	1.01
ZAF	0.98	**ZAF**	0.98	**ZAF**	1.00
CAN	0.97	**CAN**	0.96	**CAN**	0.96
USA	0.97	**USA**	0.97	**USA**	0.95
MEX	0.96	**MEX**	0.97	**MEX**	0.96
BRA	0.93	**BRA**	0.91	**BRA**	0.90
Hungary		**Turkey**		**South Africa**	
Predictor	**Ratio**	**Predictor**	**Ratio**	**Predictor**	**Ratio**
AR-model MSFE = 0.0001367		**AR-model MSFE** = 0.0001323		**AR-model MSFE** = 0.000129	
HKG	1.01	**HKG**	1.02	**HKG**	1.01
JPN	0.99	**JPN**	1.00	**JPN**	0.97
SGP	1.00	**SGP**	1.00	**SGP**	1.00
CHN	1.00	**CHN**	1.00	**CHN**	1.01
KOR	1.01	**KOR**	1.01	**KOR**	1.02
MYS	1.00	**MYS**	1.00	**MYS**	1.01
TWN	0.99	**TWN**	0.99	**TWN**	0.99
IND	1.03	**IND**	1.02	**IND**	1.03
GBR	1.00	**GBR**	1.01	**GBR**	1.00
GER	0.99	**GER**	0.99	**GER**	0.99
FRA	1.01	**FRA**	1.01	**FRA**	1.01
ESP	1.00	**ESP**	0.99	**ESP**	0.97
SUI	1.02	**SUI**	1.05	**SUI**	1.02
RUS	1.00	**RUS**	0.99	**RUS**	1.00
TUR	1.01	**HUN**	1.02	**HUN**	1.02
ZAF	1.00	**ZAF**	1.00	**TUR**	1.01
CAN	0.92	**CAN**	0.91	**CAN**	0.92
USA	0.99	**USA**	1.00	**USA**	1.00
MEX	0.96	**MEX**	0.96	**MEX**	0.96
BRA	0.90	**BRA**	0.89	**BRA**	0.89

Notes: The entries for the AR benchmark model report the MSFE; the other entries report the MSFE Ratio (MSFE of Individual ADRL/MSFE of AR benchmark); the highlighted entries indicate the markets with non-overlapping trading hours.

The average declines in MSFE ratio also varies less than in the Asian region, i.e. from 3.1% to 4.4% (versus from 2.2% to 5.6% in Asia). However, similarly to Asia, only a few models can provide a sizable reduction in MSFE in comparison to the AR benchmark. The following patterns are identified for the European and African regions.

First, there is a lack of evidence that the predictive power of meteor-shower-like effect across markets with non-overlapping trading hours is more pronounced than across markets with overlapping trading hours. The out-of-sample forecasts, built using the returns of the markets with non-overlapping trading hours, either failed to outperform the AR benchmark or produced a reduction in MSFE of just 1%. Absence of overlap in trading times applies only in predictors from Asia, so the conclusion can be reached that returns on the Asian markets are not able to forecast European and African returns.

As with the previous subsection, the results for Europe and Africa contradict main stream literature, because no significant predictive power of the US is found for the target country panel (0-3% MSFE declines). The one exception is the 5% decline in MSFE generated by the ARDL model that used the US returns to build an out-of-sample forecast for Russia. Alternatively, among the developed market-predictors the most influential market for Europe and Africa is Canada, which suggests an ability to forecast in the emerging markets of Hungary, Turkey and South Africa and is established with declines in MSFE of 8%, 9% and 8% respectively.

While Mexico demonstrated significant ability to forecast the majority of futures returns in Asia, it does not have predictive power for Europe and Africa (i.e. the highest MSFE decline 6% in forecasting of the UK market, for the rest declines range from 3-4%). However, Brazil showed the best relative forecasting performance for the majority of markets with a decreasing MSFE ratio of 6% for UK, 5% for Germany and France, 7% and 9% for Spain and Switzerland, 10% for Russia and Hungary, and 11 % for Turkey and South Africa. These findings are supported by the results reported in Chapter 5 and the conclusion that Brazil is one of the main contributors to return spillovers among emerging markets.

Overall, the foreign markets that open and close before European and African markets open do not demonstrate predictive power. The Asian markets could not predict returns in Europe and Africa. However, the forecasting abilities of markets situated in different regions are still more pronounced in comparison to the predictive power of markets from the same region. For example, for the case of Germany among all the predictors from Europe and Africa, only two ARDL modes, which used Spain and South Africa, were able to outperform the AR benchmark. The declines in MSFE are not sizable (2% and 1%). These results are evident for all markets in this region. Both emerging and developed markets from the Americas region demonstrated sizable reduction in MSFE for the majority of out-of-sample forecasts. These results provide further evidence on the channels of information transmission, indicating that returns on the American market affect European returns.

To further clarify the channels of information transmission, it is necessary to investigate the predictive power of foreign information for the final region in the sample – the Americas.

7.3.3 The Americas

Previous subsections provide the evidence of the predictive power of the American markets to forecast returns in the regions of Asia, Europe and Africa It is worthwhile to consider the futures returns of the US, Canada, Mexico and Brazil from another perspective, that is, as dependent variables. This is particularly relevant for the developed markets of the US and Canada. For example, while the ability of the US returns to predict information on foreign markets has been widely studied (Pan & Hsueh, 1998; Rapach et al., 2013), the issue of , whether foreign markets are able to predict US stock market return is relatively unexplored. Table 7.3 summarizes the results of an individual ARDL forecasting model, indicating the forecasting accuracy of each predictor over the AR-model benchmark.

Table 7.3 Individual ARDL model forecasting results for 2014:10:03-2015:10:02 out-of-sample period, forecasting horizon =1, the Americas.

Canada		USA		Mexico		Brazil	
Predictor	**Ratio**	**Predictor**	**Ratio**	**Predictor**	**Ratio**	**Predictor**	**Ratio**
AR-model MSFE = 0.0001309		**AR-model MSFE** = 0.000128		**AR-model MSFE** = 0.000132		**AR-model MSFE** = 0.0001416	
HKG	1.02	**HKG**	1.02	**HKG**	1.01	**HKG**	1.01
JPN	0.98	**JPN**	1.00	**JPN**	0.98	**JPN**	1.00
SGP	0.99	**SGP**	1.00	**SGP**	1.00	**SGP**	0.99
CHN	1.00	**CHN**	1.01	**CHN**	1.01	**CHN**	0.98
KOR	1.00	**KOR**	1.02	**KOR**	1.01	**KOR**	0.99
MYS	1.00	**MYS**	1.00	**MYS**	1.00	**MYS**	1.00
TWN	0.99	**TWN**	0.99	**TWN**	0.99	**TWN**	0.99
IND	1.02	**IND**	1.02	**IND**	1.01	**IND**	0.99
GBR	0.99	**GBR**	1.01	**GBR**	1.00	**GBR**	0.98
GER	0.99	**GER**	0.99	**GER**	1.00	**GER**	0.98
FRA	1.01	**FRA**	1.01	**FRA**	1.01	**FRA**	1.00
ESP	0.97	**ESP**	0.99	**ESP**	0.98	**ESP**	0.97
SUI	1.02	**SUI**	1.02	**SUI**	1.02	**SUI**	1.01
RUS	0.99	**RUS**	0.99	**RUS**	1.00	**RUS**	0.99
HUN	1.01	**HUN**	1.03	**HUN**	1.04	**HUN**	1.00
TUR	1.01	**TUR**	1.02	**TUR**	1.00	**TUR**	0.99
ZAF	0.93	**ZAF**	0.93	**ZAF**	0.96	**ZAF**	1.00
USA	1.00	**CAN**	1.01	**CAN**	1.00	**CAN**	0.99
MEX	0.95	**MEX**	0.96	**USA**	0.95	**USA**	0.93
BRA	0.91	**BRA**	0.90	**BRA**	0.91	**MEX**	0.90

Notes: The entries for the AR benchmark model report the MSFE; the other entries report the MSFE Ratio (MSFE of Individual ADRL/MSFE of AR benchmark); the highlighted entries indicate the markets with non-overlapping trading hours.

The total number of ARDL forecasts that outperformed the AR benchmark, according to MSFE ration criterion, is 36 out of 80 (i.e. 45%). For Canada, 10 models outperformed the AR benchmark, with an average decline in MSFE of 3.1%, for the US, 7 models outperformed, with 3.5%, for Mexico, 6 models, with 3.8% and for Brazil, 13 models, with 2.5% respectively.

