EMERGING FINANCIAL MARKETS: SPATIAL RISKS, ELICITABILITY OF RISK MODELS, AND SHAPE SHIFT CONTAGION

By

Peterson Owusu Junior

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Supervisor: Professor Imhotep Paul Alagidede

ABSTRACT

The need to compare and contrast emerging market economies (EMEs) has never been greater, especially following shocks to the global financial system. The quest to characterise EMEs does not only emanate from risk mitigation purposes but also to maximise investment returns and to articulate appropriate policy reforms even amidst financial turmoil. Moreover, increasing integration of otherwise segmented economies has been largely amplified by the impact of these market disturbances as seen in episodes of contagion. While the extant literature is ripe with studies aimed at unearthing the differences and similarities in EMEs, most of them have centred on all too ubiquitous dimensions such as returns and volatility behaviour, macroeconomic fundamentals, and even cultural ethos, among others. Although these attributes are helpful, they fail to provide deeper insights into EMEs for the rich understanding needed to make the best of investment and policy decisions. This thesis provides empirical examination of additional dimensions by which to characterise EMEs in order to provide a broader insight for prudent investment and policy strategies. The thesis comprises three empirical studies on spatial risks, elicitability of risk models, and *"shape shift-contagion"* of emerging markets equities, as the subtle extents by which to compare and contrast EMEs, using advanced econometric techniques.

The first empirical study contrasts time-varying and spatial risks in order to assess systemic vulnerabilities that affect emerging markets equity returns as well as to aid portfolio diversification. The study spanned between Eurozone Crisis-Global Financial Crisis (EZC-GFC) and post-GFC to represent turbulent and tranquil periods. With the joint (VaR, ES) models and Global Liquidity Indicators (GLIs) for 12 EMEs which indicate time-varying and time-invariant (spatial) risk measures, respectively, the study provides evidence that, the ranking of joint (VaR,

ES) forecasts and spatial autocorrelations differ significantly. The results reveal that the overall spatial autocorrelation between the 12 EMEs is smaller and negative for post-GFC as opposed to positive and bigger for EZC-GFC periods. This suggests that EMEs may have employed prudent liquidity policies to enhance their resilience to systemic susceptibilities as bitter lessons learnt from crises experiences. The implications are that (VaR, ES) forecasts rankings are irrelevant, since time-invariant systematic debacles have no respect for time-varying tail risks. For investors, international portfolio diversification tends to yield its expected risk-minimising outcomes during the post-GFC period. The study posits *"Financial distance"* as an extension of Cultural, Administrative/Political, Geographic, and Economic (CAGE) distance dimensions to characterise markets. This study is a subtle departure from the use of returns and volatilities used in describing economies.

The second study examines the dynamics of emerging markets tail risk modelling and selection behaviour under comparative back testing requirement in the Basel III paradigm. The study does not only contribute to the growing need to correctly forecast and select the best tail risk model for internal risk management purposes, but it also fits well into the aim of reducing regulatory arbitrage. Across three market periods signifying tranquil and turbulent times, the study finds evidence of time-, percentile-, equity-, and market period-dependent Superior Set Models (SSMs) for 24 EMEs. These imply homogeneous vis-à-vis heterogeneous risk models which provide portfolio diversification impetus for specific markets. Further, while some of the equities show similar SSMs, there is no definite factor (such as either size of the market, geographical proximity, and financial market maturity, among others) that can be attributed to this pattern. This study throws a further challenge to the mechanism of "bucketing" different markets into one class – a typical practice of indexing institutions.

The last study investigates the role of higher moments in establishing the levels of connectedness and contagion in EMEs under time-varying conditions. The findings surmise that EMEs respond differently to both asymmetric and extreme returns across the spectrum of tranquil and turbulent market periods. The novel rolling-window based generalised lambda distribution (GLD), combined with the wavelet multiple correlation (WMC) and wavelet multiple cross correlation (WMCC), and Baruník and Křehlík (2018) (BK18) spillover techniques show frequency-dependent connectedness and time-dependent fleeting higher moment contagious episodes which are removed from the EZC and GFC periods. The results also expose the dominance of some EMEs in the transmission of shocks instead of the United States, for instance. Nonetheless, the United States emerges a **net transmitter** of shocks rather than a **net recipient.** These dynamics sound caution to policy makers and investors alike to be more wary of shocks emanating from EMEs as compared to those from the United States and by extension, other large developed markets. Finally, the study establishes *"shape shift-contagion"* in emerging markets equities in the short-term post both EZC and GFC episodes. This is consistent with *shift-contagion* and *delayed shift-contagion* hypotheses. Moreover, it corroborates the notion that shock transmissions tend to amplify even for an appreciable lapse in time after crisis episodes have died-off. Nevertheless, this phenomenon varies from one EME to another. Hence this points to usefulness of employing higher moments shocks to augment the mechanisms of classifying market economies.

The results from all three empirical studies have one thing in common: EMEs are alike albeit dissimilar in terms of spatial liquidity susceptibilities, the behaviour of equities risk models pertaining to the reduction of regulatory arbitrage, and how they respond to financial market shocks. These are some important fronts to distinguish EMEs from each other that are hitherto missing from the literature. A number of investment and policy recommendations arising from the findings in this thesis are offered for stakeholders to take advantage of the unique characteristics of EMEs.

Keywords: Elicitability; Financial distance; Global liquidity indicators; Higher moments; Loss function; Regionalisation; Shift-contagion; Spatial autocorrelation; Spatial risk.

JEL classification: C1, C5, C8, C10, C14, C58, F30, G1, G11, G17

LIST OF PUBLICATIONS AND RESEARCH OUTPUTS

Prior to submission, portions of the thesis and other related areas have been published in the peer-reviewed journals while others are under review.

Peer-reviewed journal publication

1. **Owusu Junior, P.,** & Alagidede, I. (2019). Risks in emerging markets equities: Time-varying versus spatial risk analysis. *Physica A: Statistical Mechanics and Its Applications*, 123474. https://doi.org/10.1016/j.physa.2019.123474
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3. **Owusu Junior, P.,** Alagidede, I., & Tweneboah, G. (2020). Shape shift-contagion in emerging markets equities: Evidence from frequency- and time-domain analysis. *Economics and Business Letters*, 2254-4380 - **forthcoming**.
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Papers under review

1. **Owusu Junior, P.,** & Alagidede, I. Shape-connectedness in emerging markets equities: Fresh evidence from frequency-domain analysis. *Economics Bulletin.* ISSN: 15452921.

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6. Tweneboah, G., Seyram, P. K., & **Owusu Junior, P.,** Modelling the asymmetric linkages between spot gold prices and African stocks. *Research in International Business & Finance.* ISSN: 0275-5319.

7. Precious, E., Mensah J. O., & **Owusu Junior, P.** Oil price shocks and stock returns in African markets: A Markov-switching analysis. *Research in International Business & Finance.* ISSN: 0275-5319.

Conferences

1. **Owusu Junior, P.,** & Alagidede, I. Risks in emerging markets equities: Time-varying versus spatial risk analysis. *American Real Estate Society (ARES) 36th Annual Meeting 2020 - Doctoral Seminar, Fort Myers, Florida, USA* ***– April 2020.***
2. Ijasan, K., **Owusu Junior, P.,** Tweneboah, G., & Alagidede, I. Asymmetric relationship between global REITs and exchange rates: Fresh evidence from frequency-based quantile regressions. *American Real Estate Society (ARES) 36th Annual Meeting 2020, Fort Myers, Florida, USA* ***– April 2020.***
3. **Owusu Junior, P.,** Anokye, M. A., & Tweneboah, G. Connectedness of Cryptocurrencies and Gold returns: Evidence from frequency-dependent quantile regressions. *6th International Conference on Applied Theory, Macro and Empirical Finance, University of Macedonia, Thessaloniki, Greece* ***– April 2020.***
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6. Tweneboah, G., **Owusu Junior, P.,** & Michael, E. Integration of African stock markets: Evidence from multi-scale wavelets correlation. *African Review of Economics and Finance Conference, Wits Business School, Johannesburg, South Africa* ***– August 2018***.

DECLARATION

I, **Peterson Owusu Junior**, hereby declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in fulfilment of the requirements for the award of Doctor of Philosophy at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Peterson Owusu Junior

Signed at: **Wits Business School, Johannesburg, South Africa.**

On the 5th day of August, 2020.

DEDICATION

To my mother - Akosua Birago, the stronghold of our family, who has never sat inside the walls of a classroom but has raised a band of intellectuals including two PhDs, and counting.

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The usual caveat applies.

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ABBREVIATION	MEANING
ADF-GLS	Augmented Dickey-Fuller-Generalised Least Squares
AIC	Akaike Information Criterion
ALD	Asymmetric Laplace Distribution
APARCH	Asymmetric Power ARCH
ARCH	Autoregressive Conditional Heteroscedasticity
AST	Asymmetric Student-t with two tail decay parameters
AST1	Asymmetric Student-t with one tail decay parameter
BIC	Bayesian Information Criterion
BIS	Bank for International Settlements
BK18	Baruník and Křehlík (2018) (BK18)
BRICS	Brazil, Russia, India, China, and South Africa
CAGE	Cultural, Administrative/Political, Geographic, and Economic
CAPM	Capital Asset Pricing Model
CGFS	Committee on Global Financial System
CVaR	Conditional Value-at-Risk
DCC	Dynamic Conditional Correlation
DMEs	Developed Market Economies
EMC	Emerging Markets Crisis
EMEA	Europe, Middle-East Africa
EMEs	Emerging Market Economies
EPA	Equal Predictive Ability
ES	Expected Shortfall
ETF	Exchange-Traded Fund
EVT	Extreme Value Theory
EZC	Eurozone Crisis
FDI	Foreign Direct Investment
FKML	Freimer, Kollia, Mudholkar, and Lin (1988)
FR-SC	Forbes and Rigobón's (2002) shift-contagion
FTSE	Financial Times Stock Exchange
FZL	Fissler and Ziegel (2016) Loss
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GAS	Generalised Autoregressive Score
GDP	Gross Domestic Product
GEV	Generalised Extreme Value
GFC	Global Financial Crisis
GFEVD	Generalised Forecast Error Variance Decompositions
GISA	Global Indicators of Spatial Association
GLD	Generalised Lambda Distribution
GLIs	Global Liquidity Indicators
GNI	Gross National Income
HQIC	Hannan-Quinn Information Criteria
IMF	International Monetary Fund
KPSS	Kwiatkowski-Phillips-Schmidt-Shin

LISA	Local Indicators of Spatial Association
LOWESS	Locally Weighted Scatterplot Smoothing
MAE	Mean Absolute Error
MCS	Model Confidence Set
MDP	Diebold and Mariano (1995), Mariano and Preve (2012)
MENA	Middle East and North Africa
MNCs	Multinational Corporations
MLE	Maximum Likelihood Estimation
MSCI	Morgan Stanley Capital International
MODWT	Maximal Overlap Discrete Morlet Transform
NIG	Normal Inverse-Gaussian
PwC	PricewaterhouseCoopers
SNORM	Skewed-Gaussian
STD	Student-t distribution
SSTD	Skewed Student-t distribution
SSM	Superior Set Model
S&P DJI	Standard & Poor Dow Jones Indices
UAE	United Arab Emirates
VaR	Value-at-Risk
VAR	Vector Autoregressive
WMC	Wavelet Multiple Correlation
WMCC	Wavelet Multiple Cross Correlation

CHAPTER ONE

INTRODUCTION

1.1 Background to the study

There is an increasing need to compare and contrast emerging market economies (EMEs), following the Asian Financial Crisis, Eurozone Crisis (EZC), Russian Crisis, and the Global Financial Crisis (GFC) of 2007-2009. Over the decades, financial crises have exerted negative impacts on businesses and governments in different market blocs. While developed market economies (DMEs) have received their share, it is EMEs that have been more vulnerable to these market disturbances (Berkmen et al., 2012; Celık, 2012; Reinhart & Rogoff, 2009; Samarakoon, 2011; Sauvant et al., 2010; Shabri Abd Majid & Hj Kassim, 2009; Takáts, 2010). However, the impacts are not uniform across the EMEs (Dimitriou et al., 2013; Jin & An, 2016; Syllignakis & Kouretas, 2011). Financial crises and their associated effects have always been important for portfolio risk management and diversification, and monetary policy (Celık, 2012). These demand that we charaterise EMEs at deeper levels. The knowledge gained from this can be used to devise strategies that address specific features of an economy in order to mitigate against future crises. Given the rising degrees of interdependence of global markets (Boubaker et al., 2016; Hashmi & Tay, 2007; Jiang et al., 2017), further characterisation of EMEs from DMEs can provide valuable information for investors who have interest across these markets to diversify risk. In this study, we use the United States an example of a DME to understand these interrelationships.

This interest to characterise EMEs does not only emanate from risk mitigation purposes but also to maximise investment returns and to articulate appropriate policy reforms which are needed amidst financial turmoil. Moreover, increasing integration of previously segmented economies has been amplified by the impact of these market disturbances as seen in episodes of contagion. While the extant literature is ripe with studies aimed at unearthing the differences and similarities in EMEs, most of them have centred on all too common dimensions such as returns and volatility behaviour. Although these attributes are helpful, they fail to provide deeper insights into EMEs for the rich understanding needed to make the best of investment and policy decisions.

The large body of literature agree on increasing levels of interdependence[1] in the global financial market place (for example, Boubaker et al., 2016; Forbes & Rigobón, 2002; Hashmi & Tay, 2007; Jiang et al., 2017). Moreover, there are stronger connectedness in financial, trade, and regional blocs such as EMEs (Ahmad et al., 2013; Bodart & Candelon, 2009; Sojli, 2007), Association of Southeast Asian Nations (Lim, 2009; Trihadmini & Falianty, 2018), BRICS (Brazil, India, China, Russia, and South Africa) (Bonga-Bonga, 2018), among others. On the one hand, these may not come as surprise because the categorisation of countries into blocs, regions, markets, economies, among others, is based on similarities dictated by either and/or geography, trade, economics, financial system, and the likes of these (see Ghemawat, 2001; Morgan Stanley Capital International (MSCI), 2018). On the other hand, one of the big topics on economic and financial systems is the globalisation of different markets through the integration of otherwise segmented markets. This can largely explain the increased integration of global markets and the transmission of shocks, for instance, from DMEs to EMEs (see Boubaker et al., 2016; Shahzad et al., 2017; Wang et al., 2017; Williams, 2017; among others).

[1] In this thesis, interdependence, connectedness, and spillover are used interchangeably.

However, one issue which captures attention is how individual EMEs respond differently to international financial market shocks, such as those emanating from the GFC and EZC (see Dimitriou et al., 2013; Jin & An, 2016; Syllignakis & Kouretas, 2011). This brings to light delicate differences that may exist in EMEs despite them being "bucketed" together as one. Among other things, EMEs can be distinguished by high returns, high risks, and low covariances with global market factors (Jorion & Goetzmann, 1999). In essence, they point to diversification potentials in portfolios comprising developed markets and emerging markets equities. Nonetheless, that diversification benefits exist within EMEs (Mensah & Premaratne, 2016; Mensi et al., 2017) is further evidence of disparity in these markets. Jorion and Goetzmann (1999) further suggest that market economies are likely to be misclassified unless a deeper dive is taken into the historical data, since markets usually emerge, re-emerge, and submerge. This suggests the need to continuously update or augment the mechanisms used in classifying markets as they go through these phases. It is particularly important that the factors employed in updating market classes be more subtle than those previously used.

While the extant literature may be replete with evidence pointing to differences and/or similarities in EMEs, most of them take a direct approach by analysing the correlations in their equity returns and volatilities (see Bekaert & Harvey, 2017; Bekaert et al., 2002; Bonga-Bonga, 2018; Sensoy et al., 2017; Wang & Moore, 2012). These bring out only the obvious layers of differences and similarities. However, there may be understated factors that generate not only academic interests but also policy significance. The body of knowledge points to the benefits of portfolio diversification when markets are reasonably distinct from each other. There is also support for negative spillover effects between markets at unreasonably high levels. This can be termed as "contagion"; and usually lasts for only a short time. For instance, interdependence between financial markets produce benignant effects (Argy, 1996; Bekaert et al., 2014; Bekaert & Harvey, 2003; Kearney, 2012). Unlike, interdependence, contagion usually have malignant impacts, especially for weak EMEs (Kristin & Kristin, 2012).

It is, therefore, important that we obtain some fresh evidence from new research that examines the marginal differences and/or similarities between EMEs. To this end, both traders and policy makers could benefit from a deeper understanding of market integration dynamics, and at the same time moderate the disadvantages of unwholesome levels of connectedness.

At the abstract level, the reason for and the need to compare and contrast EMEs is both natural and logical. Why would anyone expect there to be differences as well as similarities between EMEs? This is an important question that needs to be addressed. We believe the answer lies in the foundation that countries share common features for which they are categorised into blocs, economies, and markets, among others. First, it is evident that EMEs (as well as DMEs) share common trade, cultural, and socio-political dynamics (Ghemawat, 2001). Second, countries are classified based on commonalities in financial systems and macroeconomic dynamics. For instance, the choice of EMEs used in this study is based on the overlapping classification by popular indexing institutions. These are MSCI, Financial Times Stock Exchange (FTSE) Russell, and Standard & Poor Dow Jones Indices (S&P[2] DJI). Generally, they use economic development (as measured by a Gross National Income/Gross Domestic Product (GNI/GDP) per capita

[2] The S&P acquired the International Financial Corporation's Emerging Markets Data Base in January 2000. https://ifcextapps.ifc.org/IFCExt/Pressroom/IFCPressRoom.nsf/0/1BA136DC61B8E3CE8525698100577E3F?OpenDocument

threshold), size and liquidity of financial markets, financial market accessibility, and stability of institutional framework as criteria for classifying economies (see FTSE, 2018; MSCI, 2018; S&P DJI, 2018). Third, there is the geographical backbone to how countries are categorised. Even though EMEs (and DMEs) spread across the seven continents[3] of the world, it is clear that many of the EMEs in Africa, Asia, Europe, and South America share close and/or adjoining borders. That is to say, the countries in the same continents will naturally possess some economic and cultural parallels (Ralston et al., 1992). Is it any surprising that countries are similar in many aspects because they are geographically close?