These results show that for American futures markets the strongest predictors are returns on stock index futures of the markets from the same geographical region, which provides evidence of the significance of intra-regional information transmission. The findings in Chapter 5 suggested that the strongest linkages between emerging and developed stock markets are within the Americas region. The out-of-sample forecast also supports this contention, because the best relative forecasting performance for the developed markets of Canada, as demonstrated by individual ARDL models, utilized Brazil (the decline in MSFE of 9%) and Mexico (5%). For the US market the best predictor is Brazil (10%). The best predictor of emerging markets in the region for Mexico are Brazil (10%) and the US (5%), for Brazil and the US (7%) and Mexico (10%). All these 'best' predictors provide a sizable reduction in MSFE, while all other predictors demonstrated a decline in MSFE ranging from 1-3%, with the exception of South Africa.

From Table 7.3, it can be seen that the returns on the South African futures markets outperformed the AR benchmark in out-of-sample forecasts of the markets of Canada and USA, with declines in MSFE of 7 % in both cases. It is worth mentioning that in Chapter 5, South Africa was found to be the third most influential emerging market in the sample, after Mexico and Brazil, These results are further re-enforced in this chapter, since South Africa is the only one market from the other geographical region which generates a significant reduction in MSFE ratio.

7.4 Forecast encompassing test

Due to the large number of predictors, i.e. 20 predictors, the combination forecasts method is a promising tool that could improve the accuracy of the out-of-sample forecasts (e.g., Bates & Granger, 1969; Granger & Ramanathan, 1984; Harvey et al., 1998; Inoue & Kilian, 2008). Since predictive power varies among predictors and the potential predictors are correlated, the empirical evidence suggests that the application of the bagging methodology can, potentially, generate better out-of-sample forecasts, as it allows the generation of a multiple version of a predictor and this can be used to produce an aggregated predictor (Breiman, 1996). The bootstrap methodology is more robust in dealing with data mining and heteroskedasticity problems, and can estimate more accurate coefficients for the regression model. Thus, the performance of the bagging method is compared to several different combination forecasts, and the forecast encompassing test is conducted for each market in the sample.

Along with Rapach and Strauss (2010), this thesis hypothesizes that the bagging model (BA) forecasts encompass the combination (CB) forecasts (H17), which assumes that CB does not contribute any useful information, apart from that already contributed by the BA model. The alternative hypothesis (H18) suggests that the combining model encompasses the bagging model for out-of-sample forecast, because BA forecasts do not contain any useful information apart from that already contributed by CB forecasts. The performance of both bagging and combination forecasts are compared with the general performance of individual ARDL models shown in the previous section, so testing hypothesis H16.

If $\lambda_{CB} = 0$, then the BA forecasts encompass the CB forecasts, because CB forecasts do not contribute any useful information apart from that already contributed by BA forecasts. If $\lambda_{CB} > 0$, then the BA forecasts do not encompass the CB, which represents the opposite situation when BA forecasts do not contain any useful information apart from that already contributed by CB forecasts. The Null Hypothesis that $\lambda_{CB} = 0$ ($\lambda_{BA} = 0$) against the one-sided (upper-tail) alternative hypothesis that $\lambda_{CB} > 0$ ($\lambda_{BA} > 0$) are tested using the Student's t distribution (p-value) and $MHLN_h$ statistics.

Table 7.4 reports out of-sample forecasting results for the BA and combination forecasts for Asian markets.

Table 7.4 Forecasting and encompassing test results for the bagging model and combining method, out-of-sample period, forecasting horizon = 1, Asia.

		BA encompasses CB			CB encompasses BA		
Combining method	**MSFE ratio**	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Hong Kong							
BA model	0.85	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.96	0.037	0.18	0.428	0.964	4.74***	0.00
Median	0.99	0.038	0.21	0.416	0.962	5.22***	0.00
Trimmed median	0.97	0.041	0.21	0.417	0.959	4.89***	0.00
DMSE, ψ=1.00	0.96	0.037	0.18	0.428	0.963	4.72***	0.00
DMSE, ψ=0.90	0.96	0.037	0.18	0.427	0.963	4.71***	0.00
C (2, PB)	0.94	0.034	0.15	0.440	0.966	4.31***	0.00
C (3, PB)	0.92	0.053	0.23	0.409	0.947	3.96***	0.00
PC	0.86	0.040	0.08*	0.470	0.960	1.57*	0.06
Japan							
BA model	0.82	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.96	-0.149	-0.73	0.768	1.149	5.01***	0.00
Median	0.99	-0.129	-0.73	0.766	1.129	5.41***	0.00
Trimmed median	0.97	-0.135	-0.70	0.757	1.135	5.13***	0.00
DMSE, ψ=1.00	0.96	-0.150	-0.73	0.768	1.150	5.00***	0.00
DMSE, ψ=0.90	0.95	-0.149	-0.72	0.764	1.149	4.97***	0.00
C (2, PB)	0.93	-0.168	-0.74	0.771	1.168	4.53***	0.00
C (3, PB)	0.91	-0.168	-0.67	0.749	1.168	4.16***	0.00
PC	0.84	-0.141	-0.29	0.615	1.141	2.04**	0.02
Singapore							
BA model	0.90	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.97	-0.104	-0.40	0.654	1.104	3.85***	0.00
Median	0.99	-0.122	-0.51	0.694	1.122	4.13***	0.00
Trimmed median	0.98	-0.102	-0.40	0.656	1.102	3.95***	0.00
DMSE, ψ=1.00	0.97	-0.104	-0.40	0.654	1.104	3.84***	0.00
DMSE, ψ=0.90	0.97	-0.105	-0.40	0.654	1.104	3.82***	0.00
C (2, PB)	0.96	-0.088	-0.30	0.619	1.088	3.48***	0.00
C (3, PB)	0.96	-0.130	-0.41	0.660	1.130	3.33***	0.00
PC	0.92	-0.193	-0.34	0.631	1.193	1.60*	0.06
China							
BA model	0.86	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.96	0.031	0.13	0.447	0.969	3.96***	0.00
Median	0.98	0.025	0.12	0.452	0.975	4.38***	0.00
Trimmed median	0.96	0.040	0.18	0.428	0.961	4.13***	0.00
DMSE, ψ=1.00	0.95	0.031	0.13	0.447	0.969	3.94***	0.00
DMSE, ψ=0.90	0.95	0.034	0.14	0.443	0.966	3.92***	0.00

Table 7.4 continued

C (2, PB)	0.94	0.020	0.08	0.469	0.980	3.50***	0.00
C (3, PB)	0.92	0.066	0.23	0.408	0.934	3.08***	0.00
PC	0.87	-0.094	-0.12	0.549	1.094	1.36*	0.09
Korea							
BA model	0.88	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.97	0.086	0.42	0.338	0.914	4.36***	0.00
Median	0.99	0.077	0.43	0.332	0.923	4.92***	0.00
Trimmed median	0.98	0.085	0.44	0.329	0.915	4.59***	0.00
DMSE, ψ=1.00	0.97	0.086	0.42	0.337	0.914	4.34***	0.00
DMSE, ψ=0.90	0.97	0.090	0.44	0.332	0.911	4.30***	0.00
C (2, PB)	0.95	0.115	0.53	0.298	0.885	3.88***	0.00
C (3, PB)	0.93	0.166	0.73	0.234	0.834	3.49***	0.00
PC	0.90	0.142	0.24	0.403	0.858	1.54*	0.06
Malaysia							
BA model	0.90	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.97	0.103	0.46	0.324	0.897	4.79***	0.00
Median	0.99	0.083	0.42	0.338	0.917	5.41***	0.00
Trimmed median	0.98	0.103	0.48	0.314	0.897	5.05***	0.00
DMSE, ψ=1.00	0.97	0.103	0.46	0.323	0.897	4.78***	0.00
DMSE, ψ=0.90	0.97	0.106	0.47	0.320	0.895	4.76***	0.00
C (2, PB)	0.96	0.113	0.47	0.319	0.887	4.38***	0.00
C (3, PB)	0.94	0.174	0.69	0.246	0.826	3.81***	0.00
PC	0.90	0.382	0.76	0.223	0.618	1.76**	0.04
Taiwan							
BA model	0.89	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.97	0.095	0.46	0.324	0.905	4.93***	0.00
Median	0.99	0.086	0.48	0.317	0.914	5.50***	0.00
Trimmed median	0.98	0.097	0.49	0.311	0.903	5.15***	0.00
DMSE, ψ=1.00	0.97	0.095	0.46	0.323	0.905	4.91***	0.00
DMSE, ψ=0.90	0.97	0.097	0.47	0.320	0.903	4.89***	0.00
C (2, PB)	0.95	0.114	0.52	0.301	0.887	4.56***	0.00
C (3, PB)	0.94	0.135	0.59	0.279	0.865	4.14***	0.00
PC	0.89	0.498	1.21	0.114	0.502	1.55*	0.06
India							
BA model	0.88	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.97	0.031	0.15	0.439	0.969	5.16***	0.00
Median	0.99	0.018	0.10	0.459	0.982	5.75***	0.00
Trimmed median	0.97	0.033	0.17	0.432	0.967	5.40***	0.00
DMSE, ψ=1.00	0.97	0.031	0.16	0.438	0.969	5.14***	0.00
DMSE, ψ=0.90	0.96	0.032	0.16	0.438	0.968	5.11***	0.00
C (2, PB)	0.95	0.041	0.19	0.424	0.959	4.79***	0.00
C (3, PB)	0.94	0.048	0.21	0.417	0.952	4.44***	0.00
PC	0.88	0.663	1.79**	0.037	0.337	1.14	0.13

Notes: The MSFE ratio reports the ratio of the MSFE for the *BA* model or CB indicated on the left to the MSFE for the AR benchmark model forecasts; $\hat{\lambda}_{CB}$ ($\hat{\lambda}_{BA}$) is the OLS estimate of the weight on the combination (*BA* model) forecast in the optimal convex combination forecast given by equation 7.7; *MHLNh* is the test statistic corresponding to the Null Hypothesis; ***,** and * indicates the rejection of the Null Hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Table 7.4 shows that for all Asian markets, the BA forecasts generate a sizable reduction in MSFE of 10-18% over the AR benchmark model at the 1-day forecasting horizon. This shows that the bagging model provides, on average, greater reduction in MSFE than the individual ARDL model. The combination forecasts employed also outperformed the AR benchmark forecast for all markets, i.e. MSFE ratios are below unity. With exceptions of the PC (and cluster combining methods, i.e. C (2, PB) and C (3, PB), for some cases), all the combination forecasts fail to demonstrate any sizable reduction in MSFE. However, both the BA and PC forecasts demonstrated better relative forecasting performance than any of the best ARDL models for all markets in the Asian region. The BA forecasts show better forecasting power than all the combination forecasts, with the one exception being principal component combination forecasts (PC) for Taiwan and India. More specifically, the BA-model significantly outperforms the AR benchmark in Japan (18%), Hong Kong (15%) and China (14%). The results indicate that the PC forecast demonstrated the lowest MSFE than all the rest of the combination forecasts, which makes the PC the best performing combination forecast in this study.

The forecasts encompassing test demonstrates consistent results for all markets in the Asian region. Table 7.4 shows that the BA forecasts encompass all the CB forecasts, while the CB forecasts do not encompass the BA forecasts. This indicates the superior relative forecasting performance of the BA model, due to the fact that the BA forecast contains information useful for prediction returns on futures markets beyond that contained in the CB forecasts. For Hong Kong and India, only, the rejection of the Null Hypotheses was found, providing evidence that the BA forecasts do not encompass PC combination forecasts at the 10% and 5% significance levels, respectively.

Similar results are obtained for the European and African regions, where for all markets in the sample, the BA forecasts encompasses the CB forecasts, while the CB forecasts do not encompass the BA forecasts. The inability of the BA model to encompass the PC forecasts was also found in Russia, Hungary, Turkey and South Africa, which indicates that information contained in both models could not be judged as superior. These results are summarized in Table 7.5.

Table 7.5 Forecasting and encompassing test results for the bagging model and combining method, out-of-sample period, forecasting horizon = 1, Europe and Africa.

		BA encompasses CB			CB encompasses BA		
Combining method	**MSFE ratio**	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
UK							
BA model	0.92	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.97	0.165	0.82	0.207	0.835	4.36***	0.00
Median	0.99	0.124	0.69	0.245	0.876	4.95***	0.00
Trimmed median	0.98	0.160	0.83	0.203	0.840	4.54***	0.00
DMSE, ψ=1.00	0.97	0.165	0.82	0.206	0.835	4.35***	0.00
DMSE, ψ=0.90	0.97	0.167	0.83	0.204	0.833	4.33***	0.00
C (2, PB)	0.96	0.219	1.05	0.147	0.781	3.94***	0.00
C (3, PB)	0.96	0.230	1.04	0.150	0.771	3.62***	0.00
PC	0.93	0.325	0.99	0.161	0.675	2.25***	0.01
Germany							
BA model	0.94	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.98	0.204	0.89	0.186	0.797	3.68***	0.00
Median	1.00	0.154	0.76	0.224	0.847	4.28***	0.00
Trimmed median	0.98	0.199	0.92	0.180	0.801	3.85***	0.00
DMSE, ψ=1.00	0.98	0.204	0.89	0.186	0.796	3.67***	0.00
DMSE, ψ=0.90	0.98	0.203	0.89	0.187	0.797	3.67***	0.00
C (2, PB)	0.97	0.269	1.15	0.126	0.732	3.30***	0.00
C (3, PB)	0.97	0.262	1.06	0.145	0.738	3.11***	0.00
PC	0.96	0.032	0.07	0.471	0.968	2.21***	0.01
France							
BA model	0.93	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.98	0.157	0.72	0.236	0.843	4.09***	0.00
Median	0.99	0.123	0.63	0.266	0.877	4.64***	0.00
Trimmed median	0.98	0.155	0.74	0.230	0.845	4.28***	0.00
DMSE, ψ=1.00	0.98	0.157	0.72	0.236	0.843	4.08***	0.00
DMSE, ψ=0.90	0.98	0.158	0.72	0.235	0.842	4.07***	0.00
C (2, PB)	0.97	0.177	0.77	0.220	0.823	3.84***	0.00
C (3, PB)	0.96	0.224	0.91	0.183	0.776	3.40***	0.00
PC	0.96	-0.079	-0.18	0.571	1.079	2.66***	0.00
Spain							
BA model	0.92	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.98	0.082	0.34	0.368	0.918	4.02***	0.00
Median	0.99	0.056	0.26	0.398	0.944	4.53***	0.00
Trimmed median	0.98	0.085	0.37	0.355	0.915	4.26***	0.00
DMSE, ψ=1.00	0.98	0.082	0.34	0.367	0.918	4.02***	0.00
DMSE, ψ=0.90	0.98	0.082	0.34	0.368	0.918	4.02***	0.00
C (2, PB)	0.97	0.109	0.42	0.336	0.891	3.83***	0.00
C (3, PB)	0.96	0.150	0.55	0.292	0.850	3.47***	0.00
PC	0.95	-0.234	-0.45	0.672	1.234	2.81***	0.00
Switzerland							
BA model	0.91	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.98	0.051	0.21	0.415	0.949	4.28***	0.00
Median	0.99	0.039	0.19	0.426	0.961	4.89***	0.00
Trimmed median	0.98	0.054	0.24	0.406	0.946	4.50***	0.00