Nevertheless, we also find reasons to believe that dissimilarities may exist between EMEs. First, the geographical argument also supports differences in the countries. Across the five continents hosting EMEs and spanning the Arctic, Atlantic, Indian, and Pacific Oceans (Monfils, 2005), economic, cultural, and socio-political differences naturally emerge. Further, even at the height of closeness in EMEs there exist some degrees of variations across the board. There is simply no two perfect countries when we put them under scrutiny. Even countries that share contiguous borders in the same continent may have opposing political, economic, and cultural frameworks. For example, India and Pakistan share a common border but they have economic and cultural differentials (Kazmi & Bilquees, 1993) despite their predominant Islamic religious setting (Jejeebhoy & Sathar, 2001). Similarly, neighbouring South Korea and North Korea have been at political odds since the Korean War (1950-1953) (Kim & Prideaux, 2006). Their economies differ to an extent that North Korea, the United States, the United Nations have had to intervene with food aid (Kim et al., 1998) at certain times. Even Hong Kong, which is a Special Administrative

[3] These are Asia, Africa, North America, South America, Antarctica, Europe, and Australia.

Region inside China, operate its own customs status, laws, and currencies (Li & Bray, 2007; Priem et al., 2000). Further, it was seen as the main driver of contagion in the 1997-1998 Asian crisis (Baur & Fry, 2009) instead of the large economy of China and notwithstanding the comovement between their stock markets (Ma et al., 2019). These pairs of countries share adjoining borders in Asia but they do not share economic, cultural, and political conditions. Ghemawat opines, for instance, that "Culturally, China is a long way away from nearly everywhere else" (Ghemawat, 2001, p.6). Another fundamental phenomenon to explain the differences in EMEs is that they comprise of countries from both Eastern and Western cultures and capitalist and socialistic economic backgrounds (Ralston et al., 1992).

The foregoing discussion shows that there are obvious similarities as well as differences between EMEs. These do not require much effort to recognise. However, there seem to be subtle differences and similarities between the markets which can be only be perceived through close examination. In this thesis, we have chosen to uncover these characterisations by examining interdependence in equity returns, the relationship between tail risks of equities, and spatial risks in EMEs.

There are also theoretical frameworks for the foregoing philosophical discussion. Two main theories which reinforce the motivation for this study are the Psychic distance framework (Beckerman, 1956; Hofstede, 1984; Hofstede & Bond, 1988; Johanson & Vahlne, 1977; Johanson & Wiedersheim-Paul, 1975; Dow & Karunaratna, 2006; Drogendijk & Martin, 2008) and Tobler's first law of geography (Tobler, 2004; Tobler, 1970). The Psychic distance framework has evolved to be seen as the difference or distance in objects or phenomena which generally affect international trade and managerial decision making. These discrepancies largely arise from cultural differences and geographical diversity between trading partners. It is believed that the closer these phenomena are the easier it is to do business by making effective decisions and vice versa. Tobler's first law of geography also supports the Psychic distance theory. Tobler's law states that; *"everything is related to everything else, but near things are more related than distant things"* (Tobler, 1970, p.236).

When we apply these theories to EMEs, we are able to characterise them by examining the relationships between tail risks in their equities, spatial risks in the markets, and shock transmissions in their equity markets. It is possible to: 1) compare and contrast the tail risk models in the emerging markets equities, 2) measure and compare the distances between their spatial risks, and 3) measure spillover of shocks between them. Given that the economies bear some degrees of similarities and have geographical proximities, it is usual to assume that events in one market have the tendency to affect the happenings in another market.

In examining the tail risks in emerging markets equities, the theory of *Elicitability* is employed. In statistical decision theory, *Elicitability* refers to risk measures for which competing estimation procedures are comparable (Fissler & Ziegel, 2016; Ziegel, 2016). This theory provides support for ordering and selecting risk models for emerging markets equities in order to examine their differences and similarities. Lastly, we make use of the *shift-contagion* hypothesis of Forbes and Rigobón (2002). The *shift-contagion* hypothesis can be defined as a significant increase (or change) in the cross-market correlations in returns after a shock transmission to one country (or group of countries). From this standpoint, it is easy to understand the similarities and differences between EMEs by investigating the dependencies in their equity returns. In the process of ascertaining the extent of similarities in the EMEs, the levels of dissimilarities also become clear.

1.2 The place of EMEs in global financial markets

In recent times, we may be equally concerned with the financial imprudence of both DMEs and EMEs which can put the global financial system in despair. This is because EMEs have become a huge and important component of international finance, given their connectedness with each other and between DMEs. For instance, the Organisation for Economic Corporation and Development Centre indicates that, economic and political power have gravitated towards EMEs over the last two decades (Kharas, 2011). This is signaled by an increasing number of these countries becoming strong centres of growth as their share of global income have risen significantly (Kharas, 2011). These features make them attractive to developed countries to intensify trade, aid, and investment, among others. Given the intensifying interrelationships, investors and policy makers have the natural tendency to keep eyes on dynamics such as risks of investments, interdependence, and contagion and the implications these tend to have. It is imperative to note that these have become concepts to deal with, because of an undeniable move of financial openness and/or liberalisation of capital flows over the years. Further, the flow of funds to and fro EMEs is, to a large extent, at the impulses of DMEs dynamics (i.e. increasing interest rates) in Europe and the United States. Many investors pulled a lot of funds from emerging market exchange-traded funds (ETFs) in the middle of 2018 due to rising interest rates in the United States. The $35 billion iShares MSCI Emerging Markets ETF had $2.2 billion wiped off in a week; the most since January 2014. In the same week, the biggest emerging markets ETF, the $65 billion Vanguard Financial Times Stock Exchange (FTSE) Emerging Markets ETF also lost about $270 million; its second-worst performance in over two years (Bloomberg, 2018). We note that these are at the backdrop of the knowledge that EMEs offer higher equity returns and hence attract more portfolio inflows than DMEs (Aftab et al., 2018; Madhur, 2008; Milesi-Ferretti & Tille, 2011).

The literature is explicit on the accompanying high risks to high returns in EMEs equities. We can explain the capital flight from these markets because of the Federal Reserves' tapering actions for many years (see Aizenman et al., 2014; Gupta, 2014; Enginar et al., 2018; Ghosh & Saggar, 2017; Mishra et al., 2014). However, the more relevant concern may be the impact of risks on EMEs' financial systems and the global market alike. The reason is that the risks could be more difficult to contain when the factors driving them are unsuspecting as well as non-uniform across EMEs. Further, the narrative underscores shock transmissions fostered by international market integration resulting from global financial liberalisation (Arouri et al., 2013; Hunter, 2006; Yao et al., 2018). Furthermore, Santiso (2003) notes that, private investment has boomed from continuous rebalancing of portfolios line with the speed of stock market liberalisation in the 1990s. The attendant effect was sporadic capital inflows and high instabilities coupled with severe currency crises spreading among EMEs such as Mexico, Thailand, South Korea, Russia, Brazil, and Argentina (Santiso, 2003). This is a further revelation that there is interdependence and contagion between EMEs and DMEs as well as among EMEs. We surmise that possessing a deeper empirical understanding of the various sources of risks that originate from the differences and/or similarities of EMEs will help forestall crises or at least manage them better.

1.3 Statement of the research problem

The problem statement for this thesis is premised on three main aspects of risk analysis that bring out the latent differences and/or similarities in EMEs. These are *spatial risks versus tail risks, elicitability of risk models, and shape shift-contagion.* Each of them are discussed as follows:

a. Spatial risks versus tail risks: Value-at-Risk (VaR) and Expected Shortfall (ES) have been the mainstay of portfolio and market risk measure for many years. The VaR and ES are popular in internal risk modelling because they are required by the Basel Accords (Basel I and II) to regulate risks in the financial system. As widespread as VaR and ES, they have important limitations documented in the literature. Among other things, VaR fails as a coherent measure (Artzner, 1997) while ES is sensitive to tails which can lead to greater periodic capital charges (Chang et al., 2019). The latter is also more sensitive towards regulatory arbitrage and parameter specification (Kellner & Rösch, 2016). More importantly, the weaknesses of the VaR has been more pronounced in the wake of the GFC. Its design fails to function properly under turbulent market conditions because it shies away from capturing extreme events (Danielsson et al., 2001).

Bearing these in mind, one wonders if the time-varying tail risk measures such as VaR and ES should be the only means to assess risk in equities and financial systems. The thesis suggests that, to adequately quantify and analyse risk in financial systems, other time-invariant country-specific (spatial) risk factors should be considered. To this end, this thesis extends the Cultural, Administrative, Geographic and Economic (CAGE) distance dimensions (Ghemawat, 2001) to include *"financial distance"* as a spatial risk dimension. In the context of this thesis, *"financial distance"* is defined as the magnitude and direction of spatial autocorrelations between the Global

Liquidity Indicators (GLIs)[4] of EMEs. We deem spatial risk to be a better measure of risk, in the context of this study, because it captures the overall vulnerability in the financial system of an economy. Proper management of this risk can help prevent systemic failures. Bierut (2013), for instance, shows that global liquidity measures do better than domestic indicators to foretell warning signs of asset price busts may cause financial stress. Modelling and managing time-varying tail risks of equities do not offer the bigger picture of the risk landscape of an economy. The implications of time-varying tail risk of equities are irrelevant when time-invariant uncontrolled spatial risks cause systematic failures. More importantly, there is evidence of liquidity vulnerabilities pertaining to EMEs (BIS, 2011).

Thus, the thesis provides a broader risks and/or opportunities assessment in EMEs equities and financial systems by juxtaposing time-varying risks with spatial risk. By so doing, the thesis deepens our understanding of EMEs risks based on their geographical distance tied with their liquidity vulnerabilities. While liquidity vulnerabilities have been given the needed attention in the literature that is not the case for geographical distance in EMEs.

b. Elicitability of emerging markets equity risk models: Due to the distributional characteristics of financial asset returns, modeling their tail risks continue to be a daunting task. There are a numerous distributional innovations to choose from to address extreme and asymmetric returns. There is the class of skewed Student t (Fernández & Steel, 1998; Zhu & Galbraith, 2010, 2011; Shushi, 2018), asymmetric Laplace (Kotz et al., 2012), skewed Gaussian (Fernández & Steel, 1998; Shushi, 2018), copulas (Sklar, 1959), extreme value (Coles et al., 2001; Gilli & Këllezi,

[4] The GLIs are provided by the Bank for International Settlements (BIS).

2006), quantile (Koenker & Bassett, 1978; Sim & Zhou, 2015), Johnson's family (Shenton & Bowman, 1975) distributions, among others. These and other distributions are able to capture the tails of returns but they cannot do so in a time-varying manner. When combined with time-varying properties of the Generalised Autoregressive Score (GAS) of Harvey (2013) and Creal et al. (2013), they can better capture the dynamics of financial returns as performed in this study. The past few decades have seen a proliferation of competing models (Bernardi & Catania, 2016), at the disposal of both econometricians and internal risk managers of financial firms. In the family of volatility models alone, the Autoregressive Conditional Heteroscedasticity (ARCH) models (Engle, 1982; Bollerslev, 1986), for instance, is perhaps the most wide-ranging of all models econometric inventions (Moosa, 2017). Non-linear state space stochastic volatility models have also been explored by Taylor (1994), Harvey and Shephard (1996), and Gallant et al. (1997). The GAS (also known as Dynamic Conditional Score (DCS)) models have also become popular in recent times (Bernardi & Catania, 2016). Hence, in recent times, the objective of risk managers has not been to find a single best model but a set of ordered superior models (Hansen et al., 2011).

Nonetheless, choosing a set of risk models should not only be an internal affair of financial firms, but must be in accordance with regulatory framework. The Basel III[5] framework requires VaR and ES models to be comparable to their standardised approach. The phenomenon is known as comparative back testing[6]. While VaR models lend themselves to be ranked (a concept called

[5] The initial Basel III was expected to be implemented by 1st January, 2019 while the *final* Basel III minimum requirements are expected to be implemented by 1st January 2022 and fully phased in by 1 January 2027 (Patton et al., 2019), https://www.bis.org/press/p181004.htm. Basel III is an internationally agreed set of measures developed by the Basel Committee on Banking Supervision in response to the financial crisis of 2007-09. The measures aim to strengthen the regulation, supervision, and risk management of banks (Basel III, 2017).

[6] Where a bank's internal risk model is held accountable to an agreed-upon standardised approach (Fissler et al., 2015). The approach involves ranking a set of competing models based on their forecast ability.

elicitability), ES lacks this property (Fissler & Ziegel, 2016; Nolde & Ziegel, 2017). In statistical decision theory, elictability refers to risk measures for which the competing estimation procedures are comparable (Fissler & Ziegel, 2016; Ziegel, 2016). However, at the higher level, the joint VaR and ES, hereafter referred to as (VaR, ES), is elicitable. The Fissler & Ziegel (2016) Loss (FZL) function is an appropriate associated score. Elicitable risk measures, therefore, serve as the bridge between internal models of financial institutions and standardised regulatory approaches. The purpose of this is to reduce regulatory arbitrage. This has opened a fledgling area in financial risk model selection for which the aim of Basel III to reduce regulatory arbitrage can be realized (Basel III, 2017). Notable works in this new area include Fissler et al. (2015), Nolde and Ziegel (2017), and Patton et al. (2019) which focus on the theoretical basis. While risk modelling of emerging markets equities abound in the literature, studies on model ranking and selection that are consistent with the current regulatory framework are largely missing. The only application to equities is the study by Taylor (2019) using the Standard & Poor 500 returns and the GARCH-based asymmetric Laplace distribution. This study is the first to use a number of emerging markets equities and different distributional innovations. Hence, thesis uncovers new perspective on EMEs dissimilarities and similarities by modelling their equity risks.

c. Shape shift-contagion: Undoubtedly, studies on interdependence and contagion have been extensive for many years. This interest can be attributed to different crises episodes at the regional and global levels (Diebold & Yilmaz, 2009; Forbes & Rigobón, 2002). However, it can also be explained by increasing financial liberalisation, which has brought otherwise segmented markets closer than before (Kearney, 2012). The literature is pronounced on the distributional properties of equity returns in examining interdependence and contagion for portfolio selection and risk management (see Amaya et al., 2015; Chang et al., 2013; Hadar & Seo, 1990; Müller & Wagner, 2018). The distributional properties of higher moments (skewness and kurtosis) for equity returns have been espoused as critical in the performance of diversified portfolios (Bessembinder, 2018). The reason is that their comoments help to quantify the marginal contribution of each asset to a portfolio's risk (Ranaldo & Favre, 2005). While studies using higher moments as channels of interdependence and contagion are gradually growing (Ang & Timmermann, 2011; Chan et al., 2019; Fry-McKibbin & Hsiao, 2018; Fry-McKibbin et al., 2018), content on EMEs is largely missing.

Hence, this thesis deviates from the large body of literature which focuses on first and second order moments in interdependence and contagion studies. We investigate the origins of interdependence and contagion with the comoments in higher order (shape parameters) moments of emerging markets equity returns. In light of Forbes and Rigobón's (2002) *shift-contagion,* the study hypothesises *"shape shift-contagion"*. Theoretically, we extend the definition and measurement of contagion and interdependence by using a time series of shape parameters in the empirical analysis. The findings of this study provide fresh evidence to support higher moments as sources of connectedness and contagion. Further, they provides a new lens to see how EMEs respond to shocks transmitted through the often-ignored higher moments of equity returns. In the end, this study documents another means to differentiate EMEs from each other.

This study is necessary to provide deeper knowledge on EMEs in order to better characterise them for the devising and implementation of investment strategies and policies. Stakeholders can take advantage as well as manage negative spillovers between EMEs when they are armed with the right amount of information on the differences and similarities between the markets. We believe the findings and recommendations from this study can be a modest source of inspiration for investors to revise their cross-border trading schemes. Governments and policy makers may also rediscover the potentials and hidden weaknesses in their economies so that they can make better plans for the future. The novel aspects of this study can also find use by the academic community to promote new ideas on EMEs research.

While there is no specific event on the emerging markets landscape that has necessitated this study, it is important to note that research is timely in the sense that it provides up to date information for policy and investment decision making. Apart from well-known events in the financial markets, the data is always rich with subtle structural changes that can be utilised only by careful observation and analysis. Pericoli and Sbracia (2003), for instance, underscores the need for investors to continuously update themselves due to the incompleteness of information. This applies to policy makers as well so that they can devise and implement best possible solutions on account of current data.

1.4 Research objectives

Given the widespread direct comparison of EMEs via their equity returns and volatilities, geographical locations, macroeconomic fundamentals such as gross national product (GDP), and efficiency of their financial systems, among others, this thesis takes an indirect route to uncover latent differences and similarities in EMEs. While a direct approach can still make satisfactory contributions to the literature, we have adopted the indirect route approach in order to make significant and novel contributions. This thesis argues that there are equally important but covert factors that can uncover deeper parallels albeit dissimilarities between EMEs which have not been revealed in the literature hitherto. Particularly, this thesis examines spatial risks, elicitability of risk models, and *"shape shift-contagion"* which have not been employed to compare and contrast EMEs hitherto. Specifically, the thesis seeks to achieve the following objectives:

1. To investigate the relationship between spatial risks in EMEs and tail risks in their equities. This objective seeks to supplement time-varying tail risk analysis in EMEs by incorporating country-specific risks that should be relevant to inform both policy and equity investment decisions.
2. To model, select, and rank emerging markets equities risks. This objective explores the dynamics of emerging markets equities risk model ranking and selection under different market conditions.
3. To investigate the origins of interdependence and contagion transmitted through the shape behaviour of emerging and developed markets equity returns.