Table 7.5 continued

DMSE, ψ=1.00	0.98	0.051	0.21	0.415	0.949	4.27***	0.00
DMSE, ψ=0.90	0.97	0.051	0.21	0.415	0.949	4.26***	0.00
C (2, PB)	0.97	0.060	0.24	0.406	0.940	4.15***	0.00
C (3, PB)	0.96	0.085	0.32	0.376	0.915	3.83***	0.00
PC	0.91	0.416	1.08	0.140	0.584	1.89**	0.03
Russia							
BA model	0.91	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.98	0.130	0.68	0.248	0.871	4.49***	0.00
Median	0.99	0.103	0.60	0.276	0.897	5.00***	0.00
Trimmed median	0.98	0.123	0.67	0.251	0.877	4.66***	0.00
DMSE, ψ=1.00	0.98	0.131	0.68	0.247	0.869	4.48***	0.00
DMSE, ψ=0.90	0.97	0.132	0.69	0.245	0.868	4.45***	0.00
C (2, PB)	0.96	0.148	0.71	0.238	0.852	4.10***	0.00
C (3, PB)	0.96	0.169	0.77	0.222	0.831	3.83***	0.00
PC	0.90	0.791	1.66**	0.049	0.209	0.46**	0.32
Hungary							
BA model	0.88	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.97	0.098	0.50	0.308	0.903	4.72***	0.00
Median	0.99	0.070	0.40	0.344	0.930	5.31***	0.00
Trimmed median	0.97	0.093	0.50	0.308	0.907	4.93***	0.00
DMSE, ψ=1.00	0.97	0.099	0.51	0.307	0.902	4.71***	0.00
DMSE, ψ=0.90	0.96	0.099	0.51	0.306	0.901	4.70***	0.00
C (2, PB)	0.95	0.104	0.49	0.311	0.896	4.36***	0.00
C (3, PB)	0.94	0.142	0.62	0.269	0.858	3.89***	0.00
PC	0.87	1.118	2.17**	0.016	-0.118	-0.25**	0.60
Turkey							
BA model	0.91	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.97	0.215	1.02	0.154	0.785	4.03***	0.00
Median	0.99	0.180	0.95	0.170	0.820	4.59***	0.00
Trimmed median	0.97	0.203	1.01	0.156	0.797	4.25***	0.00
DMSE, ψ=1.00	0.97	0.218	1.03	0.151	0.782	4.00***	0.00
DMSE, ψ=0.90	0.97	0.220	1.04	0.150	0.780	3.99***	0.00
C (2, PB)	0.95	0.247	1.07	0.143	0.754	3.59***	0.00
C (3, PB)	0.94	0.302	1.18	0.120	0.698	3.07***	0.00
PC	0.86	1.271	2.72*	0.003	-0.271	-0.71	0.76
South Africa							
BA model	0.91	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.96	0.292	1.40*	0.082	0.708	3.76***	0.00
Median	0.99	0.239	1.28	0.101	0.761	4.34***	0.00
Trimmed median	0.97	0.275	1.38*	0.084	0.725	4.00***	0.00
DMSE, ψ=1.00	0.96	0.294	1.40*	0.081	0.706	3.73***	0.00
DMSE, ψ=0.90	0.96	0.295	1.40*	0.081	0.705	3.71***	0.00
C (2, PB)	0.95	0.340	1.44*	0.075	0.660	3.21***	0.00
C (3, PB)	0.93	0.396	1.52*	0.065	0.604	2.75***	0.00
PC	0.88	1.119	2.04**	0.021	-0.119	-0.25	0.60

Notes: The MSFE ratio reports the ratio of the MSFE for the *BA* model or CB indicated on the left to the MSFE for the AR benchmark model forecasts; $\hat{\lambda}_{CB}$ ($\hat{\lambda}_{BA}$) is the OLS estimate of the weight on the combination (*BA* model) forecast in the optimal convex combination forecast given by Eq. 7.7; *MHLNh* is the test statistic corresponding to the Null Hypothesis; ***,** and * indicate the rejection of the Null at the 1%, 5%, and 10% significance level respectively.

The evidence for South Africa suggests that the BA and the CB forecasts do not encompass each other. There are numerous rejections of the Null Hypothesis at the 10% and 5% significance levels. Nevertheless, the BA, and all combination forecasts, outperformed the AR benchmark, i.e. both the BA and the combination forecasts have MSFE ratio below unity. The BA model generates the reduction in MSFE ratio from the highest, 12% (Hungary), to the lowest, 6% (Germany), which generally indicates a worse performance of the BA model in Europe and Africa than in the Asian region. The BA model demonstrated a better relative forecasting performance than all the combination forecasts, with the exception of the PC model in Hungary, Turkey and South Africa. The PC forecast encompasses the BA model, according to the results obtained for Turkey and South Africa, indicating superior information is contained in the PC. The evidence for South Africa also shows that the median forecast and the BA forecast encompassed each other. Neither the BA, nor the median forecasts, contain any further useful information other than that already contained in the other. The combination forecasts employed also outperformed the AR benchmark forecast for all markets, i.e. MSFE ratios are below unity. However, with exceptions of the PC (and cluster combining methods, i.e. C (2, PB) and C (3, PB), for some cases), all the combination forecasts do not demonstrate a sizable reduction in MSFE. For the majority of markets in Europe and Africa, only the BA or PC demonstrated a better relative forecasting performance than any of the individual ARDL models. The markets of Switzerland and Russia were the exceptions, where individual ARDL models for the best predictor generated a forecast with higher, or similar, reduction in MSFE of those of both the BA and the PC forecasts.

Table 7.6 demonstrates out-of-sample forecasting results for the BA and combination forecasts, providing evidence for the American region. The findings on relative forecasting performance of the BA model over the AR benchmark are similar to the corresponding results for Asia, Europe and Africa. The BA forecasts generate declines in MSFE ratio of 11% in Canada and Brazil, 10% and 7% in the US and Mexico. Similarly to the results discussed above, the BA model outperformed all the combination models, with the exception of the PC model, which generated the forecasts with the lowest MSFE ratio in Canada, the US and Mexico. The results of the encompassing test, summarized in Table 7.6, have interesting differences with the findings presented in Tables 7.4 and 7.5.

Table 7.6 Forecasting and encompassing test results for the bagging model and combining method, out-of-sample period, forecasting horizon = 1, the Americas.

		BA encompasses CB			CB encompasses BA		
Combining method	**MSFE ratio**	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Canada							
BA model	0.89	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.96	0.226	1.37*	0.086	0.774	4.50***	0.00
Median	0.99	0.189	1.27	0.103	0.811	5.00***	0.00
Trimmed median	0.97	0.213	1.35*	0.088	0.787	4.72***	0.00
DMSE, ψ=1.00	0.96	0.227	1.38*	0.085	0.773	4.48***	0.00
DMSE, ψ=0.90	0.96	0.229	1.38*	0.084	0.771	4.45***	0.00
C (2, PB)	0.95	0.236	1.36*	0.088	0.764	4.22***	0.00
C (3, PB)	0.94	0.267	1.46*	0.073	0.733	3.97***	0.00
PC	0.88	0.617	2.18**	0.015	0.383	1.42*	0.08
USA							
BA model	0.90	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.97	0.235	1.33*	0.093	0.766	4.29***	0.00
Median	0.99	0.207	1.28	0.101	0.793	4.67***	0.00
Trimmed median	0.97	0.227	1.34*	0.091	0.773	4.47***	0.00
DMSE, ψ=1.00	0.97	0.236	1.33*	0.092	0.764	4.27***	0.00
DMSE, ψ=0.90	0.97	0.239	1.34*	0.090	0.761	4.24***	0.00
C (2, PB)	0.96	0.255	1.37*	0.086	0.745	4.01***	0.00
C (3, PB)	0.94	0.284	1.44*	0.076	0.716	3.69***	0.00
PC	0.89	0.685	2.14**	0.017	0.315	1.10	0.14
Mexico							
BA model	0.93	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.97	0.370	1.81**	0.035	0.630	3.78***	0.00
Median	0.99	0.314	1.71**	0.044	0.686	4.35***	0.00
Trimmed median	0.97	0.350	1.79**	0.037	0.650	4.04***	0.00
DMSE, ψ=1.00	0.96	0.372	1.82**	0.035	0.629	3.77***	0.00
DMSE, ψ=0.90	0.96	0.373	1.82**	0.035	0.627	3.73***	0.00
C (2, PB)	0.96	0.402	1.85**	0.033	0.598	3.47***	0.00
C (3, PB)	0.95	0.434	1.85**	0.033	0.566	3.16***	0.00
PC	0.91	0.905	2.44***	0.008	0.095	0.30	0.38
Brazil							
BA model	0.89	$\hat{\lambda}_{CB}$	$MHLN_h$	$p-value$	$\hat{\lambda}_{BA}$	$MHLN_h$	$p-value$
Mean	0.96	0.166	0.91	0.182	0.834	3.91***	0.00
Median	0.98	0.144	0.86	0.195	0.856	4.36***	0.00
Trimmed median	0.97	0.163	0.93	0.177	0.837	4.09***	0.00
DMSE, ψ=1.00	0.96	0.166	0.91	0.182	0.834	3.89***	0.00
DMSE, ψ=0.90	0.96	0.165	0.90	0.185	0.835	3.88***	0.00
C (2, PB)	0.95	0.161	0.85	0.198	0.839	3.69***	0.00
C (3, PB)	0.94	0.174	0.87	0.193	0.826	3.42***	0.00
PC	0.90	0.238	0.72	0.235	0.762	2.11**	0.02

Notes: The MSFE ratio reports the ratio of the MSFE for the *BA* model or CB indicated on the left to the MSFE for the AR benchmark model forecasts; $\hat{\lambda}_{CB}$ ($\hat{\lambda}_{BA}$) is the OLS estimate of the weight on the combination (*BA* model) forecast in the optimal convex combination forecast given by Eq. 7.7; *MHLNh* is the test statistic corresponding to the Null Hypothesis; ***,** and * indicate the rejection of the Null at the 1%, 5%, and 10% significance level respectively.

For Canada, the US and Mexico it was found that the BA forecasts, and all the combination forecasts, do not encompass each other. These findings do not provide judgments regarding the relative forecasting advantages of one of the models over others, as both the BA and the CB forecasts contain information useful for forecasting stock index futures returns that is not contained in the other. The first exception is found for Canada and the US, where the BA forecast encompassed the median forecasts. The second exception is that the PC forecasts do encompass the BA forecasts in Mexico and the US. The out-of-sample forecasting evidence for Brazil is consistent with previous forecasting encompassing test results, indicating that the BA forecasts encompassed all the CB forecasts.

7.5 Chapter summary

This chapter analysed the relative forecasting performance of 420 individual ARDL forecasts generated for the stock index futures returns of 21 emerging and developed markets. It was found that only 37% (157 out of 420) of individual ARDL models can outperform the AR benchmark, i.e. 38% in Asia, 33% in Europe and Africa, and 47% in the Americas. However, some of the predictors demonstrated better relative forecasting performance than others. For example, while results obtained from previous chapters show that China is not susceptible to foreign shocks, the out-of-sample forecast demonstrated the ability of the Mexican market to predict Chinese stock index futures returns.

For Asian markets, it was evident that the markets with non-overlapping trading hours have a higher forecasting power than markets with an overlap in trading hours, due to the fact that for each market the most influential foreign predictors are situated in a different geographical time-zone. These results indicate that returns on developed Asian markets can be predicted by emerging markets from other regions. The evidence for Europe shows a lack of the predicting power of meteor-shower-like effect across markets with non-overlapping trading hours, because the out-of-sample forecasts built, using the returns of the markets with non-overlapping trading hours, either failed to outperform the AR benchmark or produced a reduction in MSFE of just 1%. The results for America demonstrate that the best forecasting power was found among markets from the same geographical regions. For example, the best relative forecasting performance for the developed markets of Canada demonstrated by individual ARDL models utilized Brazil and Mexico as predictors. This is consistent with results provided in Chapter 5, suggesting that the strongest linkages between emerging and developed stock markets are within the Americas region.

In addition, this chapter tested the relative forecasting performance of bagging and combination forecasts, comparing the results with the performance of individual ARDL models discussed in previous sections. Both BA and CB forecasts generate sizable reductions in MSFE for all countries in the sample. However, for the majority of cases, the BA forecasts outperform all the CB forecasts, with the exception of the PC method, which is found to be superior among CB forecasts. For example, the PC forecasts generated the lowest MSFE ratio in Canada, the US and Mexico. For the majority of cases, both BA and PC, demonstrate better relative forecasting performance than individual ARDL models, which justifies the usefulness of these methods for the forecasting of returns.

The forecast encompassing test show that the BA forecasts encompass all the CB forecasts, while the CB forecasts do not encompass the BA forecasts in all Asian markets. Similar results are obtained for the European and African regions, where, for all markets in the sample, the BA forecasts encompasses the CB forecasts, while the CB forecasts do not encompass the BA forecasts, with the exception, again, of the PC forecasts (the inability of the BA model to encompass the PC forecast was found in Russia, Hungary, Turkey and South Africa). In the Americas region, for the markets of Canada, the US and Mexico, it was found that the BA forecasts and all the combination forecasts do not encompass each other. These findings do not allow any judgment of the content of information contained in the BA and the CB forecasts, because both of them contain information useful for prediction of stock index futures returns which is not contained in the other.

Chapter 8 Discussion of findings and conclusion

8.1 Introduction

The main empirical results presented in the three empirical chapters of this study are helpful for an understanding of international transmission mechanisms and provide the answers to the main research questions outlined in Chapter 3. Due to the extensive set of research hypotheses tested in each empirical chapter, further discussion of the results is essential to clarify which research hypotheses are confirmed and which rejected for each specific market or region. The results are rich in detail, and significant for both theory and practice. Special attention to the explanations as to why the research contributes to, and enhances, existing knowledge, as well as providing practical help to those planning trading strategies has been given.

This final chapter outlines the findings presented in each empirical chapter and discusses the main research contribution of the thesis. It is organized as follows:

Section 8.2 summarizes the findings presented in each empirical chapter as they relate to the three research questions. The results are structured in order to match the empirical evidence to the research hypotheses tested, providing a conclusion as to whether it has been accepted or rejected in the context of particular market, market pair or region.

Section 8.3 discusses the contribution to knowledge made by this thesis, placing the research within the context of existing literature. It also outlines the potential implications of the research findings.

Section 8.4 discusses the limitations of the study and provides recommendations for further research.

8.2 Summary of findings

Chapter 5, 6 and 7 discussed the empirical results in detail. However, there is a need to further summarize the main findings to demonstrate how the results help to fill the identified literature gaps. Three research questions have been considered:

1) Do any differences exist in patterns of return and volatility spillovers across emerging and developed stock market indices and across stock index futures?

2) Do any asymmetric patterns exist in return and volatility spillovers across futures markets with non-overlapping stock exchange trading hours?

3) Does foreign information help forecast the return of stock index futures on domestic markets?

The findings are summarized in relation to each research question.

8.2.1 Difference in patterns of information transmission

The findings of this thesis suggest that there are differences in the patterns of information transmission, identified by a comparison of return and volatility spillovers across stock indices with stock index futures, in relation to the magnitude of spillovers, but not in relation to the cyclical movements of spillovers.

Hypotheses 1 and 2 could not be rejected, based on the evidence provided in Chapter 5. These hypotheses assumed that *cyclical movements of total spillover indices for returns (volatility) are similar for both futures and spot markets*. The spillover plot for stock index futures and stock indices data for the subsample period demonstrated that the cyclical movements of spillovers are similar for futures and spot markets. However, the results of Chapter 5 suggest that the magnitude of spillovers is higher for futures markets than spot markets during the subsample period and this is evident for both return and volatility. Hypotheses 3 and 4 (i.e. *the magnitude of return/volatility spillovers is higher across stock indices than across stock index futures*) are proven to be incorrect based on the evidence and, consequently, are rejected in this thesis. For example, the empirical results report that Korea, Taiwan and India have the lowest values of Contribution to Others, 4.77%, 2.03% and 4.81%

for volatility spillovers across stock market indices, while for stock index futures these values are 43.77%, 29.04% and 34.28%. The findings prove that futures markets provide more efficient channels of inter-regional information transmission than stock markets, because the magnitude of return and volatility spillovers is larger using stock index futures. These results can be explained with reference to Antoniou and Holmes (1995), who claimed that futures trading expanding the channels over which information can be transmitted to the market, and, due to the lower costs of trading and the greater leverage potential, futures markets become attractive for both uninformed and informed traders (e.g., Antoniou et al., 2005; Chen & Gau, 2010). The logical conclusion is that cross-market information conveyance can be more efficient through stock index futures than spot markets.

The research Hypothesis 5 (i.e. *the intensity of intra-regional return and volatility spillovers is higher than intensity of inter-regional spillovers*) could not be rejected based on the empirical evidence provided in Chapter 5. The research provides significant evidence of intra-region information transmission for both futures and spot markets, but evidence of inter-regional spillovers is more limited. The results show that the intensity of intra-region return and volatility spillovers is high for the Asian region. The findings suggest that the Hong Kong stock market is the most influential in the Asian region, mainly due to the high spillovers from Hong Kong to other Asian markets. The results also show that Asian markets are less susceptible to external shocks. The strongest return spillovers for all Asian markets come from the UK. The strongest intensity of volatility spillovers is from the UK to the developed markets of Hong Kong, Japan and Singapore. Similarly, these markets are influenced by shocks from markets from the Americas region, for example the USA and Brazil. This could be explained by the fact that developed Asian markets are more integrated into the world economy when compared with emerging markets from the same region. Consequently, Hypothesis 6 (i.e. *the magnitude of return and volatility spillovers for developed-developed market pairs is higher than for emerging-emerging market pairs*) cannot be rejected, confirming a higher intensity of transmission between developed markets. The highest magnitude of volatility spillovers is found across developed European countries, such as the UK, Germany, France, Spain and Switzerland, and this provides the evidence to reject H5 and H6 simultaneously. These findings can be explained first, through the historically higher level of financial integration among developed European markets reported by Coelho et al. (2007), and second, due to the impact of the European Debt Crisis which affects the results obtained for the target estimation period. However, both explanations do not contradict each other, i.e. higher integration caused more intensive transmission of the crisis shock between developed European markets, increasing the return and volatility spillovers.