1.5 Research questions

The thesis seeks to find answers to the following questions to enable comparison of EMEs:

1. What is the relationship between spatial risks in EMEs and time-varying tail risks in their equities and how does it affect policy and investment decision making?
2. How do risk managers model, select, and rank risks emerging markets equities?
3. What is the nature of interdependence and contagion transmitted through the shape parameters of equity returns within EMEs and between DMEs?

1.6 Significance and contribution to knowledge

Emerging markets literature that enforce EMEs resemblance (Bekaert, 1995; Bekaert & Harvey, 2002; Kearney, 2012; Morck et al., 2000) and those that entrench their difference (Dawar & Chattopadhyay, 2002; Goetzmann & Jorion, 1999; Hammoudeh & Choi, 2007; Olbrys, 2013) is widespread. Although these and many other studies have provided important knowledge on EMEs for both investment and policy, they have mostly bordered on the common features of macroeconomic, financial system infrastructure, political landscape, return and volatility, among others. These leave out the hidden layers unexplored and hence suggest an important gap in the literature. Unearthing these covert structures in EMEs extends knowledge that is useful to implement investment strategies and policies. This will also help in taking advantage of both the differences and similarities between markets and at the same time extenuate the potential negative spillovers.

The significance of this study is manifest in the contributions to the extant literature. The first contribution is aimed at addressing the scarcity in the knowledge on risk assessment of EMEs equities with spatial risk dimensions. In the direction of international trade, for instance, this sheds light on the importance of country-specific features that can be useful for international portfolio risk analysis. From an understanding of spatial autocorrelations in liquidity risks in EMEs, spatial-stamped risk-minimising portfolio construction can be undertaken. Further, the findings of this study brings to the fore the insufficiency of time-varying tail risk analysis. Additionally, by recognising the *"financial distance"* between EMEs, policy makers can take prudent measures to maintain appropriate levels of liquidity in order to forestall systemic financial disasters.

Second, while an abundance of literature on risk modelling and selection for EMEs equities exist, they do not appeal to the need to decrease regulatory arbitrage via comparative back testing. By exploring the elicitability feature of the (VaR, ES) and with the Model Confidence Set (MCS) procedure of Hansen et al. (2011), the study offers new insights on characterising EMEs. It is fair to say that this could stimulate more confidence in emerging markets equities for the vogue international investor. One can imagine the prospects of capital flows into EMEs under the circumstance. Moreover, the thesis portrays how the burden on risk managers can be reduced in their quest for a single best model. They can create a set of ordered optimal models instead of searching for a single perfect model. Empirically, the size of an optimal set of models suggests homogeneity (or heterogeneity) in the risk model. This information is useful in constructing well-diversified portfolios for the respective equity, given that different distributional assumptions are applied to the returns.

Third, the study fosters on an innovative way of investigating interdependence and contagion. By establishing the *"shape shift-contagion"* hypothesis, the study extends the definition of contagion, in general, and specifically, the definition by Forbes and Rigobón (2002). Through this, the thesis complements the content on the origins of shock transmission with time-varying higher moments of emerging markets equity returns. This encapsulates a very rich information for all EMEs stakeholders. Further, this study offers new evidence for understanding spillovers within EMEs and between DMEs so that both investors and policy makers can take the necessary actions to manage marginal interdependence and contagion. This study provides yet another means of distinguishing one EME from another by way of how they react to higher moments' shocks. Finally, this thesis has the prospects of provoking renewed interests in EMEs research in areas that have been less explored hitherto as well as a rethinking of the extant knowledge on the economic bloc.

1.7 Structure of the thesis

The complete thesis report consists of six (6) chapters. Chapter Two (2) reviews the literature covering the thematic areas of the thesis. It appraises the theoretical concepts of tail risk types, spatial risks premised on the CAGE distance framework, interdependence and contagion. On the empirical side, Chapter Two provides an assessment of time-varying tail risk measures, the variables used, elicitability of these measures, the CAGE distance dimensions, and liquidity distance measures. Further, the origins and incidences of interdependence and contagions are reviewed in light of higher moments of returns. The next three (3) chapters: Chapter Three, Chapter Four, and Chapter Five empirically address each of the research objectives (or questions). Lastly, Chapter Six (6) covers conclusions, investment and policy implications, and recommendations for investment and policy based on the finding from the thesis. The chapter also highlights areas of future research opportunities.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter gives a brief review of the literature on tail risks and spatial risks, elicitability and ranking of tail risk models, and transmission mechanisms of interdependence and contagion of emerging markets equities. Both theoretical and empirical aspects of the literature are covered for these themes. The chapter synthesises literature review for the three thematic areas which form the basis of the next three chapters; Chapter Three, Chapter Four, and Chapter Five. The theoretical literature in this chapter can be viewed as supporting the two main theoretical frameworks of Psychic distance and Tobler's first law of geography. The theoretical frameworks also provide basis for *"financial distance"* and *"shape shift-contagion"* hypotheses for this thesis. Section 2.2 examines the types of tail risk measures; theories of interdependence and contagion; transmission channels of contagion, the incidence of contagion, and distance dimensions for spatial risks in EMEs. From the last two phenomena the thesis hypothesises *"shape shift-contagion"* and *"financial distance"*, respectively. In so doing, theoretical frameworks for *"shape shift-contagion"* is presented as an extension of the broad definition of contagion but specific to the *shift-contagion* hypothesis of Forbes and Rigobón (2002). Further, a theoretical framework for *"financial distance"* is given to extend the CAGE distance dimensions of Ghemawat (2001). The empirical review in Section 2.3 mirrors the theoretical review to cover all three themes of the thesis.

2.2 Theoretical literature

This subsection deals with the literature on the theories and concepts that together support the two main theoretical backbone of the study (i.e. Psychic distance framework and Tobler's first law of geography). In addition, it covers the concepts of tail risk, spatial risk, and interdependence and contagion to support the specific objectives of this study.

2.2.1 Tail risks and spatial risks

In this subsection, we discuss the contrast between time-varying tail risks and spatial risks to understand the why it is important pay closer attention to spatial risks for a holistic risk assessment in emerging markets equities.

2.2.1.1 Value-at-Risk (VaR) and Expected Shortfall (ES)

The widespread use of Value-at-Risk (VaR) as a portfolio risk management tool came to the foreground in 1998 when J. P. Morgan (Morgan, 1996) invented the RiskMetrics toolbox. It has since featured in the prudential frameworks of various Basel Accords. However, the VaR has not been the *de rigueur* tail risk measure since the popularisation of Expected Shortfall (ES) by Artzner et al. (1999), and especially because of the 2007-2009 GFC. Among others things, its main criticism has been the fact that the VaR model assumes normal distribution of asset returns; which is a big flaw in light of the extant literature. It has been described as far as "The Number That Killed Us" by Pablo Triana; not only for its mathematical flaws but also its administrative shortfall – in that is a method designed by industry and adopted by regulators to monitor the industry that created it (Triana, 2010). Yet another weakness of the VaR is its reliance on historical correlations (i.e. financial events are fairly predictable) in the computation of market risk. One of the loudest voices against this assumption is Nassim Nicholas Taleb with his "The Black Swan". The Black

Swan[7] metaphorically describes events that are improbable but possible to occur and thus cannot be predicted based on past experiences. Taleb (2007) notes *"although these unpredictable deviations are fairly rare, they cannot be dismissed as outliers because cumulatively, their impact is so dramatic" (p. 27).* In effect the Black Swan analogy can be likened to *"expecting the unexpected"*. Following the GFC the Basel Accord has implemented a series of policy measures culminating in Basel III to make the financial system "sounder and safer" (European Central Bank, 2019). Since the theoretical basis of the VaR and ES are widely researched and written about, only a brief review is given in this thesis.

In simple intuitive terms VaR is a number that summarises the worst loss in an asset or a portfolio over a target time horizon. This loss should not be exceeded with a given level of confidence under normal market conditions. By convention VaR is expressed as a non-negative number which describes the quantile of the projected distribution of gains and losses over the target time horizon (Jorion, 2006). The ES, an inspiration for Basel III, is aimed at strengthening the weaknesses in the design of VaR exposed by the GFC. The main drawback was the insufficiency of the capital required against trading book exposures to absorb losses. In technical terms that means the requirement was not able to capture "tail risk" (Bank for International Settlements (BIS), 2013). Since May 2012 Basel III has proposed to move from VaR to ES to measure the riskiness of a position by considering both the size and likelihood of losses above a certain confidence level. The ES is basically VaR calibrated to stressed market conditions; thus a "regulatory capital charge that is sufficient not only under benign market conditions, but also during periods of significant

[7] All swans were believed to be white until a group of black swans was spotted in Australia in 1697.

financial stress" (BIS, 2013, p.18). For internal models-based approach, Basel III uses a 97.5% ES to calibrate capital requirements to rationalise the financial markets.

The VaR suffers practical as well as coherent risk measure weaknesses. On the practical side Artzner (1997) and Artzner et al. (1999) show that the VaR ignores any losses beyond it. Here is where the assumption of normal distribution in asset returns becomes a problem. By this, VaR does not factor into the model important information regarding the tails of the underlying distribution. This is expected because the VaR was designed to work under tranquil market conditions - it is unable to capture extreme events which reflect in the tails of distributions. This explains the alternative name of ES as Conditional VaR (CVaR) (i.e. given a realised VaR, what is the expected loss?). That is to say, the underlying distribution in the estimation of VaR should be able to capture the extreme events in the tails of the distribution - at least any asymmetric probability distributions could be a good alternative.

Further, VaR fails to conform to the axiom of sub-additivity as a property of coherent risk measures. Because of these shortcomings VaR could mislead investors in their quest to maximise portfolio utility (Yamai & Yoshiba, 2002). Thus, the strength of ES is in its coherence and ability to quantify dangers beyond VaR (see also Acerbi et al., 2001; Acerbi et al., 2001; Acerbi & Tasche, 2002).

Regardless of the seemingly desirable features of ES, VaR has not completely being dismissed as a capital requirement measure for legitimate reasons. The daily or periodic distribution of capital charges to banks (or with respective to a specific equity or portfolio) is dependent upon the risk function adopted (that is either VaR or ES) and their estimated counterparts. Though ES has been espoused as a better measure of risk, its sensitivity to tails can lead to greater periodic capital charges (Chang et al., 2019). Kellner and Rösch (2016) also show that the ES ($\alpha = 0.975$) is more sensitive towards regulatory arbitrage and parameter specification. In addition, the mathematical rigour of ES may pose challenges in computation and practical implementation to financial firms. However, this challenge is easily overcome in the current era of computational power of personal computers and the widespread availability of statistical codes and packages. Additional shortcomings of ES are the lack of elicitability and robustness in estimation procedures (see Burzoni et al., 2017; Cont et al., 2010; Fissler & Ziegel, 2016; Fissler et al., 2015; Nolde & Ziegel, 2017).

These explain why the extant literature is noted for assessing the relative merits VaR and ES for risk modelling. But in recent times, the debate has included the joint (VaR, ES) models and scoring functions such as the FZL due to their contribution to the Basel III prudential framework.

2.2.1.2 Elicitability and FZL

The quality and robustness of risk measure estimates remain important – this is appropriately assessed through back testing. But what is more important is that internal risk models should approximate standardised regulatory frameworks in order to reduce regulatory arbitrage. As regulatory capital requirements VaR and ES of internal models should be akin a standardised approach outlined by the regulation body. The Basel III achieves this through comparative back testing. To undertake comparative back testing risk models should be elicitable (possess the ability to be ranked based on their forecast ability). While ES is a coherent risk measure, unlike the VaR, it is non-elicitable (Patton et al., 2019).

This presents a challenge for risk modelling in light of the weaknesses vis-à-vis strengths of VaR and ES. However, Fissler et al. (2015), Fissler and Ziegel (2016), and Nolde and Ziegel (2017) have shown that ES is jointly elicitable with VaR at a higher order (i.e. jointly with VaR). Following from this, Fissler and Ziegel (2016) propose a joint loss function for VaR and ES (VaR, ES) which is useful for comparative back testing. They have proved, based on Acerbi and Szekely (2014), that (VaR, ES) jointly minimises the expected values of a family of scoring functions as a prerequisite for elicitability (see also Fissler et al., 2015; Patton et al., 2019). Using the (VaR, ES), the FZL promises to replace the traditional back testing (dissociated from regulatory oversight) with comparative back testing in Basel III to mitigate against regulatory arbitrage. In this study we employ GAS (VaR, ES) models scored by the FZL for tail risk measures for EMEs equities.

2.2.2 "Distance Still Matters"

"Distance Still Matters" is a phrase coined by Pankaj Ghemawat to dispute the general notion that due to globalisation the world has effectively become a "global village" where differences between countries have ceased to exist. He ponders that argument that distance is dead is a dangerous assertion which must be ignored in order for businesses to be successful in any form of cross-border trade. Why is this important? Because generally these differences or distances have negative effects on cross-border interactions. In subtle ways there are opportunities concomitant in these distance dimensions as well. The notion that distance is dead has led to the failure of many a MNCs in their quest to expand. A deeper assessment of differences in countries proffers interesting revelations. For instance, Ghemawat (2001) opines that “Culturally, China is a long way away from nearly everywhere else” (Ghemawat, 2001, p.6).

Distance in various dimensions can dramatically change the assessment of the attractiveness of foreign markets be it trade, foreign direct investment (FDI) or equity flows. This has been proven both in international trade and recently, in cross-border equity flows. Thus, economies and countries have to be recognised as being different along many lines of specific attributes such as geographical location, religious preferences, political system, administrative system, national culture, time zones, and the likes of these. This phenomena identifies with the overall objective of studying the similarities and/or differences in EMEs despite their common denominator - there exist pertinent differences that must be addressed from investment and risk analysis perspectives.

2.2.2.1 The CAGE distance dimensions

In the breakdown of “Distance Still Matters” the author has classified many attributes of countries under Cultural, Administrative/Political, Geographic, and Economic (CAGE) distance framework. This has been pioneered since the early 2000s as an international trade tool to identify and prioritise differences between countries for the development and implementation of cross-border strategies and has received support from other researchers as well (Ghemawat, 2001; Giudici et al., 2018).

The CAGE framework has been designed mainly for industry and country levels which has a broad array of unilateral and bilaterally implications. The emphasis is placed on the bilateral country level to align with the objects of this thesis. Cultural distance could comprise varied languages, ethnicities, religions, trust issues, norms, values, and dispositions. Administrative/Political dimensions centre around colonial ties, shared regional trading bloc, common currency, and political hostility. Geographically, distance is measured through physical location, lack of border, time zones, and differences in climatic conditions. Lastly, Economic distance dimensions are composed of rich/poor countries, cost or quality of natural, financial resources, human resources, infrastructure, and information or knowledge base (Ghemawat, 2001).

In this study we break down the economic distance dimensions. That EMEs are put together largely based on their wealth status and soundness of their financial systems does not preclude them from further distance analysis. Hence, we take closeness of EMEs financial soundness and delineate it into subtle differences between them. In the end we hypothesis *"financial distance"* using liquidity indicators for EMEs as inputs.

2.2.3 "Financial distance"

Following the CAGE distance framework different distance measures have been espoused, mainly economic, to identify differences and/or similarities between economies in order to ascertain risks and opportunities they exhibit. Fisher et al. (2015) define economic distance between two countries as the largest percentage difference in unit costs among all sectors using cross-country data for 35 sectors in 40 countries. They indicate, if all goods are traded, their measure of distance is the smallest uniform ad valorem tariff that shuts down bilateral trade. In examining the importance of cross-country spillovers to explain economic growth, Conley and Ligon (2002) use the transportation costs of the factors of physical and human capital as a measure of economic distance.

The United Parcel Service[8] shipping rates and airline fares are used to estimate the two costs of transporting capital.

In a rather different twists, but analogous to CAGE, Drogendijk and Martin (2008) construct country distance based on the Psychic Distance[9] with data from 170 Spanish Small and Medium-scale Enterprises and 99 potential export markets. They define country distance as the objective differences between two countries along the dimensions of national culture, language, educational level, level of industrial development, political systems, religions, and time zones. Martín and Drogendijk (2014) further develop a country distance index using partial least squares along three dimensions - socio-economic development, physical, and cultural and historical distance.

In this study we borrow from international trade and the CAGE framework and propose *"financial distance"* via country-specific liquidity measures. There is sufficient support in the literature for the use of liquidity as an indicative measure of risk. Given the importance of global liquidity it has become *de rigueur* driver for international financial stability in recent years. Notwithstanding, the ambiguity surrounding its measurement needs to be clarified. The BIS in May 2011 tasked the Committee on Global Financial System (CGFS) to investigate the measurement, drivers, and policy implications of global liquidity (see also Domanski et al. (2011). The current indicators (used in this study) of global liquidity is the result of that arrangement (CGFS, 2011).

[8] United Parcel Service is an American multinational package delivery and supply chain management company, https://www.ups.com/us/en/global.page.
[9] Distance between objects or phenomena as seen in (Dow & Karunaratna, 2006; Drogendijk & Martin, 2008).

2.2.3.1 Liquidity risk distance

Defined generally as ease of financing or ease of credit, liquidity is required by investors as financial resilience assurance from markets in which they invest; this resilience is in their best interest if it does not depend on the specific asset in which they invest. Access to credit is no doubt a sign of goodwill. So country-specific liquidity measure is an important factor to consider for systematic risk (of the economy or the country) rather than only idiosyncratic risk (of the asset) for risk assessment in international portfolio diversification.

The BIS conceive global liquidity indicators (BIS GLI) to be composed of and created from private and public sources, the former being dominant. Public liquidity is created by the funding that is unconditionally available to settle claims through monetary authorities whereas private liquidity is birthed out of cross-border operation of banks and other non-bank financial institutions. Private global liquidity displays both an increasing trend and a strong cyclical component. The rising pattern is caused by deeper financial integration between countries and financial innovation (spurred by regulatory changes). At the same time it is highly cyclical because it is driven by divergence in growth rates, monetary policies, and above all risk appetite across countries (CGFS, 2011).

The BIS GLI comprises both domestic and international total credit flows' direct lending from abroad to non-bank residents, indirect lending from abroad via resident banks, and local lending in foreign currencies. This is mainly nonbanking lending/borrowing or liquidity provided to support financial systems. Countries have become large international borrowers and banks judge them by their overall monetary discipline. This has become possible for many EMEs and developing countries as quality and timely monetary data have become available. Liquid markets are generally perceived as desirable because of the many benefits they offer, including improved allocation and information efficiency. Among others, liquid markets render financial assets more attractive to investors, who can transact more easily. It also allows financial institutions to accept larger asset-liability mismatches; reducing the risk of Central Banks acting a lenders of last resort. The IMF recognise the pressure on Central Banks in their definition of liquidity risk. It states *"systemic liquidity risk is the tendency of financial institutions to collectively underprice liquidity risk in good times when funding markets are functioning well because they are convinced that the central bank will almost certainly intervene in times of stress to maintain such markets, prevent the failure of financial institutions, and thus limit the impact of liquidity shortfalls on other financial institutions and the real economy"* (IMF, 2011, p.76). The state of market liquidity can ideally prevent and predict systemic liquidity crisis.

Why should foreign investors in EMEs equities be concerned with global liquidity? Several studies have found there is a bi-directional relationship between liquidity and risk (or risk appetite) - risk appetite is influenced by liquidity conditions and vice versa. For instance, Fang et al. (2009) find there is a direct relationship between stock liquidity and firm performance. PricewaterhouseCoopers (PwC, 2015) indicated that financial assets/markets with lower liquidity tends to have higher liquidity risk premia, and market players in these markets tend to face higher transaction costs and wider bid-ask spreads. They also request a premium for bearing liquidity when the liquidity shock tends to be systematic and persistent (Acharya & Pedersen, 2005; Pástor & Stambaugh, 2003; Sadka, 2006). This goes to corroborate the generic definition of liquidity. It is a multi-dimensional concept, generally referring to the ability to execute large transactions with limited price impact, and tends to be associated with low transaction costs and immediacy in execution. Deep and liquid financial markets are important to financial stability as market participants require liquid markets in order to effectively manage risks and to satisfy their own funding needs.

Prudent levels of liquidity is vital for the sustainability of financial systems of economies as well. Liquidity, one may argue, is seen as the life blood of all financial units - from the least of them to the largest. It is the more reason sound regulations require financial systems to maintain prudent levels of liquidity under a wide array of market conditions to enhance their resilience to shocks (Cifuentes et al., 2005). The intuition is that, for market players, especially those faced with illiquid markets, would endeavour to insure against liquidity shortfalls (as market discipline action) by wielding more liquid assets (Cifuentes et al., 2005; Jackson et al., 2002). At the systemic level, liquidity requirements, among other things, can mitigate contagion, provide capital buffers[10] in preventing systematic debacle. Cifuentes et al. (2005), for instance, suggest that under some scenarios liquidity requirements may be more effective than capital buffers in curtailing systematic effects. The authors imply liquidity is a public good whose requirement can internalise some of the externalities that are at the mercy of bearish market conditions. This extends to major financial distressing periods when risk appetites are at their lowest (leading to malfunctioning of markets) and capital buffers may be inadequate to forestall contagion.

[10] As stipulated in Basel III developed by the Bank for International Settlements (BIS).

Further, Bradrania and Peat (2014) examine whether the impact of liquidity on equity returns can be explained by stock-specific liquidity levels or market-wide systematic liquidity risk. Their CAPM liquidity-adjusted risk model tests the stock-characteristic risk against systematic risk for liquidity effects from 1931 to 2008 support the notion that liquidity risk should be perceived and treated as systematic factor, rather than idiosyncratic. The IMF (2010) find that rising global liquidity is linked with rising equity returns and declining real interest rates in 34 cross-border credit borrowing economies. As policy makers, the European Commission also recognise the cyclical importance of liquidity to capital markets and allude to this succinctly "*Improving the effectiveness of markets would enable the European Union to achieve the benefits of greater market size and depth. These include more competition, greater choice and lower costs for investors as well as a more efficient distribution of risk and better risk-sharing... Well-functioning capital markets will improve the allocation of capital in the economy, facilitating entrepreneurial, risk-taking activities and investment in infrastructure and new technologies*" (European Commission, 2015, p.9).

Liquidity level have also been documented to be a determining factor in cross-border capital flows, especially to EMEs. On the one hand, Lesmond (2005) show increases in investments in emerging markets can yield substantial returns that can easily exceed 90% per any year. This has been an attractive feature for foreign investors and it's evidenced in increasing investments in EMEs since 1985. On the other, the prospects of these high returns are equally tempered by EMEs features such as high risk, volatility, and illiquidity as compared to DMEs' returns. However, Rouwenhorst (1999) find no evidence that average returns are related to liquidity, as measured by share turnover in EMEs.

Ahmed and Zlate (2014) note that since 2002 net private capital inflows to EMEs are determined by growth and interest rate differentials between EMEs and advanced economies and global risk appetite, as economically important factors. Further, that net portfolio flows have changed post-GFC due risk awareness. Even though Forbes and Warnock (2012) do not find enough support for liquidity changes (in the United States, for instance) to be a major driver for capital inflows, unlike they do for global risk aversion.

Liquidity in this context is mainly seen as credit and poses pertinent concerns for borrowing economies. Ahmed et al. (2017) deduce that the run-up in bank credit to the private sector (measured as the change in the ratio of bank credit to GDP over the five years prior) is an important factor in the transmission of shock to financial markets in different EMEs. Those with higher run-up in bank credit suffered severe currency depreciation. This is echoed by Bruno and Shin (2018) who find emerging market firms' United States dollar denominated borrowings render their economies vulnerable to a depreciation of the domestic currency against the dollar. In addition to currency depreciation, the BIS notes that since global liquidity is created from the interaction between borrowers and lenders in funding trading activities it can contribute to the build-up of financial vulnerabilities such as asset price inflation, excess leverage, or maturity or funding mismatch (see also Gerdesmeier et al., 2010). Recent history is almost replete with evidence that unbridled credit growth is highly linked with the build-up of systematic vulnerabilities. That is why assessing liquidity is important because poor market conditions could amplify shocks and exacerbate asset price adjustments which can lead to financial instability (IMF, 2018). This brings to the foreground the relative importance of liquidity concerns when investing in EMEs.

In financial risk analysis the right indicator for liquidity is crucial. Goyenko et al. (2009) underscore the importance of liquidity in finance research and that the identification of the right high quality proxy (for liquidity) is equally essential. Global liquidity provide an advance indicator of financial stress both in the financial sector and real economy by tracking diverse cross-border flows. It is a consistent quantitative measure of credit that is a broader measure than money and better measure than interest rates. In their construction of liquidity, the IMF include bid-ask spreads, turnover ratios, and price impact measures to gauge different aspects of market liquidity, namely; tightness (costs), immediacy, depth, breadth, and resiliency. They suggest a number of measures be considered given that there is no single theoretically correct and universally accepted measure to determine a market's degree of liquidity and because market-specific factors and peculiarities must be considered (Lybek & Sarr, 2002). Cerutti et al. (2017) also share the same opinion that factors in “financial center” economies (G4; United States, Euro Area, United Kingdom, and Japan) affect the provision of cross-border credit, for instance.

Several measures and proxies of liquidity have splattered the financial literature landscape. Lee (2011) uses Acharya and Pederson (2005)’s approach to estimate the world price of liquidity risk. The motivation for this measure is that liquidity risks are priced independently of market risks in international financial markets and varies across countries according to geographic, economic, and political environment. This measure connotes the systematic dimension of liquidity and hence provides implications for international portfolio diversification. Kim and Lee (2014) also construct four different aggregate illiquidity measure (as the opposite of liquidity) to assess the pricing implications of liquidity risk in liquidity-adjusted capital asset pricing model of Acharya and Pedersen (2005).

Lesmond (2005) indicate that using equity returns are inappropriate to create any measure of liquidity given the evidence of zero returns prevalent in many EMEs equity indices (e.g. Brazil, Chile, Colombia, Peru, Philippines, Indonesia, Pakistan, Sri Lanka, Russia, and South Africa) which is found to be over 60% per annum. To circumvent the zero return problem, Bekaert et al. (2007) transform the proportion of zero daily firm returns averaged over the month as proxy for liquidity. They find that future returns significantly are predicted by liquidity. Noting the proportionality of transaction costs with liquidity, they suggest local market liquidity is a relevant driver of expected returns in EMEs as liberalisation has not fully done away with this impact. Yet other strands of studies use trading volume as proxies for liquidity. These include abnormal return of repository receipts (Miller, 1999), turnover (Dahlquist & Robertsson, 2001; Rouwenhorst, 1999), institutional trades (Domowitz et al., 2001), among others.

While Lesmond (2005) allude difficulty in liquidity measurement concerns to requiring supplemental data apart from prices (and uses daily prices to construct a liquidity measure) this thesis finds the concerns as rather welcoming. Similar to Lesmond (2005) the studies reviewed use either prices, returns, volume of trade, or other measures that are the fallout of trades on stock exchanges as proxies for liquidity. But this thesis takes a different stance. Since the aim is to use liquidity as an additional measure of risk to VaR and ES it is better to use an indicator that is independent of daily trading activities and also time-invariant in order to draw relevant conclusions. In the context of this study time-invariant refers to measures that do not rely on daily through to monthly trading data. Liquidity indicator here is used as spatial (country-specific) indicator as an extension of the CAGE distance framework. That is why the study employs the BIS Global Liquidity Indicators (BIS GLI). Also, the BIS GLI is a better measure because it has broader scope than many of these indicators since it conforms to the IMF construction of liquidity. The CGFS has, in recent times, favoured that quantity measures are better suited to capture the buildup of potential risks.

Since the objective is to understand the spatial risk characteristics of EMEs via *“financial distance”*, we employ time-invariant country-specific risk attributes. Choosing time-invariant measure is in line with the extant literature as time-invariant factors have been associated with CAGE and physic distance components (see Dow & Karunaratna, 2006; Drogendijk & Martin, 2008; Giudici et al., 2018; Martín & Drogendijk, 2014)**.** Given that the literature is inconclusiveness on what a measure of liquidity is, and the fact that there is support for aggregate credit as a rather adequate proxy for liquidity, we have adopted GLIs as *“financial distance”* dimension in this study. Domanski et al. (2011) hint at several arguments that speak in favour of using credit aggregates as a proxy for global liquidity. For one global credit aggregates allow for an analysis of global liquidity from various vantage points, including from the perspective of the recipient country. They go further to indicate “*recipient economy perspective focuses on the evolution of borrowing by non-banks in individual economies. This perspective can, for instance, inform assessments of whether cross-border credit flows are associated with a build-up of vulnerabilities in the recipient country’s financial system”*, p.63. It has also been shown that fluctuations in cross-border credit (international component) has been highly correlated with booms and busts in global financial conditions. Further, from a financial stability perspective, global credit is one of the key indicators since the stock of credit generally grows with ease of financing conditions. Defined this way, global liquidity depends primarily on the actions of private investors and financial institutions (McGuire & Sushko, 2015)**.** Also Bierut (2013) shows that global liquidity measures do better than domestic indicators to foretell warning signs of asset price booms whose eventual busts may cause financial stress. The more reason these indicators are useful as a risk assessment is that they measure these country-specific footprints rather than global liquidity itself.

2.2.4 Spatial neighbourhoods and spatial autocorrelation

The classical spatial analysis is premised on the assumption that observed sample data collected for regions[11] or points in space are not independent, but rather they are positively spatially dependent. This means the observations from one location is inclined to exhibit behaviours similar to those from nearby locations (LeSage & Pace, 2009). Linking each country observation to its point latitude-longitude coordinates allows for many aspects of spatial analysis. In like manner to spatial econometrics, inter-country linkages (or dependencies) can be assessed through spatial neighbourhoods and autocorrelations which can be used in the assessment of spillover and contagion studies (Dell'Erba et al., 2013).

Determining the neighbours of the countries in the sample relies on the distance weight function of the measures used (in this case liquidity indicators). Not only does this make sense quantitatively, it also fits in well with the theoretical basis of the distance dimensions framework employed. The EMEs as the focus of this study lends itself for spatial analysis. Grouped into one market class, they exhibit similarities in many forms; the most common is their equities giving higher returns than DMEs and the non-convergence of mean-variance portfolio properties with DMEs (Eun & Lee, 2010). This in an advantage as well as posing disadvantages because of the

[11] In spatial analysis regions have a broad range of spatial scales such as regional blocs, countries, administrative regions, among others. Countries are used in this study.

dependencies in EMEs attributes. This notion is easily extended to financial (liquidity) distance analysis in this study.

The concept of spatial autocorrelation is applicable to the liquidity measures employed and this is supported in the literature. CGFS (2011) point out that the increasing trend in global liquidity is caused by deeper financial integration between countries and financial innovation (spurred by regulatory changes). It goes without saying that financial integration and interdependence (and spillovers) move together. As country-specific indicators, the cross-section of global liquidity for EMEs permits for spatial analysis in terms of spatial weight, spatial distance, and spatial autocorrelation.

2.2.5 Transmission mechanisms of interdependence and contagion

2.2.5.1 Interdependence and/or contagion

While interdependence may have a somewhat concise and less embattled definition, the same cannot be said of contagion. However, popular in the literature, the definition of contagion is still not known for certain. Hence, a myriad of approaches are used to measure the concept. Despite the urgent need for financial markets regulations to forestall contagion, Pritsker (2001) submits that unless a theoretical underpinnings of how shocks are transmitted across markets are firmly understood any new regulations are bound to falter. It is reckoned that a consensus on the channels of transmission can clarify the definition of contagion (channels of contagion is reviewed in Section 2.2.5.2). However, Pericoli and Sbracia (2003) rather supports an explicit identification of financial crisis in order to define and measure contagion. They identify *currency crisis* (devaluation from a peg or an extreme value recorded by a pressure indicator), *stock market crisis* (plummeting index or soaring asset price volatility), and *banking crisis* (a break-down in the ratio of non-performing assets to total assets or demise of a huge banking institutions). In order to define contagion one has to clearly differentiate between the types of contagion that have been referred to in the literature. “Irrational/pure/true/non-fundamental-based” and “fundamental-based” contagion are the two theoretical categories of contagion. The former, as the name implies, is based on irrational behaviour (“irrational exuberance” as described by Federal Reserve Chairman Alan Greenspan) of investors. Kaminsky et al. (2003) have no doubts that this irrational exuberant investor behaviour has the potential to affect the trend of capital flows and can aggravate financial markets booms and busts alike. Pritsker (2001) offers a brief definition of pure-contagion as co-movement of idiosyncratic residuals from a set of macroeconomic factors model. The immediate critique here is that the correct set of fundamentals are not fully controlled for. Contrarily, “fundamental-based” contagion is generally explained to mean one that occurs when shocks are transferred from one market to another through trade and/or financial market linkages.

However, Pericoli and Sbracia (2003) in a unifying framework to highlight the possible channels of financial shocks sample five representative definitions of contagion in the literature in order to come up with a sixth[12] comprehensive definition. Having identified three key types of contagion contingent on transmission channels (i.e. fundamental, panics, and incomplete information, learning, and updating by international investors), they stress the last two engender discontinuities in the international transmission of the initial crisis. They, thus, in line with Forbes and Rigobón’s (2002) *shift-contagion* label the latter two as *contagion*, otherwise the first channel is only

[12] See Pericoli and Sbracia (2003) for the various definitions.

interdependence. This is similar to Corsetti et al. (2005) who define contagion “as a structural break in the linear transmission mechanism of financial shocks”.

The continued debate on contagion is not any less about its measurement than about its definition. The various measures of contagion propounded in the literature is varied as it is voluminous. However, after highlighting the key similarities and differences between various contagion modelling approaches, Dungey et al. (2005) come to a startling conclusion. They settle that all the definitions are construed as emanating from the same model, however, disparities arise from the information loading used to detect contagion. Nonetheless, after reviewing most of these methodologies[13] and finding almost a consistency in producing a misleading conclusion of “contagion” instead of “interdependence”, Forbes and Rigobón (2002) invent the *shift-contagion* (hereafter referred to as FR-SC).

The strength of the *shift-contagion* is two folds; first is in the “shiftness” - that there is a significant increase (or more generally a change) in cross-market linkages after a shock to one country (or group of countries). The second strength is achieved by criticising previous studies for not correcting for heteroscedasticity in correlation measures which leads to biased estimates and conclusions. From thence the heteroscedasticity-adjusted correlation has been applied as information loading in many studies (Collins & Biekpe, 2003; Lee et al., 2007, for example). But this has been criticised as some studies that have used the same sample with the recommended heteroscedasticity adjustments reached contradictory findings of contagion (see Chiang et al., 2007; Hon et al., 2004; Mollah et al., 2016).

[13] For a comprehensive list see Pericoli and Sbracia (2003) and Dungey et al. (2005).