Hypothesis 7 postulates that developed markets are the net-donors of international return and volatility transmission, while emerging markets are net-recipients. The rejection of this hypothesis supports 'decoupling hypotheses' discussed in the relevant literature (e.g., Bekiros, 2014). The supporting evidence for the 'contagion' hypothesis is found. Hypothesis 8 (i.e., *there are no bursts in return and volatility spillovers during the crisis periods*) is strongly rejected based on cyclical movements of return and volatility spillover for both stock indices and stock index futures. The burst in spillovers during the GFC and the EDC are verified.

Finally, besides the hypotheses tested, the findings in Chapter 5 revealed that the magnitude of return spillovers is higher than the magnitude of volatility spillovers. For example, the Total Spillover Index for returns (71%) is higher than the estimated Total Spillover Index for volatility (56%). This is evident for all markets, but is especially pronounced for Taiwan; i.e. the results in the row, *Contribution to Others*, are 40.89% for return and only 1.0% for volatility.

8.2.2 The asymmetry in return and volatility spillovers

This thesis identifies the fact that the asymmetry in return and volatility spillovers across stock index futures is evident for some market combinations in the sample, but not for all of them. Hypotheses 9 and 10 have been tested for returns for each market in the sample, while Hypotheses 11 and 12 have been tested for volatility. For example, Hypothesis 9 (*i.e. the transmission of negative return shocks across markets with non-overlapped trading hours is more pronounced than the transmission of positive shocks*) is rejected for a market if, for the majority of cases, the transmission of negative shocks is confirmed. The basic Null Hypotheses of absence of causalities has been tested 416 times in Chapter 6 and the results provide considerable evidence. The findings have been discussed in detail in Chapter 6, and the findings are summarized in Table 8.1 below.

Table 8.1 Asymmetry in return and volatility spillovers.

Market (as recipient)	Research Hypotheses			
	Return		Volatility	
Dominant shock	H9* (- shocks)	H10** (+shocks)	H11* (- shocks)	H12** (+shocks)
Hong Kong	**confirmed**	rejected	rejected	**confirmed**
Japan	**confirmed**	rejected	rejected	**confirmed**
Singapore	rejected	rejected	rejected	**confirmed**
China	rejected	rejected	**confirmed**	rejected
Korea	rejected	rejected	rejected	**confirmed**
Malaysia	**confirmed**	rejected	rejected	**confirmed**
Taiwan	**confirmed**	rejected	rejected	**confirmed**
India	rejected	rejected	rejected	rejected
Germany	rejected	rejected	rejected	rejected
France	rejected	rejected	rejected	rejected
Spain	rejected	**confirmed**	rejected	rejected
Switzerland	rejected	rejected	rejected	rejected
Russia	rejected	rejected	**confirmed**	rejected
Hungary	rejected	rejected	rejected	rejected
Turkey	**confirmed**	rejected	rejected	rejected
South Africa	rejected	rejected	rejected	rejected
Canada	**confirmed**	rejected	rejected	**confirmed**
USA	rejected	**confirmed**	rejected	rejected
Mexico	rejected	rejected	rejected	rejected
Brazil	rejected	rejected	rejected	**confirmed**

Notes: *The Hypothesis is confirmed if, for the majority of cases, the target market is more susceptible to negative than positive shocks; **The Hypothesis is confirmed if, for the majority of cases, the target market is more susceptible to positive than negative shocks.

Although the simultaneous rejection of H9 and H10 for return, and H11 and H12, for volatility, indicates the absence of asymmetry in spillover effect, this situation does not necessarily mean the absence of causal linkages. For instance, while for Japan and Hong Kong, results demonstrate clear evidence of asymmetry in causalities between returns, for Singapore it was found that returns are susceptible to transmission of both positive and negative types of shock. As such, both H9 and H10 are rejected. The evidence of asymmetry does not characterize the market that has very strong causalities with others. For the Hong

Kong market, asymmetry in spillover was found due to the fact the Hong Kong is susceptible only from the one type of shocks transmitted from Brazil, and independent of both types of shock from any other markets. The evidence, overall, suggests that Hong Kong is a market in the Asian region that is comparatively isolated from foreign shocks, as are those of China and India.

Therefore, asymmetry in return transmission is evident for the futures markets of Hong Kong, Japan, Malaysia, Taiwan, Turkey and Canada, where markets are more susceptible to transmission of negative shocks; and for the markets of Spain and the US, where spillovers of positive shocks are more pronounced. The results show that although there are mutual causal linkages existing between markets with non-overlapping trading hours, asymmetry of return spillovers are identified for 8 out of 21 markets in the sample. The asymmetry in volatility spillovers is found for 10 out of 21 markets. In Hong Kong, Japan, Singapore, Korea, Malaysia, Taiwan, Canada and Brazil the conveyance of positive volatility shocks, i.e. destabilizing volatility spillovers, dominates, while the evidence for China and Russia suggested the reverse pattern, i.e. stabilizing volatility spillovers. Overall, the results show that transmission of negative return shock and positive volatility shocks dominate in this observation sample. Summarizing the results for different combinations of markets, i.e. developed-developed, emerging-emerging, emerging-developed and developed-emerging (where the former market is a recipient of information) it was found that the strongest asymmetry is for market pairs where the recipient is an emerging market. There is no evidence of asymmetry for developed-developed and developed-emerging market combinations.

8.2.3 Predictive power

The results of this thesis suggest that foreign returns can be used for the prediction of domestic market returns. However, the forecasting power of predictors may vary for each market. The findings show that Mexico, Brazil and South Africa have the highest predictive power in the sample, supporting the results outlined in Chapter 5, which suggests that these markets are the most influential emerging markets. Hypotheses 13-15 are tested for 21 markets from different geographical regions.

Hypothesis 13 postulates that *there is no predictive power of information transmitted from markets with non-overlapping trading hours to forecast domestic returns.* This is rejected for the Asian markets, since the most influential foreign predictors do not have overlapping trading hours with the forecasting market. Alternatively, H13 is confirmed for markets in Europe and Africa, because none of the predictors that have no overlapping trading times were able to outperform the AR benchmark or produced a reduction in MSFE of more than 1%. This hypothesis is also confirmed for the American futures returns market. The results show that the predictors with non-overlapping trading hours have an MSFE ratio above unity or generate declines in MSFE of between 1 and 2%.

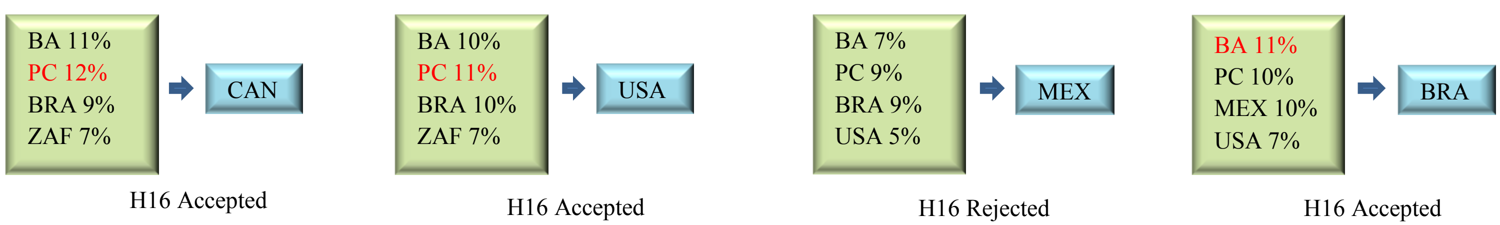
While H13 has been rejected for Asian markets, the Hypothesis 14 (i.e., *there is no predictive power of information transmitted from markets with overlapping trading hours to forecast domestic returns*) cannot not be rejected for markets from this region because the predictors which have overlapping trading times with a dependent market, do not generate a sizable reduction in MSFE. For the European markets the most significant predictor is Brazil with a decreasing MSFE ratio of 6%, for the UK, 5%, for Germany and France, 7% and 9% for Spain and Switzerland, 10% for Russia and Hungary, and 11 % for Turkey and South Africa. Since the Brazilian market has an overlap in trading times with all the above mentioned markets, H14 can be rejected. The evidence for the Americas further suggests the rejection of this hypothesis, due to the fact that the best relative forecasting performance demonstrated by models, used markets from the same geographical regions to generate an out-of-sample forecast. For example, the trading hours of the markets of Brazil and Mexico fully overlap with Canada. However, the ARDL models, utilizing the Brazilian and Mexican markets to forecast Canadian futures returns, showed the best relative forecasting performance. H14 can be rejected for this region.

Consequently, Hypothesis 15, (i.e., *the predicting power of return transmission across markets with non-overlapping trading hours is stronger than predictive powers of return transmission across markets with overlapping trading hours*) is confirmed for Asian markets, since markets without overlapping trading hours have a greater forecasting power than markets with overlapping trading hours. Additionally, the findings suggest that the returns on the developed Asian markets can be predicted by emerging markets from other geographical regions. H15 can be rejected for all other markets in the sample from the Americas, Europe and Africa.

The results of this thesis demonstrate that there is no universal model (universal influential predictor) that can be used for the forecasting of stock index return in all markets. Several foreign predictors may have an influence on domestic market returns and this suggests the necessity of using bagging and combination forecast methodologies. Both approaches, the BA and the CB, were able to outperform the AR benchmark. However, the BA forecasts still generate better declines in MSFE than all the CB forecasts, with the exception of the PC combination forecast, which is found to be the best of the combination forecasts. These findings are consistent for all markets in the sample. The performances of the BA and CB forecasts have been compared with the best performing individual ARDL models, testing Hypothesis 16 (i.e., *the combination of information transmitted from several foreign markets can improve the forecasting performance of domestic market returns*). The hypothesis has been confirmed for the majority of markets with the exceptions of Mexico, Switzerland and Russia, indicating that using several foreign market predictors to forecast domestic markets returns is beneficial. The results obtained for each region are summarized by Figure 8.1 below.

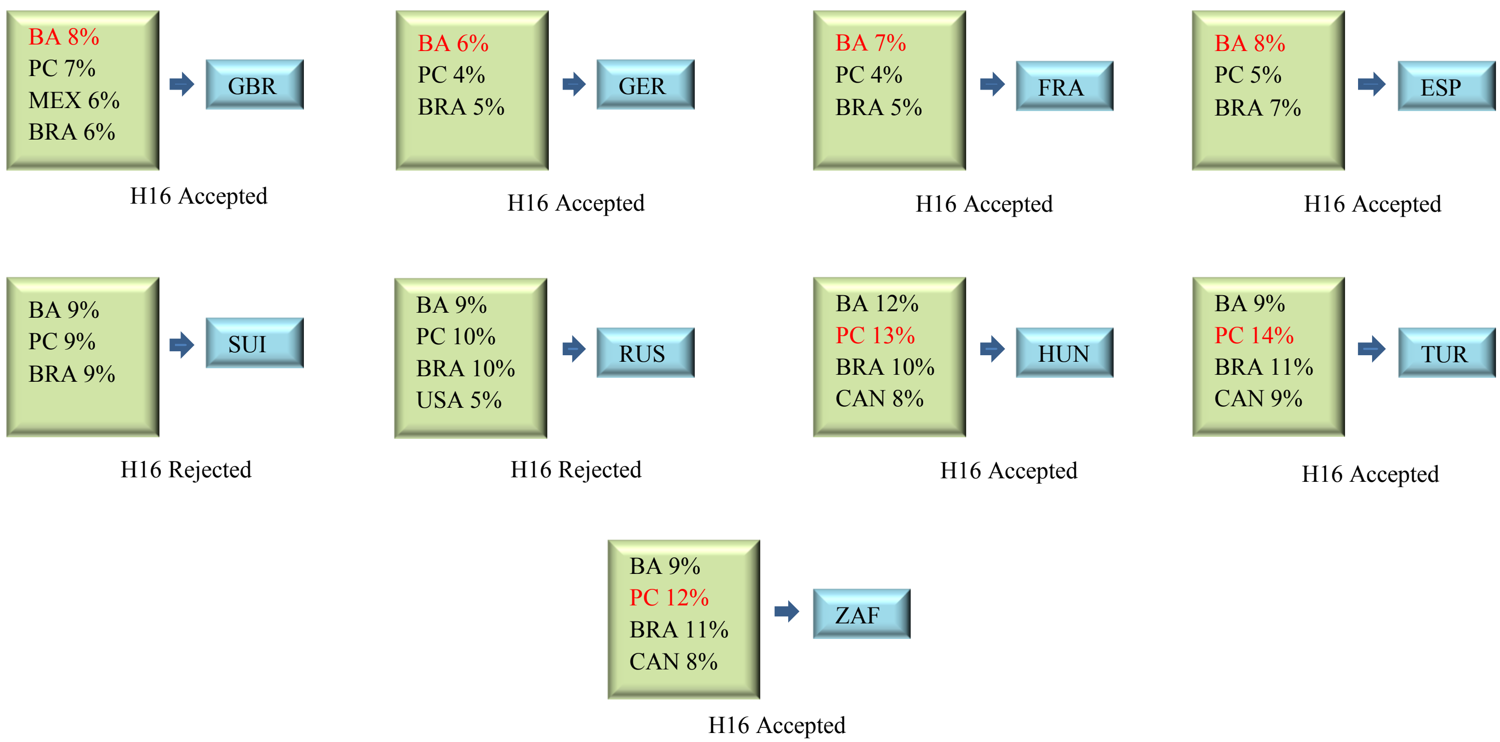
Figure 8.1 Relative forecasting performance, Asia.

Figure 8.2 Relative forecasting performance, the Americas.



Notes: Figure compares the relative forecasting performance of the BA and the PC forecast with performance of the best individual ARDL model for each market. The relative forecasting performance is compared using reduction in MSFE over the AR benchmark. The highest percentage point, i.e. the best relative forecasting performances, are highlighted in red. If any of the BA or PC generates greater reduction in MSFE criterion, H16 is accepted, alternatively, if not, H16 is rejected.

Figure 8.3 Relative forecasting performance, Europe and Africa.



Notes: Figure compares the relative forecasting performance of the BA and the PC forecast with performance of the best individual ARDL model for each market. The relative forecasting performance is compared using reduction in MSFE over the AR benchmark. The highest percentage point, i.e. the best relative forecasting performances, are highlighted in red. If any of the BA or PC generates greater reduction in MSFE criterion H16 is accepted, alternatively, if not, H16 is rejected.

Regarding the informational content of the BA and CB forecasts, the evidence for the Asian region suggests that the BA forecasts encompass all the CB forecasts, while the CB forecasts do not encompass the BA forecasts. Hence Hypothesis 17 (i.e., *the bagging model contains information useful for prediction of domestic market return beyond that contained in the combination forecasts*) is confirmed. Hypothesis 18 (i.e., *the combination forecasts contain information useful for prediction of domestic market return beyond that contained in the bagging model*) is rejected. These findings are consistent with evidence provided for Europe and Africa. The CB models do not contain any useful information beyond that already contained in the BA model (with the exception of the PC forecasts). Another exception is that the evidence of the forecast encompassing test in South Africa suggests rejection of both H15 and H16. Similarly, for the Americas region, both hypotheses are rejected since neither the BA forecasts, nor any of the combination forecasts, encompass each other.

8.3 Contribution and implications

The findings of this thesis enrich the extant literature in several important ways.

First, it provides a new insight on intra- and inter-regional return and volatility transmissions across 21 developed and emerging markets from the Asian, American, European and African regions by combining stock index futures and stock equity indices in one empirical study. The findings show that futures markets provide more efficient channels of inter-regional information conveyance than stock markets, because the magnitude of return and volatility spillovers is larger among stock index futures. The results suggest that utilizing stock index futures in an analysis of return and volatility spillovers has more significant practical implications, for example, the construction of a trading strategy based on foreign information transmission. The findings in all three empirical chapters of this thesis are more practically realistic since the evidence from futures markets is provided.