Nonetheless, critical assessment reveal important weakness of the FR-SC. To start with, an analysis of return distribution that goes as far as only the second moment (variance) leaves much to be desired. This is the FR-SC's focus on heteroscedasticity bias adjustment which ignores the relevance of higher moments as noted earlier. This does not account for asymmetries which need to be assessed in the context of the full conditional density of asset returns as emphasized by recent risk portfolio risk models (see Bessembinder, 2018; Ranaldo & Favre, 2005). Further, the FR-SC does revel in normality assumption of asset returns in its estimation of variance (volatility) and determines significant increases in correlation based on the t-test. The normal distribution; with finite variance[14], is perhaps one of the most disputed axioms in finance, especially in capturing conditional volatility (Graff & Young, 1997). Though an improved choice over the Gaussian distribution - by providing an additional parameter to cater for degrees of freedom, the t-distribution still belongs to the elliptical family. As symmetric, the elliptical family does not live up to the demands of adequately capturing extreme values in financial asset returns (Landsman & Valdez, 2003). What is more? Given that the FR-SC is a study under extreme market conditions, the distributional choice of fitting data cannot be trivialised.

To contribute to the extant literature on contagion, this thesis combines the "shiftness" in *shift-contagion* with shape parameters of return distributions extracted from the generalised lambda distribution (GLD) to define and measure contagion in emerging markets equities. The GLD is elected from the family of Stable Distributions for its mathematical simplicity and ability to adequately fit extreme tails of data easily with an incredible range of shape of distributions (Karian

[14] Under some assumptions, the Central Limit Theorem strongly suggests that the only probability distribution with finite variance is the normal distribution. For the family of Stable Distributions which adequately capture extreme tail events in financial time series variances may not always exist (i.e. are infinite) under certain circumstances (Young, 2008).

& Dudewicz, 2016; Su, 2007, 2010). This is quite an important feature in the examination of contagion due to the propensity of tail events. To sidestep the bottleneck of distributional assumptions, we define interdependence and contagion through non-parametric correlations coefficients derived from the frequency-domain wavelet multiple correlations (WMC), wavelet multiple cross correlations (WMCC) (Fernández-Macho, 2012), and time- and frequency-time domain connectedness of Baruník and Křehlík (2018) (BK18).

This study argues that regardless of the channels of shock transmission, the incidence is best reflected in the higher moments of return distributions from which non-parametric correlation analysis are performed. Among others, Bali et al. (2011), Bessembinder (2018), and Müller and Wagner (2018) underscore the importance of higher moments in distribution of stock returns and their impact on the performance of diversified portfolios. Further, the shifting dynamics of cross-market linkages occur through time and at different trading time scales (scales). Therefore, we assess contagion and interdependence with WMC, WMCC, and BK18 because they are able capture the frequency- and time-varying features of cross-market linkages. The techniques decomposes time series into both time- and frequency-domains simultaneously, thus permit higher and lower frequencies to be outlined. The techniques appeal to the heterogeneous market hypothesis (HMH) (Müller et al., 1993). The HMH suggests the need to delimit spillovers into short-, medium, and long-run horizons to suit different investment preferences. This is an innovative way to explore the intricate subtleties of financial time series (Bekiros & Marcellino, 2013). Further, the BK18 framework has a rolling window estimation mechanism to circumvent the heteroscedasticity bias of FR-SC. Moreover, we estimate shape parameters on a rolling window basis to further deal with heteroscedasticity.

In this study, strong WMC and WMCC at higher frequencies can be designated as “contagion” whereas those at the lower frequencies are termed as “interdependence” (see Gallegati, 2012; Saiti et al., 2016; Vincent & Bertrand, 2005). The BK18 also helps to measure contagion in similar fashions as Saiti et al. (2016), Adam (2013), and Diebold and Yilmaz (2009). In principle, this is in consonance with Forbes and Rigobón (2002) (i.e. a sharp increase in cross-market spillovers at some frequency band(s) as opposed to continuous high levels of connectedness). Though time-varying contagion has been studied widely, tracing the origins through the shape parameters of returns, especially in EMEs context, has not been attempted to date. This thesis is the first of its kind.

2.2.5.2 Contagion diffusion channels

Regardless of the belief in irrational behaviour as a potential cause of contagion, the literature is almost silent on that in studying transmission pathways of contagion. It may only be associated with herding behaviour of investors which Calvo and Mendoza (1997) suggest could be due to irrational behaviour or otherwise. Instead, majority of studies focus on fundamental-based contagion to identify diffusion channels for shocks.

In order to determine the probable number of shock transmission channels, Claessens and Forbes (2013) first devised a framework of potential interlinkages that can propagate shocks across countries. These include; the economy, real sector, financial markets, banks, and non-bank financial markets players. Taking these apart results in a huge number of shock transmission channels. Bekaert et al. (2014) also in a factor model propose six channels as factor loadings, namely; international banking sector, financial policies, the “globalisation hypothesis”, reduced information asymmetry, "Wake-up call hypothesis", and global risk and liquidity indicators[15]. However, in generic terms, propagation pathways have been grouped into two, namely; trade and financial linkages, especially of shocks emanating from DMEs.

To simplify, Didier et al. (2012) pin the trade channel to early 2008 when DMEs started to experience economic downturn. As a consequence and due to nose-diving stock market prices, consumers suffered wealth decline which reduced their demand for goods and services from the rest of the world. Due to the invisible hand of demand and supply, global prices plummeted sending waves of distress across emerging markets and low-income countries all over the world. Imports into these countries also successively reduced as a reverse effect.

In terms of financial channel, Didier et al. (2012) further suggest transmission occurs via economy-wide financial account connectedness with the international financial system. The evidence is in the credit and/or capital crunch suffered globally in the wake of the demise of Lehman Brothers. Again, this is negative wealth effect from developed markets resulting in shrinking foreign investments. As a direct impact, international investors, through their intermediaries tend to reduce their exposure to emerging markets as a feedback to shocks affecting their investment portfolio subtleties. However, indirectly, regulatory and stringent internal banking requirements may lead to sell-off of foreign holdings and the impact on these foreign economies is ostensible.

[15] A detailed account of these factor loading are can be found in Bekaert et al. (2014).

2.2.5.3 Contagion incidence: Shape shift-contagion

Since this thesis is not focused on the channels of contagion but rather the incidence of the same, an examination of these channels is not undertaken. The objective is to model the incidence of contagion after they have been transmitted. In a remote study to the "*shape shift-contagion*", Wang (2016) has shown that tail risks can serve as global transmission channel of contagion during crisis using data for 40 countries over a 30-year period. However, their approach, based on Bekaert et al. (2014)'s capital asset pricing model (CAPM)-like factor model with a t-statistic as test of significance do not live up to the expectations of a desirable return distribution as proposed in this study; especially so in the context contagion. In this thesis, a theoretical framework of the *"shape shift-contagion"* is included as an extension to the definition of contagion hitherto. The framework is premised on the following assumptions:

- the pathways of contagion transmission are numerous and varied albeit analogous and difficult to delineate.
- incidence of contagion are reflected in the returns of financial assets.
- return distributions are empirically non-normal.
- contagion is best traced from the higher moments (shape parameters) of returns distributions.
- asymmetric distributional models can be used to extract the non-normal higher moments of returns.

Hence, based on Forbes and Rigobón (2002) the *"shape shift-contagion"* can be defined as a significant increase (or change) in the cross-market shape parameter estimates of returns after a shock to one country (or group of countries).

2.3 Empirical review

2.3.1 Asymmetric return distribution in emerging markets equities

The asymmetric nature of asset returns has received extensive consensus in the finance literature. This ranges from basic to advance methodological approaches. With specific regard to emerging markets, return distributions permeate the literature but not at the level of sophistication fit for modelling the asymmetric behaviour of these returns.

Many studies have focused on the testing for the non-normality in returns rather than modelling the same and hence leave some pertinent questions unanswered. Tests of normality in return distributions have been basic over the years and especially so for emerging markets. Harvey (1995) and Bekaert and Harvey (2002) judge the asymmetric distribution of emerging markets returns using the third and fourth moments. In the former, they use a chi-square joint test of skewness and kurtosis to reveal non-normality in 14 out of 20 emerging markets. However, in the latter the authors find skewness and fat tails in all 20 emerging markets for both pre- and post-liberalisation periods. In a small leap, Bekaert, et al. (1998) factor in the time-varying nature of skewness and kurtosis of EM returns and further analyse the fundamental features of each in order to explain the patterns of these asymmetric distributions. Not only are these studies dated, they are also basic and less robust. An analysis of the fundamental characteristics of the cross-section of economies for the patterned deviation from normality does not provide a cross-sectional evidence of the actual asymmetric distributional behaviour of each of these countries. Also the fact that these studies precede the apparent financial crises that have bedeviled international finance effectively render them obsolete. Other studies that meet this chronological criterion could fall into the same category as out of date.

Further, on tests of normality, Adu et al. (2015) query the assumption of normality as the initial point for many asset pricing models and proceed to perform a multivariate joint test for skewness and kurtosis for the BRICS[16]. That the authors find stock returns are peaked with fatter and longer tails regardless of data frequency and unit of measurement do not come as a surprise. It is worth pointing out that the failure to model the third and fourth moments with a technique suited for asymmetric returns is hard to overlook.

In the literature, return distribution behaviour has also been narrowly, and perhaps shallowly studied. To adequately analyse return behaviour one ought to establish the empirical asymmetric distribution of the returns. However, this is hardly done. In investigating stock return behaviour of emerging markets in the International Finance Corporation Emerging Markets Data Base, Claessens et al. (1995) document return anomalies based on seasonality, size, turn-of-year, and small-firm effects. The distributional aspects the authors considered only used the basic measures of skewness and kurtosis which the Jarque-Bera tests of normality is heavily dependent upon. For EMEs in Africa, Alagidede and Panagiotidis (2009) apply smooth transition and conditional volatility models to examine dynamics as well as weak form of market efficiency from the first two moments which are apparently generated from normality assumptions. In a similar manner, Alagidede (2011) focus on the first two moments to garner evidence for time-varying return predictability, risk-returns trade-off, and mean reversion. Most recently, Balaban et al. (2018) jointly examine the intra-and-intraday stock return distribution with particular emphasis on conditional volatility at the firm-level with respect to the Bourse Istanbul. It is worth noting that

[16] The BRICS are Brazil, Russia, India, China, and South Africa.

by return distribution the authors only investigated day-of-the-week effects, trading session effects, and risk-returns trade-off, rather than higher moments of the returns.

To beat the obsolete benchmark established in this review; and separating financial crashes into three stages of plunging, rebounding, and soaring, Li and Liaw (2015) explore the indices of 10 stock market return distributions. Finding dual fractal structures via the Hurst exponent, they discover the tail distribution of returns meet the criterion for a power law for DMEs, however, they exhibit a dual power law for emerging markets. The authors leave the tails in these returns “unmodelled”. These researches have constricted the attributes of return distribution. They may better caption their studies without the use of the term “distribution” because it has statistical connotations of data being fitted by one of many distributions which are not represented accordingly. It is clear from these studies that the necessary steps to model the non-normality is the emerging markets returns are left out.

In term of attempts to model emerging markets return distributions and with respect to shape behaviour, some studies have made significant strides. For instance, Maghyereh and Al-Zoubi (2008) make use of the McNeil and Frey (2000), Wagner and Marsh (2005), and Byström (2005), extreme value theory (EVT)[17] to scrutinise asymptotic tail distribution of daily returns in the Gulf region. The authors continued to use the “Peaks-Over-Threshold” model to estimate the tails of the innovational distribution as they examine extreme returns. The models exploit tail behaviour and the Gulf equity markets can rely on EVT-based risk model in their risk assessment, as argued

[17] See McNeil and Frey (2000) Wagner and Marsh (2005) and Byström (2005) for details on Peaks-Over-Threshold and EVT.

by the authors. In most of emerging European countries[18], Heinz and Rusinova (2015) prove heavy tails in the exchange market pressure index[19] through the EVT. They opine that disregarding these tail properties have the tendency to underestimate tail events. Though the model manifests tail behaviour, the Peaks-Over-Threshold model from which EVT is estimated only extracts tail parameters (lower and upper) from return distributions. Without the parameter for the peakedness (height) a complete picture of the return distribution is unavailable to make strong risk-based estimates for investment decision making.

The biggest emerging market, China, could not be left out of the narrative. Employing the Generalised Extreme Value (GEV), Generalised Logistic, and Generalised Pareto distributions, Hussain and Li (2015) model extreme returns of the Shanghai Stock Exchange Composite Index from 1991 to 2013. The authors find the GL a better fit for the minima series whereas the GEV distribution fits the Block Maxima Minima series better with estimates by the Power Weighted Method. In selecting the a probability distribution for the fitted data, the authors apply the L-moment ratio diagram as a test propounded by Hosking (1990) which has four parameters; two each for scale and shape. This work seems adequate in that it involves data of varying frequencies (week, month, quarter, half-year, and annual) and uses two generalised distributions[20], however, its sufficiency is questionable. Both GEV and Generalised Logistic are three-parameter models which are shy of one parameter for a complete conventional distribution modelling. Also that only Power Weighted Method is used for estimation limits the robustness of the selected fits. Further, other emerging markets could have been included in the sample to allow for comparison.

[18] In this study they are Czech Republic, Greece, Hungary, Poland, Russia, and Turkey.
[19] See Heinz and Rusinova (2015) for the index composition.
[20] The GP is not empirically estimated because it is embedded in the L-moments method.

Nonetheless, having modelled the distributional behaviour of returns is only the first to make any meaningful practical implications to stakeholders. One may not be able to make any reasonable interpretation of the shape parameters of a distribution. It may be unproductive to force an interpretation on shape parameters since it not always needed and also limits the usefulness of the shape of the distribution. The important question is "what the shape parameters of the fitted distributions can be used for"? In this study, we use the shape parameters to estimate Value-at-Risk, Expected Shortfall, correlations, and spillover indices for equity and portfolio risk analysis.

2.3.2 Value-at-Risk (VaR), Expected Shortfall (ES), and elicitable loss functions

The empirical literature is replete with studies that compare estimates of VaR and ES in their quest to examine their robustness. Only a few studies connote the use of distance dimensions, albeit without explicitly acknowledging the fact. For instance, Iglesias (2015a) compares the values of VaRs based on economic factors (nature of industry/sector strength) and geographic situations (Ireland - financially rescued and Spain - not rescued). The author intended it for very-risk-averse investors to choose their portfolios in the Eurozone for risk management purposes. The study finds differences as per geographic situation where the stocks are traded in two countries (see also Iglesias, 2015b). Assaf (2015) also examines the forecasting performance of VaR models in MENA[21] equity markets. Finding that short position returns have significantly fatter tails than the normal distribution, the study employs Asymmetric Power ARCH (APARCH) models. The Student APARCH models perform better than Normal APARCH counterparts. Further, Gençay and Selcuk (2004) model the daily equity returns of nine EMEs to investigate the performance of

[21] Middle East and North Africa - Egypt, Jordan, Morocco, and Turkey were used.

VaR models for stress testing. They find EVT-based VaRs are more accurate at higher quantiles as per generalised Pareto distribution parameters. The underlying limitation in these studies is that they fail to explicitly analyse spatial dependencies in countries to offer a wider scope of information for risk management purposes.

The performance of VaR and ES have also been studied away from country or regional bloc equities. The majority of studies are with respect to distributional type and estimation innovations. For instance, Abad and Benito (2013) provides a detailed comparison of VaR estimates ranging from historical simulation, Monte Carlo, and EVT. For properly estimated variances, they find that parametric models to estimate VaR successfully. Zhang et al. (2014) find VaR estimates for Vine copula models to perform sufficiently accurate than ES models but the latter forecasts accurately based on the former values using 10 international stock indices. A similar analysis is performed for crude oil prices with the addition of generalised autoregressive conditional heteroscedasticity (GARCH)-type models. They find back testing results suggest that the combination can produce better risk measures of oil portfolio (Yu et al., 2018).

By estimation novelty, Cifter (2011) introduces wavelet-based EVT for univariate VaR estimation on Istanbul Stock Exchange and the Budapest Stock Exchange. Consistent with Basel II, the superior forecasting performance of the wavelet-based EVT model is suggested for use by financial institutions. However, given that Basel II is extinct and the revised approach in Basel III is meant, amongst three objectives, to *"provide a fall-back in the event that a bank's internal market risk model is deemed inadequate …"*(BIS, 2013, pp. 5-6), estimation novelty and the robustness of VaR or ES are not as important as the ability for internal models to compare with standardised approach. In this regard, either VaR or ES falls short as a standalone risk measure. Under coherent risk measure properties, VaR is elicitable but not sub-additive, expectiles are both coherent and elicitable whereas ES is coherent and comonotonically additive but not elicitable (see Acerbi, 2002; Acerbi & Szekely, 2014; Acerbi & Tasche, 2002; Yamai & Yoshiba, 2002).

2.3.3 The CAGE distance dimensions, financial distance, and liquidity risk distance

From the “Distance Still Matters” the author has classified many attributes of countries under Cultural, Administrative/Political, Geographic, and Economic (CAGE) distance framework. Since the early 2000s this has been used as an international trade tool to identify and prioritise differences between countries for the development and implementation of cross-border strategies (Ghemawat, 2001; Giudici et al. 2018).

In furtherance, we break down the economic distance dimensions. That EMEs are put together largely based on their wealth status and soundness of their financial systems does not preclude them from further distance analysis. Thus, the study takes the closeness of EMEs financial soundness and delineate their subtle differences. We borrow from international trade and the CAGE framework and propose *“financial distance”* using country-specific liquidity measures. Defined generally as ease of financing or ease of credit, liquidity is required by investors as financial resilience assurance from markets in which they invest; this resilience is in their best interest if it does not depend on the specific asset in which they invest. Access to credit is no doubt a sign of goodwill. So country-specific liquidity measure is an important factor to consider for systematic risk (of the economy or the country) rather than only idiosyncratic risk (of the asset) for risk assessment in international portfolio diversification.

The BIS GLIs are composed of and created from private and public sources. Private global liquidity displays both an increasing trend and a strong cyclical component which are caused by deeper financial integration between countries and financial innovation (spurred by regulatory changes) (BIS, 2011). The IMF (2011) opine that the state of market liquidity can ideally prevent and predict systemic liquidity crisis. Despite the generic definition of liquidity, this study takes a different stance. Since the aim is to use liquidity as an additional measure of risk to the (VaR, ES) model, we elect to use an indicator that is independent of daily trading activities. The choice of time-invariant measure is in line with the extant literature as time-invariant factors have been associated with CAGE and physic distance components (see Dow & Karunaratna, 2006; Drogendijk & Martin, 2008; Giudici et al., 2018; Martín & Drogendijk, 2014).

2.3.4 Interdependence and/or contagion in EMEs

For many decades, the body of literature on interdependence and/or contagion among market economies has rightfully focused on comovements and what has become known as "synchronisation" in both stock markets and macroeconomic variables. As Abate and Servén (2018) note, global equity returns comovements are perceived as replicating inescapable common shocks or local linkages between countries. They establish that, for over two decades across 40 advanced and emerging countries, strong cross-country dependencies of equity returns emanate from spatial effects and common shocks alike. By including GDP growth, real interest rate, and credit, their study is similar to other earlier studies such as Akın (2012), Pappas et al. (2016), and Walti (2005). While Akın (2012) found that global financial integration does not significantly affect output synchronisation across 51 countries (EMEs and DMEs included), Walti (2005) indicates trade and financial integration has positive impact on synchronization. However, the authors largely failed to show the place of financial crisis in the dynamics of comovement and synchronisation.

In recent times any study of interdependence and/or contagion could hardly be bereft of the effects of one crisis or another, especially the GFC. In an impact and response study of GFC on emerging financial markets, Batten and Szilagyi (2011) make their analysis from the perspectives of asset pricing and contagion. They find emerging financial markets, to a large extent, have demonstrated resistance to the ravages of the GFC having learnt bitter lessons from the Asian Financial Crisis. However, they contend this resilience could be attributed to the less complicated structure and products of financial institutions that many emerging markets are noted for. The authors draw an incomplete picture of the impact of financial as well as economic crisis since they ignored the places of the Eurozone crisis and the standalone Russian crisis. Adding the Eurozone crisis into the narrative, Mollah et al. (2016) learn contagion spread from the United States, for dollar-denominated equity market indices, to DMEs and EMEs across 55 markets from 2003 to 2013.

Studies of interdependence and contagion in a large volume of literature have been strongly linked with periods of financial crisis. For instance, Fry-McKibbin et al. (2014), in a regime-switching model delineate nine different crisis episodes and juxtapose them against contagion transmission hypotheses. The study spans from Asian financial crisis to the European debt crisis of 2010 to 2013. They analyse interconnectedness of equity markets through the lens of correlation, coskewness, and covolatility. Their findings claim emerging markets crises spread sporadically, especially to DMEs, as trade linkages are less probable to be the source of crisis transmission compared to finance ties. This test was only applied to Eurozone equity returns from 2005 to 2014 limiting the range of emerging markets captured (Fry-McKibbin et al., 2018).

As regards the definition of contagion and economic fundamentals, the asset returns- economic fundamentals link mechanism as well as how the economic fundamentals differ from one country to another, the divergence in opinions is advanced in the literature on emerging markets. In a two-factor model[22] Bekaert and Harvey (2003) assess the time-varying dynamics of stock market integration across Europe (both EMEs and DMEs), South-East Asia, and Latin America. Their model, incorporating time-varying betas, document contagion in crisis periods in addition to revealing both world and regional market integration. In a similar setting but over a broader sample, Bekaert et al. (2014) inspect the diffusion of the GFC (as contagion) to 415 country-industry equity portfolios with a factor model. They find the United States, as the global financial sector, the transmitters of small contagion effects.

Further, it is quite evident the United States subprime crisis is an originator of contagion spreading across many developed markets and emerging markets. For instance, Dimitriou et al. (2013) and Dungey and Gajurel (2014) agree on the matter from different perspectives. The former indicates patterns of contagion for all BRICS (including South Africa) after the fall of Lehman Brothers. However, the latter discover large portion of contagion from the United States in aggregate equity market indices than for the financial sector indices for both developed markets and emerging markets. Additionally, Celık (2012) finds even more contagion for most developed markets and emerging markets during this period using foreign exchange markets indices.

[22] The authors defined contagion by the correlation of the model residuals.

Inquiry on interdependence and contagion between emerging stock markets and global stock markets has also been a large strand of emerging markets studies, especially with the large developed equity markets of United States, United Kingdom, France, Germany, and Japan. For example, Al Nasser and Hajilee (2016) examine both short- and long-run relationships among emerging stock markets (Brazil, China, Russia, and Turkey) vis-à-vis the United Kingdom, United States, and Germany. Their results confirm stock market integration for both time horizons at varying degrees. In spite of the pervasiveness of crisis effects on stock markets, the authors failed to shed light on the influence these have on their estimates and recommendations for the period studied. Similarly, Ahlgren and Antell (2010) find short-term linkages in periods of crisis rather than contagion in South Korea and Mexico. While Ireland, Italy, Spain, Brazil, India, Russia, China, and South Africa were strongly contagious during the Eurozone crisis, Indonesia and South Korea were only interdependent (Ahmad et al., 2013). These studies corroborate Forbes and Rigobón (2002) who found only interdependence but no contagion during the 1997 Asian crisis, 1994 Mexican devaluation, and 1987 United States and Hong Kong stock market crashes. These studies have an important message - that not all markets experience contagion under stressed conditions.

There has been a gradual shift in the methodological approach to the study of interdependence and contagion. Several works have employed models based on either frequency-domain or time-domain of different versions of correlations. For example, Sewraj et al. (2018) in a supposed advanced unifying approach to identifying contagion in 25 stock markets specify a time-indexed parametric model shying away from the frequency metadata of the return series. Similarly, in a multiscale correlation style Wang et al. (2017) identifies stock market contagion during the GFC at different time scales of the return series. In a different dimension, Bodart and Candelon (2009) offered a new measure of contagion from frequency analysis of causality. Tested on the Mexican "Tequila" crisis of 1994 and the Asian "flu" crisis of 1997, the time stamps in this model are Pre-crisis and Post-crisis periods a few years apart. This makes analysis of contagion at short time intervals unattainable. Other popular frameworks of contagion and interdependence analysis are also premised on dynamic conditional correlation (DCC). For instance, in analysing sectoral dynamics of financial contagion in Europe (including emerging markets), Alexakis and Pappas (2018) employ the asymmetric DCC generalised autoregressive conditional heteroscedasticity (GARCH) model. Also, Syllignakis and Kouretas (2011) engage DCC multivariate GARCH model to analyse financial contagion in Central European Economies emerging stock markets. The DCC, by courtesy Engle and Sheppard (2001), assumes conditional time-varying correlations and variances, without frequency footprints. Many researchers often elect to use DCC over time-scale models citing complexity in interpretation in the latter.

However, an increasing number of studies have used frequency-time (time-scale) domain techniques such as wavelets and cospectral for some years now. Aloui and Hkiri (2014) contend the use of different models other than those simultaneously allowing for comovement assessment at both frequency and time levels. They opine that those models yield conflicting results since they are devoid of multiscale decomposition of the time series of returns. The wavelet methodology, (Grossmann & Morlet, 1984) has the desirable property of time-scale decomposition of return series lacking in the other techniques. It has, thus, been applied in recent years for interdependence and contagion studies (Balaban et al., 2018; Dewandaru et al., 2017; Ftiti et al., 2015). The concerns for complexity in fitting and interpretation can be alleviated by wavelet cross correlation and wavelet multiple cross correlation (Fernández-Macho, 2012) and spillover connectedness (Baruník & Krehlik, 2018). These are able to handle multiple variables at both frequency and time-varying scales. These two techniques are for analysis in this study.

2.3.5 Shape interdependence and/or contagion in EMEs

Due to different episodes of extreme market conditions culminating in crisis in respective markets, a growing number of studies on comovements has fused in these phenomena. Extreme market conditions largely reflect in the distributional properties of returns referred to as tail events. Tail events particularly have consequences for risk management and portfolio diversification. Many studies on contagion have also accounted for the GFC, and Asian financial crisis, and other crises. For instance, Boubaker and Raza (2016) investigate the dynamic dependence together with asymmetric tail co-movement of the United States with Central European Economies equity markets via time-variant copula. They find significant indication of co-movement display big time-variations and asymmetry in the tails. Similarly, Mensah and Alagidede (2017) study emerging African markets relations with developed markets and discover that except for South Africa, other African EMEs do not suffer risk spillover effects from DMEs. They also find tail dependence suggestive of alternating comovements between rising and plummeting market cycles. The strength of the copula technique is the ability to capture the marginal distributions of returns. However, copulas provide a single parametric measure of the tail of returns. These studies fall short to provide a complete description of returns distribution. To account for these empirical limitations, we use rolling skewness and kurtosis estimates from the GLD to examine interdependence and/or contagion in EMEs. This provides supports for this study to arrive at the *"shape shift-contagion"* hypothesis.

2.4 Conclusion

The chapter provides a brief roadmap for both the theoretical and empirical underpinnings of this study from the extant literature. Literature pertaining to the three main themes (i.e. time-varying versus spatial risks, elicitability of risk models, and higher moment interdependence and contagion) of the study are reviewed. For time-varying risks, it becomes clear that while tail risk of VaR and ES have been used extensively to analyse risks in emerging markets equities, the (VaR, ES) model has not been used hitherto. The latter has been adopted as the de facto time-varying tail risk measure in this study. The reason is that the (VaR, ES) model pulls together the strengths of VaR and ES to provide the elicitable feature that allows for model ranking and comparison. Again, emerging markets equities risk models selection and ranking have never been put to the test under comparative back testing and elicitability standards simultaneously.

Further, it is quite obvious from the literature that most time-varying risk analyses of emerging markets equities have not been accompanied by time-invariant (spatial) risk dimensions. Moreover, the review reveals that GLIs can be used as country-specific risk measures supplement tail risk assessment. Further, using liquidity as a spatial element does not only enhance equity risk examination, but it can also extend the CAGE distance dimensions framework. Based on this, the study hypothesises the “Finance Distance” as the spatial autocorrelation between the GLIs of selected EMEs to fill this gap in the literature.

Furthermore, the review shows that interdependence and contagion studies in general, and those involving EMEs in particular, have been narrow in addressing their origins. Given the importance of higher moments in return distributions, risk analysis, and diversification, their exclusion as sources of shock transmission present an important gap. The study surmises their inclusion are useful to examine the marginal sources of connectedness and spillover among EMEs. Following from this notion and the FR-SC, the thesis proposes the *"shape shift-contagion"* for emerging markets equities.

These three gaps point to the overall trend in the literature that compare and contrast EMEs with the metrics of indexing institutions and all too common returns and volatilities of equities. This study presents a different approach of unearthing the elusive differences and similarities between EMEs with equally hidden elements. These hidden elements of EMEs are the focus of this thesis. These make modest but important contributions to the emerging markets finance literature.

The standalone studies in the next three chapters are based on the literature review in this chapter. Hence, readers can refer to this chapter for a detailed review following the introductory section of each study.

CHAPTER THREE

TIME-VARYING VERSUS SPATIAL RISK ANALYSIS IN EMERGING MARKETS EQUITIES

3.1 Introduction

Since J.P. Morgan invented the RiskMetrics toolbox in 1995 (Morgan, 1996), VaR has been *de rigueur* regulatory bank capital requirement measure as well as portfolio risk management for many years. The reputation of VaR has reduced since the GFC and with the popularisation of Expected Shortfall (ES) by Artzner et al. (1999). In the aftermath of the GFC, Basel III proposed a framework that calibrates stressed market conditions by moving from VaR to Expected Shortfall (ES) since May 2012. The ES is due Artzner (1997) in his assessment of coherent risk measures.

The VaR suffers practical as well as coherent risk measure weaknesses. On the practical side Artzner, (1997); Artzner et al. (1999) show that the VaR ignores any losses beyond it (see also Danielsson et al., 2001). By design, the VaR works best under tranquil market conditions so it is unable to capture extreme events which usually reflect in the tails of distributions. This explains the alternative name of ES as Conditional VaR (CVaR) (i.e. given that the VaR is realised what is the expected loss?). That is to say the underlying distribution in the estimation of VaR should be able to capture the extreme events in the tails of the distribution which can partially be achieved by using any asymmetric probability distribution as an alternative to the Gaussian. Further, VaR fails to conform to sub-additivity[23] (or sub-additivity) which has the potential to mislead investors in portfolios decision making (Yamai & Yoshiba, 2002). Thus, the ES desirable in being coherent and able to quantify dangers beyond VaR (see also Acerbi et al., 2001; Acerbi & Tasche, 2002).

[23] $\rho(X+Y) \leq \rho(X) + \rho(Y)$ for a functional ρ (Fissler & Ziegel, 2016; Ziegel, 2016).

Regardless of the seemingly desirable features of ES, VaR has not completely been dismissed as a capital requirement measure for legitimate reasons. An important weakness of the ES is the sensitivity to tails which can lead to greater periodic capital charges as opposed VaR (Chang et al., 2019). Kellner and Rösch (2016) also show that the ES ($\alpha = 0.975$) is more sensitive towards regulatory arbitrage and parameter specification. Further, the ES lacks the properties of elicitability and robustness in estimation procedures (see Burzoni et al., 2017; Cont et al., 2010; Fissler & Ziegel, 2016; Fissler et al., 2015; Nolde & Ziegel, 2017). On the one hand, in terms of robustness, some prefer VaR to ES (see Cont et al., 2010; Kou et al., 2013). On the other hand, Krätschmer et al. (2014, 2015) do not favour the classical notion of robustness as necessary in the context of risk measurement. Nonetheless, Fissler and Ziegel (2016) submit that the tide seems to be in favour of ES being coherent and comonotonically additive and qualifying as a spectral risk measure[24].

Notwithstanding, the quality and robustness of risk measure estimates remain important. These are assessed by means of back testing. More importantly, as regulatory capital requirements, VaR and ES of internal models should be appropriately comparable to a standardised approach as outlined in Basel III. This is achieved through comparative back testing. This serves as a motivation to rank emerging markets equities time-varying risk forecasts. Moreover, the ability to rank competing models is permitted by elicitability of the (VaR, ES). Given that ES is a coherent risk measure, unlike the VaR, it is unsettling to observe the rareness of empirical applications[25] of ES in emerging markets risk analysis. Studies on joint dynamic models for VaR and ES are also limited. Patton et al. (2019) cite the non-elicitability of the ES be the most likely explanation. Nonetheless,

[24] Spectral risks relate risk measures directly to the user's risk aversion functions (Cotter & Dowd, 2006).
[25] See (Andersen et al., 2006; Komunjer, 2013; McNeil, Frey, & Embrechts, 2015).

with the advent of joint elicitability of VaR and ES there is a momentum in empirical studies in this direction. This study is the first to undertake the exercise for emerging markets equities.

In addition to modelling emerging markets tail risks to appeal to Basel III, the study provides spatial risk dimension as a supplementary technique to assess and select emerging markets equities. It is important that the geographic footprints of EMEs are combined with the financial factors to adequately assess their equities. In answering the question as to how investors can assess emerging markets equity investment risks in the face of time-varying and time-invariant spatial risks the study makes modest but important contributions to both theory and empirics. First, study robustly quantifies time-varying tail risks in emerging markets equities in agreement with regulatory framework (i.e. Basel III) which has been non-existent hitherto. Attempts at this have been made by Dimitrakopoulos et al. (2010) and Corlu et al. (2016) which involve only VaR and a limited number of EMEs. By this they leave out the nearest rival to tail risk measurement; ES without recourse to the inadequacies of VaR. With the use the (VaR, ES) model we bridge the limitations of both VaR and ES as well as offering a new mechanism to assess risks in emerging markets equities. This provides fresh knowledge for international portfolio investors to make decisions regarding emerging markets equities. That is to say, emerging markets equities may elicit international investors, motivated not only by high returns, but also with the knowledge that risks are adequately quantified. More importantly, the study surmises that due to the size and importance of EMEs on the world stage, accurate risk analysis is essential for global economic and financial stability (Dimitrakopoulos et al., 2010; Kharas, 2010).

Second, the study augments the mechanism of assessing emerging markets equity risks with country-specific (spatial) time-invariant risks measures. The study uses GLIs as proxy for country-specific (spatial) time-invariant risks measures. Unlike time-varying (VaR, ES) forecasts[26], spatial risks help to juxtapose systemic risk independent of daily trading to provide a wholesome risk and/or opportunity assessment. To this end, we extend the Cultural, Administrative, Geographic and Economic (CAGE) distance dimensions framework of Ghemawat (2001) by proposing *"financial distance"*. There is sufficient support in the literature for the use of liquidity as an indicative measure of systemic market risk. Given the importance of global liquidity it has become *de rigueur* driver for international financial stability in recent years in spite of the ambiguity surrounding its measurement. Primarily seen as credit, Ahmed et al. (2017) deduce that the run-up in bank credit to the private sector (measured as the change in the ratio of bank credit to GDP over the five years prior) is an important factor in the transmission of shock to financial markets in different EMEs. Those with higher run-up in bank credit suffered severe currency depreciation (see also Bruno & Shin, 2018).

Third, a comprehensive and systematic quantification of risk in EMEs demands continuous updating of the process given unstable market dynamics. Both Dimitrakopoulos et al. (2010) and Corlu et al. (2016) fail to account for these. In this study, the sample horizon is sub-sampled into EZC and GFC period between 5/1/2007 and 7/6/2013; Post-crisis period from 10/6/2013 to 19/2/2019. The selected sub-sample periods align with the extant literature (see Dimitrakopoulos et al., 2010; Mobarek et al., 2014; Mobarek et al., 2016; Mollah & Mobarek, 2016; Mollah et al.,

[26] Time-varying and time-invariant data are defined as daily emerging markets equity indices data and GLIs quarterly data, respectively.