Second, the burst in spillovers during the Global Financial Crisis and the European Debt Crisis is verified, contributing to contagion literature and supporting the results of previous studies (e.g., Ahmad et al., 2013; Dimitriou et al., 2013; Bekiros, 2014; Karanasos et al., 2014; Choudhry & Jayasekera, 2014; Syriopoulos et al., 2015.). The findings demonstrate evidence of contagion opposite to the results reported by Morales and Andreosso-O'Callaghan (2014). The research results are particularly important for financial regulators, due to the fact that contagion during crisis episodes affects macroeconomic stability. However, contrary to extant literature, for example, Zhang et al. (2013) who have claimed that after the Global Financial Crisis, diminishing diversification benefits had become a long-run and world-wide phenomenon, this thesis demonstrated a decrease in both return and volatility spillovers from 2012 to 2014. These findings contribute to IPD literature since the decline in the degree of co-movements is established. These results have important implications for policy makers and financial regulators. Linkages of economic cycles with intensity of global return and volatility spillovers provide the opportunity to use the Spillover Index as an indicator of recession and recovery, since it increases during periods of turmoil and decreases during tranquil periods.

Third, this thesis provides further implications for IPD and suggests that among all regions, the best diversification opportunities can be achieved by investing in Asian markets, which are less susceptible to external shocks. Chapter 5 also suggests that spillovers between emerging and developed markets situated in different geographical regions are relatively weak. IPD benefits are achievable by combining them in one portfolio. Consequently, investing in Asian emerging markets is the most promising from a diversification perspective. These findings are consistent with the study by Claus and Lucey (2012) that demonstrated that Asian emerging markets have relatively lower degrees of financial integration. The lowest value of return spillovers from other markets is that of the Chinese stock market (37.61%). The asymmetric causality test also revealed the relative independence of the Chinese futures market from global financial markets. These results are consistent with Huang et al (2000) and contradict Hou and Li (2015). The isolation of the Chinese futures markets from external shock can be explained due to the fact that stock index futures is a new instrument in China and still has numerous trading barriers (e.g., Yang et al., 2011). The findings in Chapter 6 confirm that the strongest intensity of intra-day information transmission among the markets with non-overlapping trading hours is from Asia to the Americas, and to Europe and Africa, while the intensity of reverse channels of transmission is rather weak. These results provide evidence of inter-regional information transmission.

The next contribution of this thesis is made through analysing the transmission of the negative and positive return and volatility shocks across markets with non-overlapping trading hours. The concept of asymmetry in return and volatility spillovers across markets is relatively unexplored (Koutmos & Booth, 1995; Baruník et al., 2015; Segal et al., 2015; Kundu & Sarkar, 2016). This research augments existing knowledge, providing recent international evidence on asymmetry in spillover effects by utilizing stock index futures data. The findings indicate asymmetry in spillovers that is consistent with results from (Kundu & Sarkar, 2016), where returns are more sensitive to negative shocks (e.g. Koutmos & Booth, 1995), and volatility to positive shocks. However, although volatility spillovers are traditionally viewed as destabilizing forces only, asymmetric tests show that decreases in volatility on one market can cause decreases in volatility in other markets. The transmission of negative volatility shocks may play a stabilizing role in the region. The results provide the new evidence of both stabilizing and destabilizing spillover effects across markets. The study identifies the strong asymmetry in spillovers for market pairs where the recipient is an emerging market, while there is no evidence of asymmetry for developed-developed and developed-emerging market combinations.

Finally, this thesis contributes to forecasting literature and has implications for stock market efficiency. Although the evaluation of relative forecasting performance demonstrated that the majority of individual ARDL models failed to outperform the AR benchmark, the performance of a few of them generated sizable declines in MSFE. In summary, while for the Asian region, the markets with non-overlapping trading hours are the most powerful predictors, and for Europe and Africa, markets from a different region (but with overlap in trading times) demonstrated the best relative forecasting performance. For the Americas region, the results suggest that the pattern is different from other regions. In the American futures markets, the strongest predictors are returns on stock index futures of markets from the same region. The results for Asia, Europe and Africa indicate the predictive ability of inter-regional information transmission, while the findings from the Americas support the forecasting power of intra-regional information conveyance. This evidence is very important because it enhances the findings provided in Chapter 5 and Chapter 6. These findings indicate that opportunities to predict futures markets returns by using foreign information transmission mechanisms can, potentially, disrupt the EMH.

The bagging and combination forecasts generated sizable reductions in MSFE for all countries in the sample. Although for the majority of cases, the BA forecasts outperform all the CB forecasts, the PC forecasts often generated the lowest MSFE ratio in the sample. Both the BA and PC models demonstrated better relative forecasting performance than the best individual ARDL forecasts (with the exception of Mexico, Russia and Switzerland). The forecast encompassing test demonstrated that the BA forecasts encompass all the CB forecasts, while the CB forecasts do not encompass the BA forecasts in markets from the regions of Asia, Europe and Africa. For the Americas region, it was found that the neither BA forecasts nor any of the combination forecasts, encompass each other. These results suggest that both the BA and the CB forecasts contain information useful for the prediction of stock index futures returns that is not contained in the other, and, consequently, suggests the rejection of the EMH. The empirical results have important implications for return predictability, trading strategy and portfolio diversification.

8.4 Limitations to, and recommendations for, further research

Although the present research employed well-known and reliable methodologies, there are certain limitations that need to be considered. These limitations can, potentially, be addressed by future researchers. This section provides some direction for further research, and identifies areas that require further attention.

The first limitation is related to the data utilized in this thesis. The study employed open-to-close daily returns to analyse information transmission mechanisms across markets with, and without, overlap in trading times. However, the recent study by Jayawardena et al. (2016) showed that incorporating overnight returns in a forecasting model can increase its predictive power (e.g., Del Corral et al., 2003). Similarly, the idea of further splitting trading time within one trading day can enhance the understanding of return and volatility transmissions (e.g., Barclay & Hendershott, 2004; Wang et al., 2009). Consequently, using data collected more frequently in research will give further evidence on the same day effect, because it allows the separation of the 'overlapping period', when markets are trading simultaneously, and 'non-overlap period'. Since this research omitted electronic trading on stock index futures (only pit-trading times are used), another way in which to extend this research is through the consideration of electronic trading hours.

The second limitation of this thesis is that it relies on the volatility estimator employed. The present research used the Rogers and Satchell (1991) volatility estimator. However, the recent study by Yarovaya, Brzeszczyński and Lau (2016) suggested that the results of empirical tests are susceptible to the choice of volatility estimators, and supports other findings on the ambiguity of the existing evidence on the directions of volatility spillovers in previous literature. The authors suggested that the research on volatility transmission should provide evidence from a different range of volatility estimators, which can help to avoid possible bias in the results. The analysis presented in this thesis could be replicated using a variety of volatility estimators.

The third limitation of this thesis lies in the interpretation of the results. The analysis carried out, undoubtedly, provided an original contribution to the literature, due to the employment of futures data, recent methodology and a broader country panel. Concentration was also placed on answering the question of ‘how’ the financial markets are interlinked, providing evidence on direction, intensity, asymmetry and predictive power of spillovers. However, the central question of future researches could well be ‘why’ return and volatility spillovers follow identified patterns. This research can be extended by utilizing macroeconomic indicators to analyse the impact macroeconomic factors have on the dynamic of spillovers. The list of explanatory variables could potentially include: bilateral trade, relative inflation, relative interest rates, market size differential, and industrial production growth. Apart from macroeconomic studies, there is a growing body of literature which suggests that cultural distance has an effect on equity market co-movements (e.g. Portes & Rey, 2005; Aggarwal, Kearney & Lucey, 2009; Lucey & Zhang, 2010). The suggested extension could result in a more in-depth interpretation and understanding of the empirical results obtained in this work. This research could be, potentially, expanded to encompass analysis of bond, equity traded funds (ETF), and commodity markets.

While this research has provided a number of insights into the inter-relatedness of markets around the world, and has contributed to the growing literature being produced on this globalisation of markets, the most significant finding of the research is that the transmission of foreign information across markets can have very real impacts on the returns from domestic markets and, moreover, it is possible to analyse the effect of such information transmissions in such a way that real life investors can utilise this phenomenon to plan an investment strategy that could maximise the returns on their investments. This has totally justified the time and effort that has gone into this thesis and, in conjunction with the identification of further areas of study, has resulted in the articulation of significant original thought in an increasingly important area.

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