2016; Wang & Moore, 2012). Given the apparent sensitivity of risk measures to stressed market conditions it will be remiss to examine tail and spatial risk different market conditions all at once.

Fourth, since time-variation in the stylised facts of equities returns are equally important, we employ different asymmetric distributions in the univariate GAS framework to estimate and forecast the (VaR, ES) model. This helps to capture skewness, fat-tails, and time-varying scale and shape parameters in emerging markets equities (see McNeil & Frey, 2000; McNeil et al., 2015). With specific reference to emerging markets equities, Cajueiro and Tabak (2005) document time-varying volatility and long-range dependence. Further, Harvey (1995), Bekaert and Harvey (1997), and Bekaert et al. (1998) examined at both pre- and post-liberalisation returns and find that they have skewness and fat tails. These have implications on how to model risk, noting that higher moments suggest that alternative distributions are considered account for them. Unfortunately, there is almost no end to the list of non-normal distributions that can be used to model tail risk. However, we employ the GAS framework which is known to have proven worthy of tail risk quantification. This has not been done before far as the literature on EMEs risk is concerned.

On the theoretical front, the study proposes *"financial distance"* dimension for use in time-invariant spatial risks analysis. Given the intrinsic geographical properties of EMEs, a study on systematic risk quantification that shies away from addressing these distance tendencies leave much to be desired. The concept of spatial autocorrelation is applicable to the GLIs. The BIS (2011) points out that the increasing trend in global liquidity is caused by deeper financial integration between countries and financial innovation in the markets. Being country-specific indicators, cross-sectional EMEs GLIs allow for spatial analysis in terms of spatial weights, spatial distances, and spatial autocorrelations. We premise our spatial risk analysis on Tobler's first law of geography which states that *"everything is related to everything else, but near things are more related than distant things"* (Tobler, 2004; Tobler, 1970, p.236). Once again, this study is the first of its kind to undertake such as exercise. No study has defined market risk based on the CAGE (or in generic terms the psychic[27] distance) framework in order to provide additional time-invariant risk measure to compare with (VaR, ES) forecasts in emerging markets equities. The study suggest neighbourhoods[28] of EMEs in terms of liquidity distance which can be used by investors as another criterion in selecting equities. Therefore, investors can avoid lumping together equities that are spatially autocorrelated albeit exhibiting lower (VaR, ES) forecast values.

Last, this study provides up-to-date market risk assessment of emerging markets equities because of their importance in global economic and financial stability (Dimitrakopoulos et al., 2010; Kharas, 2010). For a justified concern over financial stability, liquidity should play a key role in research since it indicates, to a large extent, vulnerability in financial systems. It deepens our understanding of EMEs risks vis-à-vis opportunities in light of their latent differences and similarities. From an understanding of spatial autocorrelations of financial risks in EMEs, spatial-stamped risk management, international portfolio, and policy decision processes may be better informed. From international trade perspective, the study proffers the importance of country-

[27] Distance between objects or other phenomena as seen in (Dow & Karunaratna, 2006; Drogendijk & Martin, 2008).
[28] That is how close of EME is from one other or from a number of other in terms of geographical distance or as measured by any particular indicator (for example liquidity risk as used in this study).

specific features that can be useful for bilateral and multilateral deals to mitigate the downsides of business and economic activities.

The findings from this study indicate that the ranking of (VaR, ES) model forecasts and spatial autocorrelations differ significantly. We opine that (VaR, ES) model rankings may be irrelevant because time-invariant spatial disasters will have no regard for the quality of time-varying tail risks estimates in the markets. Further, the overall spatial autocorrelation between the 12 EMEs is positive and bigger for EZC-GFC but smaller and negative for post-GFC period. These imply some level of change in macroprudential policy actions between the two market periods, with the latter providing more safety for the EMEs. The results also confirm the relevance of *"financial distance"* to be used in assessing the risks in EMEs. Policy and investment recommendations are discussed based on the findings of this study.

3.2 Theoretical models and empirical methodology

As a statistical function, ES is not elicitable because there exists no loss or scoring function/rule which it can distinctively minimise in expectation (Gneiting, 2011; Weber, 2006). This poses the problem of infeasibility in consistently ranking competing forecasts of ES based on such a loss function. Attendant to this is back testing of forecasts being problematic (Dimitriadis & Bayer, 2017). As noted by Fissler et al. (2015) elicitability is important since it allows for model selection, estimation, generalised regression, forecast comparison, and forecast ranking among others. Traditionally, the performance of a risk management procedure can be monitored by way of comparing the realised losses with risk measure forecasts, which has come to be known as back testing (Christoffersen, 2004; McNeil et al., 2015). In particular Emmer et al. (2015) suggest back testing of ES is not as straightforward as VaR and suggest replacing ES by a set of four quantiles so that the back testing methods of VaR can be applied on ES. Though this study is not an econometric exercise to examine the best fitting model for (VaR, ES), it is of essence that different distributional assumptions together with different robustness tests are explored to ascertain an appropriate time-varying tail risk measure. Despite tail risks occurring with small probabilities, their financial impacts could be large and devastating and as such a well-paced procedure is necessary for selecting the right model.

3.2.1 Time-variation in model parameters

The Generalised Autoregressive Score (GAS) models were introduced, in their generality, by Creal et al. (2013) and Harvey (2013) (referred to as dynamic conditional score) as a class of observation-driven time series models. GAS models fall under observation-driven as against parameter-driven models classified by Cox et al. (1981). GAS models use a score (or loss) function as the driver of time-variation in the parameters of non-linear models as a distinctive feature (Ardia et al. 2016b). The emergence of GAS is motivated by the difficulty in handling time-varying parameters inherent in time series data (especially financial time series). Specifically, Creal et al. (2013) and Harvey (2013) indicate that many suggested models are neither easy to estimate nor do they properly account for the shape of the conditional distribution of the time series. To side-step this the authors propose the use of the score of the conditional density function as the main determinant of time-variation in the parameters. Estimation by maximum likelihood is straightforward because the GAS updates the model parameters over time with the scaled score likelihood function (Creal et al., 2013). The time-varying parameters are in GAS are based on the score function of the predictive model density at time $t$instead of only means and higher moments. Being conditional on time t, Harvey (2013) suggests score functions discount extreme values hence making them robust to outliers.

It seems logical and intuitive that the (VaR, ES) model may better be estimated by the GAS given the underlying mechanism of “score function” between the two (i.e. (VaR, ES) has the FZL as an associated score function). That is to say, both functions are score-driven and thus fosters better interfacing than models of differing “driving” functions.The GAS framework lends itself to be extended to asymmetric dynamics, for instance, at no cost of complexity.

3.2.2 Univariate GAS model specification

The following specification of the basic GAS is based on Creal et al. (2013). Let $N \times 1$ vector y_t be dependent variable, f_t the time-varying parameter vector, x_t a vector of covariates, and θ a vector of static parameters. Let the filtration $\{f_t, F_t\} \in \mathcal{F}_t$ be given as

$$\mathcal{F}_t = \{Y^{t-1}, F^{t-1}, X^t\}, for\ t = 1, \dots, n, \tag{3.1}$$

where $Y^t = \{y_1, \dots, y_t\}, F^t = \{f_0, f_1, \dots, f_t\}$, and $X^t = \{x_1, \dots, x_t\}$,

It is assumed that y_t is generated by observation density and parameter vector θ driven by the score of the conditional distribution in

$$y_t \sim p(y_t | f_t, \mathcal{F}_t; \theta). \tag{3.2}$$

The time-varying parameter f_t is updated by an autoregressive mechanism

$$f_{t+1} = \omega + \sum_{i=1}^{p} A_i s_{t-i+1} + \sum_{j=1}^{q} B_j f_{t-j+1}, i = 1, \dots, p, j = 1, \dots, q, \tag{3.3}$$

where ω is a vector of constants, and A_i and B_j are matrices of requisite dimensions, and $s_t = s_t(y_t, f_t, \mathcal{F}_t; \theta)$ a function of historical data. It follows that the three unknown coefficients are all functions of θ (i.e. $\omega = \omega(\theta), A_i = A_i(\theta), B_i = B_i(\theta)$) evaluated at $r_t = lnP_t - lnP_{t-1}$, (log-returns in conventional notations). With a realised y_t, f_t is updated to f_{t+1} in (3.3) via

$$s_t = S_t \nabla_t, \quad \nabla_t = \frac{\partial lnp(y_t | f_t, \mathcal{F}_t; \theta)}{\partial f_t}, \quad S_t = S(t, f_t, \mathcal{F}_t; \theta), \tag{3.4}$$

where $S(.)$ is a matrix. The equations (3.2 – 3.4) define the GAS model with orders p and q, $GAS(p, q)$ given dependence of the driving mechanism in (3.3) on the scaled score vector in (3.4). In this study $GAS(1,1)$ is used in all estimations (see Creal et al., 2013; Ardia et al., 2016).

3.2.3 Selected distributions for the univariate GAS model

We follow the empirical evidence that financial returns are skewed and heavy-tailed with-varying variances or volatility clustering (Cajueiro & Tabak, 2005; McNeil & Frey, 2000; McNeil et al., 2015) and use distributions that are flexible to incorporate these stylised facts in forecasting the (VaR, ES) for EMEs equities in a univariate GAS framework; skewed-Gaussian (SNORM), student-t distribution (STD), skewed-student-t distribution (SSTD) (Fernández & Steel, 1998); asymmetric student-t with two tail decay parameters (AST), asymmetric student-t with one tail decay parameter (AST1) (Zhu & Galbraith, 2010, 2011); and asymmetric Laplace distribution (ALD) (Kotz et al., 2012).

3.2.3.1 SSTD, STD, and SNORM

Given $\mathcal{F}_{t-1}$as the autoregressive conditional distribution of r_t can be stated as

$$r_t | \mathcal{F}_{t-1} \sim SSTD(r_t, \mu, \sigma_t, \zeta, \nu) \tag{3.5}$$

with location parameter $\mu \in \mathbb{R}$, time-variant scale $\sigma_t > 0$, and skewness and shape parameters $\zeta > 0$, and $\nu > 2$, respectively. Following Bauwens and Laurent (2005), Ardia et al. (2016b) reparametarise (3.5) such that $\mathbb{E}_{t-1}[r_t] = \mu$ and $Var_{t-1}[r_t] = \sigma_t^2$. In the special case when $\zeta = 1$, the SST becomes STD and SNORM[29] when $\zeta = \infty$. Parameter estimates are obtained through the maximum likelihood estimator (MLE) of Blasques, Koopman, and Lucas (2014) with one-step ahead prediction in closed form.

3.2.3.2 AST and AST1

The AST is an improvement upon two distributions by Jones and Faddy (2003) and Aas and Haff (2006) of the class of skew t-type distributions with two tail parameters to control left and right tail dynamics (Zhu & Galbraith, 2010). The density function of the AST, rescaled for computational efficiency can be defined as

$$ST(r_t;\theta) = \begin{cases} \dfrac{1}{\sigma}\left[1 + \dfrac{1}{\vartheta_1}\left(\dfrac{r_t - \mu}{2\alpha\sigma\mathrm{K}(\vartheta_1)}\right)^2\right]^{-(\vartheta_1+1)/2}, r_t \leq \mu \\ \dfrac{1}{\sigma}\left[1 + \dfrac{1}{\vartheta_2}\left(\dfrac{r_t - \mu}{2(1-\alpha)\sigma\mathrm{K}(\vartheta_2)}\right)^2\right]^{-(\vartheta_2+1)/2}, r_t > \mu, \end{cases} \tag{3.6}$$

where $\theta = (\alpha, \vartheta_1, \vartheta_2, \mu, \sigma)^T$ with skewness, left tail, right tail, location, and scale parameters respectively. Further, $\mathrm{K}(\vartheta) = (\Gamma(\vartheta+1)/2)/[\sqrt{\pi}\vartheta\Gamma(\vartheta/2)]$, for $\{\vartheta_1, \vartheta_2\} \in \vartheta$.

3.2.3.3 ALD

Kotz et al. (2012) note that the ALD is deemed the most suitable skewed simplification of the classical Laplace law. Given r_t, it has an ALD if there exist location, scale, and skewness

[29] For full descriptions see (Ardia et al., 2016a; Bauwens & Laurent, 2005; Zhu & Galbraith, 2010).

parameters such that the characteristic function is distributed as $r_t \sim ALD(\theta, \sigma, \kappa)$. Yu and Zhang (2005) also state the generalised probability density function (pdf) of the ALD as

$$f(r_t; \theta, \sigma, \kappa) = \frac{\kappa(1-\kappa)}{\sigma} exp\left(-\frac{(r_t - \theta)}{\sigma}[\kappa - I(r_t \leq \theta)]\right), \qquad (3.7)$$

with reparameterisations from Kotz et al. (2012), where $0 < \kappa < 1$, $\sigma > 0$, $-\infty < \theta < \infty$, are skewness, scale, and location parameters, respectively and $I(.)$ is the indication function. The MLE estimation of parameters apply to all the distributional innovations described in Kotz et al. (2012).

3.2.4 The FZL function

The occurrence of a scoring function engenders an inherent means to compare forecasting accuracy of different models (Gneiting, 2011). For a forecast $x \in \mathbb{R}^k$ issued in the occurence of the event $y \in \mathbb{R}^d$, the forecast model is *penalized* by the real value $S(x, y)$, and k, d are dimensions of the forecasting model, where $S(.)$ is a squared error or absolute inversely relating forecast values and their original counterparts. Recently, one-dimensional forecasts (i.e. $k = d = 1$) in literature is due Gneiting (2011) indicating that scoring functions should be an incentive for truthful reporting of forecasting results by minimizing their expected loss or Bayes risk $\mathbb{E}_F[S(x, y)]$.

Fissler and Ziegel (2016) recommend a *strictly* $\mathcal{F}$-consistent for functional $T(F)$ of a random variable X. This should be the unique minimiser of the *expected loss* $\mathbb{E}_F[S(x, y)]$ for every $F \in \mathcal{F}$ if the probability distribution of $\mathcal{F}$ is in the domain of T. Given a non-strictly consistent scoring function $S: \rightarrow \mathbb{R}^2 \rightarrow \mathbb{R}$, for any random variable X with finite mean, and for $\alpha \in (0,1)$, ES can be defined as

$$ES_\alpha(X) = arg\ min_{e\in\mathbb{R}}\mathbb{E}[S(e,X)] \tag{3.8}$$

and

$$ES_\alpha(X) = \frac{1}{\alpha}\int_0^\alpha VaR_\beta\,(X)d\beta, \tag{3.9}$$

where $VaR_\alpha(X) = \inf\{x \in \mathbb{R}: \mathbb{P}(X \leq x)\}$. Unlike ES, VaR at $\alpha \in (0,1)$ has a strictly consistent scoring function of the form

$$S_V(v,x) = (\mathbb{I}\{x \leq v\} - \alpha)(G(v) - G(x)) \tag{3.10}$$

and thus elicitable with a unique α-quantile, where G is strictly increasing.

However, as stated earlier, Fissler et al. (2015) and Fissler and Ziegel (2016) show that at a higher order ES is elicitable. To wit (VaR_α, ES_α) is conjointly elicitable as

$$(VaR_\alpha(X), ES_\alpha(X)) = argmin_{v,e\in\mathbb{R}^2}\mathbb{E}[S_{V,E}(v,\mathrm{e},X)\ ] \tag{3.11}$$

with a scoring function

$$\begin{aligned} S_{V,E}(v,e,x) = (\mathbb{I}\{x \leq v\} - \alpha)\big(G_1(v) - G_1(x)\big) \\ + \frac{1}{\alpha}G_2(e)\mathbb{I}\{x \leq v\}(v - x) + G_2(e)(e - v) \\ - \mathbb{G}_2(e), \end{aligned} \tag{3.12}$$

where $V, E, v,$ and e denote $VaR_\alpha, ES_\alpha,$ and their corresponding estimates. It is clear from (3.10) that G_1 and G_2 are strictly increasing continuously differentiable functions such that $\mathbb{E}[G_1(X)]$ exists, $lim_{x\to-\infty}G_2(x) = 0$, and $\mathbb{G}_2' = G_2$(Fissler et al., 2015). The second part of $S_{V,E}$ exhibits the dependence of ES_α on VaR_α to be elicitable. The function in (3.12) is referred to as the FZL function. The FZL used in the GAS framework is the parametrisation of Patton, Ziegel, and Chen (2019) by defining the difference for two forecasts (v_{1t}, e_{1t}) and (v_{2t}, e_{2t}) as

$L_{FZ}(X_t, v_{1t}, e_{1t}; \alpha, G_1, G_2) - L_{FZ}(X_t, v_{2t}, e_{2t}; \alpha, G_1, G_2)$. The resulting loss function FZ0 is given as

$$L_{FZ0}(X, v, e; \alpha) = \frac{1}{\alpha e} \mathbb{I}\{X \leq v\}(v - X) + \frac{v}{e} + \log(-e) - 1 \qquad (3.13)$$

following the axioms: 1) both VaR and ES are strictly negative and 2) the loss differences generated are homogeneous of degree zero *iff* $G_1(x) = 0$ and $G_2(x) = -1/x$ (see Patton et al., 2019).

3.2.5 Predictive adequacy and back testing

Given that more than two models are employed in this study, the multivariate version of Diebold and Mariano (1995), Mariano and Preve (2012) (MDP) is employed to test the null hypothesis of equal predictive ability (EPA) of competing forecasting models. With a Wald-type test W, is asymptotically chi-squared distributed and invariant to the ordering of competing models. After this, four back tests are implemented on the (VaR, ES) model; namely unconditional coverage, Kupiec (1995); correct conditional coverage, Christoffersen (1998); dynamic quantile, Engle and Manganelli (2004); and quantile loss (Koenker & Bassett, 1978). We follow a typical out-of-sample exercise (i.e. estimates are made using in-sample period of length M, predictions on the conditional distribution in the out-of-sample period H, and model comparison made according to their out-of-sample performance). Hence h-step ahead prediction of the return distribution at time $M + h$ along corresponding (VaR, ES) model level are generated in a recursive manner in line with Marcellino et al. (2006) until the end of the series T. We use $h = 1$ for one-step ahead daily forecasting. The mechanism of correct conditional coverage tests the series of (VaR, ES) exceedance $\{d_{t+M}, M = 1, \dots, H\}$ referred to as "hitting series". If correct coverage is achieved, (VaR, ES) exceedances (the number of times actual loss equals or exceeds the predicted (VaR, ES) threshold) should be distributed independently over time. The dynamic quantile on the other hand jointly tests for unconditional coverage and correct conditional coverage and it is documented to have more power than the aforementioned alternatives under some model misspecifications (see Ardia et al., 2016c). If two models achieve unconditional coverage/correct conditional coverage, the quantile loss can be used to make a decision based on quantile losses average over the forecasting periods. Smaller averages are preferred (González-Rivera et al., 2004). Given the shared properties of the (VaR, ES) model with VaR and ES, it lends itself for the same back testing to be applied on it.

In light of multiple models we are inspired by Blazsek and Hernández (2018) to measure forecast precision by the mean absolute error (MAE). It is given as $1/T_f \sum_{t=1}^{T_f} |p_t - \bar{p}_t|$, where p_t, $\bar{p}_t$, and T are realised values, forecast values, and sample length, respective. We use the MAE to rank all six (VaR, ES) models. The one with least MAE is chosen for each market as the best and candidate[30] model for back testing.

3.2.6 Spatial risks, neighbourhoods, and spatial autocorrelation

Cross-border equity flows studies, for instance, employing distance measures have resorted to the use of the parametric gravity model and spatial econometric models to achieve their results. As with any parametric model, distributional assumptions and/or properties of variables tend to temper with the adequacy of estimated results and hence inferences thereof. Their non-parametric

[30] We have not carried out back testing for the selected models since the conventional back testing techniques for VaR and ES may not adequately function for the nascent (VaR, ES).

cousins are can provide more robust outputs analysis as they avoid the bottlenecks implicit in distributional properties of data variables. In this study we use non-parametric geospatial analysis to derive spatial weights for use in identifying neighbours. Thence, we estimate spatial autocorrelation or spatial dependence analysis based on country-specific GLIs. The classical spatial analysis is premised on the assumption that observed sample data collected for regions[31] or points in space are not independent, but rather they are positively spatially dependent (LeSage & Pace, 2009). Similar to spatial econometrics, inter-country linkages (or dependencies) can be assessed through spatial neighbourhoods and autocorrelations which can be used in the assessment of spillover and contagion studies (Dell'Erba et al., 2013). We use the local Moran's I (Moran, 1948) as a measure of spatial autocorrelation.

We create spatial weights, neighbourhoods, and autocorrelations using the Local Indicators of Spatial Association (LISA) framework. Based on spatial weights, the local Moran's I statistic is used to assess country risk dependencies (Anselin et al., 2007; Anselin et al., 2006). Anselin (2010) suggests the operational definition of LISA as any statistic that satisfies the following conditions:

i. the LISA for each observation exhibits an indication of the extent of significant spatial clustering of similar values around that observation
ii. the sum of LISAs for all observations is proportional to a global indicator of spatial association (GISA).

Formerly, a LISA for a variable y_i, observed at location i, is a statistic L_i such that

[31] In spatial analysis regions have a broad range of spatial scales such as regional blocs, countries, administrative regions, among others. Countries are used in this study.

$$L_i = f(y_i, yJ_i), \tag{3.14}$$

where yJ_i are values observed in the neighbourhood J_i of i for all observations $j \in J_i$. The neighbourhood for each of observation is formalised by means of a spatial weight W. To infer statistical significance of the pattern of spatial association at $Prob[L_i > \delta_i] \leq \alpha_i$, where δ_i and α_i are critical value and chosen significance level, respectively. Further, LISA is related to a global statistic as $\sum_i L_i = \gamma \wedge$, with $Prob[\wedge > \delta] \leq \alpha$, where $\wedge$ is a global indicator of spatial association and γ is a scale factor for the whole data set. The LISA is used as the basis to test the null hypothesis of no local spatial association. The local Moran's I (Moran, 1948) for an observation i may be defined as in

$$I_i = z_i \sum_j w_{ij z_j}, \tag{3.15}$$

where z_i, z_j are deviations from the mean, and the summation over j is such that only the neighbouring values $j \in J_i$ are used. Distance weight w_{ij}

$$w_{ij} = f\left(d_{ij}, \theta\right), \tag{3.16}$$

is chosen over contiguity weights since the EMEs do not share common borders, where θ is a vector of parameters, d_{ij} is the distance between observations i and j with ϕ as the bandwidth. This is based on the distance cut-off represented as spline function such that 1 is for neighbours with $d_{ij} < \phi$ and 0 otherwise. To respect Tobler's first law of geography, distance decay, $\frac{\partial w_{ij}}{\partial d_{ij}} < 0$ (i.e. value of the distance function decreases with an increasing distance). The actual distances functions used are the inverse $w_{ij} = 1/d_{ij}^{\alpha}$ and negative exponential $w_{ij} = e^{-\beta d_{ij}}$ with α, β being parameters. It is joined with a distance cut-off criterion so that $w_{ij} = 0$ for $d_{ij} > \phi$ (see Anselin, 2000, 2010; Anselin et al., 2007). The GeoDa[32] software is used in this exercise.

3.3 Data, samples, and preliminary analysis

We fully quantify the risks in the 12 emerging markets equities (with available GLIs data) as per the Morgan Stanley Capital International (MSCI) classification of emerging markets across both tranquil and stressed market periods spanning 3/6/1997 to 19/2/2019. Aside being one of the most widely indexing house, the MSCI's classifications overlap with other popular indices of EMEs from Financial Times Stock Exchange (FTSE) Russell and Standard & Poor Dow Jones Indices (S&P DJI). Generally, these institutions use economic development (as measured by a GNI/GDP per capita threshold), size and liquidity of markets, market accessibility, and stability of institutional framework as criteria for classifying economies (see FTSE, 2018; MSCI, 2018; S&P DJI, 2018). To delineate the dynamics of emerging markets equities' risks of one market condition from the other(s) return series are sub-sampled into two groups, namely; Eurozone crisis and GFC (EZC-GFC) between 5/1/2007 and 7/6/2013; and Post-crisis period from 10/6/2013 to 19/2/2019. Daily prices and return series employed are those of the MSCI EMEs equity indices for the sampled periods.

As out-of-sample forecasting exercise each sub-sample is split into in-sample and out-of-sample. Since back testing periods are based on the forecast length, the out-of-sample period is chosen as the forecast length such that it is a minimum of one year and percentiles are 97.5 and 99 as prescribed by the BIS (BIS, 2013). The estimation and forecasting periods are as follows: EZC-

[32]https://gisgeography.com/geoda-software/

GFC has M = 1117 (5/1/2007 – 18/4/2011), H = 559 (19/4/2011 – 7/6/2013) while Post-crisis has M = 740 (21/11/2014 – 14/7/2017), H = 368 (22/7/2017 – 19/2/2019).

"Financial distance" is proxied by Global Liquidity Indicators (GLIs) compiled quarterly by the BIS since 2000. It is defined as United States dollar denominated credit to non-banks[33] outside of the United States. The available data span 31/03/2000 –31/12/2018. There are GLI indices for twelve (12) EMEs, namely; Brazil, Chile, Mexico, China, India, Indonesia, Malaysia, Korea, Russia, Turkey, South Africa, and Taiwan[34]. Two sub-samples of the GLI for these countries corresponding to EZC-GFC and Post-crisis are chosen as 31/3/2007 – 31/12/2013 and 31/3/2014 – 31/12/2018, respectively. For these periods the aggregate of the quarterly GLI is used to represent each of the 12 EMEs. Emerging markets equity indices were gleaned from the Bloomberg Financial and Thomson Reuters DataStream Terminals. Quarterly GLIs were rather obtained from the BIS's website[35].

3.3.1 Descriptive statistics

The daily fluctuations in the prices and log-returns[36] across the board are hard to miss when one employs high frequency data. We present the price and log-returns plots in Figures 2.8A and 2.8B in the Appendix 3.1. Table 3.6 (in Appendix 3.1) depict skewness and kurtosis values indicating non-normality and leptokurtic behaviour in the equity returns across the board. The Shapiro-Wilk test confirm this by rejecting the normality assumption at all conventional levels of significance.

[33] The BIS define non-banks as non-bank financial entities, non-financial corporation, governments, households, and international organization.
[34]Also known as Chinese Taipei in the vocabulary of the BIS.
[35]https://www.bis.org/statistics/gli.htm?m=6%7C333%7C690
[36] P_t and P_{t-1} are index prices (in United States dollars) at time t and $t-1$, respectively.

These go to support the need for using asymmetric distributions in modelling the tail risks in the equities. Contrary to EZC-GFC period where all GLIs are on an upward trajectory, save Russia, in the Post-crisis period they seem to be compositely decreasing except for Taiwan and South Africa which exhibit upward trends. The plots are presented in Figures 3.9A and 3.9B in Appendix 3.1. Summary statistics presented in Table 3.7 (in Appendix 3.1) bear witness.

3.4 Empirical results

3.4.1 Forecasting univariate GAS (VaR, ES) more forecasts

At this stage the six different distributional assumptions of the univariate GAS models are applied to one-step ahead (VaR, ES) in the out-of-sample period at the 99% and 97.5% levels. The MDP test of EPA is displayed in Table 3.1. From Table 3.1, it is clear that the MDP test fails to reject the null hypothesis of EPA for all countries at all conventional levels of significance except Russia (Post-crisis) at 2.5% level. This outcome raises concerns about the robustness of the test since adjudging six models of different distributional assumptions as being of equal predictive accuracy is almost hard to ignore.

Moreover, in the context of this study all six models cannot be used as models of choice and together with few rejections further tests are warranted. Since the (VaR, ES) is elicitable and has a consistent scoring function such as the FZL, the models can be ranked in order of predictive ability.

Table 3.1: Multivariate Diebold-Mariano (2012) test of model equal predictive accuracy

Market	α	EZC-GFC		Post-crisis	
		W	p-value	W	p-value
Brazil	1%	85.94	1.00	90.02	1.00
	2.5%	127.36	1.00	44.18	1.00
Chile	1%	31.33	1.00	61.34	1.00
	2.5%	39.42	1.00	83.61	1.00
Mexico	1%	40.11	1.00	40.45	1.00
	2.5%	39.58	1.00	58.29	1.00
Russia	1%	34.01	1.00	58.73	1.00
	2.5%	58.75	1.00	**-2.38**	**0.00**
South Africa	1%	45.27	1.00	50.81	1.00
	2.5%	92.39	1.00	49.08	1.00
Turkey	1%	74.71	1.00	28.38	1.00
	2.5%	112.29	1.00	57.64	1.00
China	1%	91.75	1.00	27.64	1.00
	2.5%	83.56	1.00	100.89	1.00
India	1%	118.66	1.00	46.89	1.00
	2.5%	74.04	1.00	86.16	1.00
Indonesia	1%	42.55	1.00	81.25	1.00
	2.5%	84.40	1.00	93.67	1.00
South Korea	1%	36.24	1.00	23.15	0.10
	2.5%	82.70	1.00	65.83	1.00
Malaysia	1%	30.17	1.00	23.15	0.10
	2.5%	34.34	1.00	45.80	1.00
Taiwan	1%	29.71	1.00	54.502	1.00
	2.5%	43.16	1.00	58.88	1.00

Note: W is the MDP test statistic. MDP does not reject the null hypothesis of EPA for all countries at all conventional levels of significance except for Russia (Post-crisis) at 2.5%, 1% and 2.5% level (in boldface).

In the spirit of Blazsek and Hernández (2018) MAE is computed for each model across the sub-samples and used to rank the models. The output of these are presented in Table 3.2. It is observed from Table 3.2 that the model that emerged as the best (i.e. one with the least MAE) is the ALD[37] across the sub-sample periods. This is followed by the SNORM and in a few instances the AST and SSTD had the least MAE. In addition, we note that in most cases the same model is elected at both $\alpha = 0.01$ and $\alpha = 0.025$. Further, AST and AST1 in almost all instances has the same MAE. This may hint at the fact that emerging markets equities cannot be distinguished by virtue of left and right tail behaviours where one is thin and the other heavy. That is to say, regardless of the

[37] Since all the distributions are applied to the univariate GAS specification, hereafter the distribution is synonymous with the GAS model.

market situation in EMEs equities the (in)equality of the relative frequency of extreme returns of losses (left tails) and gains (right tails) cannot be established using either AST class of distributions as claimed by Zhu and Galbraith (2010, 2011) in VaR and ES estimates.

It may not come as a surprise that ALD appears to be the chosen model in most instances. In a recent study Taylor (2019) show that the ALD is appropriate to jointly estimate dynamic models of VaR and ES and for forecasting the same. Specifically, the author shows the negative log-likelihood the ALD interfaces with one of the loss functions in Fissler and Ziegel (2016) which makes it most appropriate for the estimation and evaluation of the (VaR, ES) in this context. It is worth noting that this applied to both 99 and 97.5 percentiles. These are the models selected as candidates for back testing the (VaR, ES) model forecasts; the outputs of which are as shown in Table 3.2.

3.4.2 Back testing and model ranking of (VaR, ES) model forecasts

Following the selected models by MAE for each country and the 99 and 97.5 percentiles the unconditional coverage, correct conditional coverage, dynamic quantile, and quantile loss back tests on their (VaR, ES) forecasts are implemented. All tests premise on the null hypothesis of correctly specified forecast model for the (VaR, ES) at respective α levels[38]. For unconditional coverage, correct conditional coverage, and dynamic quantile tests, statistics are provided with p-

[38] For consistency, all tests are carried out at the same α levels in agreement with 99 and 97.5 percentiles of the (VaR, ES) forecasts.

values whiles quantile loss gives only loss values. In the latter a model with lower loss is preferred. In Table 3.3 these test results are presented.

In both sub-samples of EZC-GFC and Post-crisis and at both $\alpha = 0.01$ and $\alpha = 0.025$ at least one of the tests accept the models as correctly specified except for Russia (2.5%) for Post-crisis. In the first period India (2.5%) and Turkey (2.5%) and their respective models are rejected as correctly specified and hence cannot adequately estimate and forecast (VaR, ES) models. These models are appropriately accompanied by very high quantile loss values to further confirm their failure and it is noted they are all at the 97.5% confidence level. For these reasons the 2.5% (VaR, ES) model forecasts are not used in estimating the single value (VaR, ES) model forecasts for spatial risk comparison. It does appear that compositely the 1% (VaR, ES) model forecasts are better off.

Further, is it observed that there is only a handful of scenarios where all unconditional coverage, correct conditional coverage, and dynamic quantile accept correctly specified model for the (VaR, ES) model forecasts across the two sub-samples with none occurring in the Post-crisis period whereas only South Korea (1%) fits the profile for EZC-GFC periods.

Table 3.2: MAE ranking of univariate GAS (VaR, ES) model forecasts per distributional innovation

Eurozone and Global Financial Crises periods: 19/4/2011 to 7/6/2013									
	$\alpha = 1\%$		$\alpha = 2.5\%$			$\alpha = 1\%$		$\alpha = 2.5\%$	
Brazil	***MAE***	***Rank***	***MAE***	***Rank***	**Chile**	***MAE***	***Rank***	***MAE***	***Rank***
snorm	3.0879	1	**3.2366**	**1**	snorm	3.7881	4	3.8072	2
std	3.5447	4	3.6475	4	std	3.7803	2	3.8504	4
sstd	3.3223	3	3.4466	3	sstd	3.7808	3	3.8345	3
ast	3.8597	5	3.7493	5	ast	4.1131	5	3.9787	5
ast1	3.8597	5	3.7493	5	ast1	4.1131	5	3.9787	5
ald	**2.9669**	**1**	3.2605	2	ald	**3.3055**	**1**	**3.5584**	**1**
Colombia					**Mexico**				
snorm	**3.1648**	**1**	**3.3292**	**1**	snorm	3.3541	2	3.4903	2
std	3.8899	4	3.9411	4	std	3.7328	4	3.7981	6
sstd	3.6905	3	3.7999	3	sstd	3.4960	3	3.6820	3
ast	4.6101	5	4.4411	5	ast	3.8052	5	3.7970	4
ast1	4.6101	5	4.4411	5	ast1	3.8502	5	3.7970	4
ald	3.3392	2	3.5877	2	ald	**3.1875**	**1**	**3.4689**	**1**
Brazil					**Chile**				
snorm	3.0879	1	**3.2366**	**1**	snorm	3.7881	4	3.8072	2
std	3.5447	4	3.6475	4	std	3.7803	2	3.8504	4
sstd	3.3223	3	3.4466	3	sstd	3.7808	3	3.8345	3
ast	3.8597	5	3.7493	5	ast	4.1131	5	3.9787	5
ast1	3.8597	5	3.7493	5	ast1	4.1131	5	3.9787	5
ald	**2.9669**	**1**	3.2605	2	ald	**3.3055**	**1**	**3.5584**	**1**
Mexico					**China**				
snorm	3.3541	2	3.4903	2	snorm	3.3763	3	3.4802	2
std	3.7328	4	3.7981	6	std	3.5752	4	3.6944	4
sstd	3.496	3	3.682	3	sstd	3.4262	2	3.5473	3
ast	3.8052	5	3.797	4	ast	4.114	5	3.9357	5
ast1	3.8502	5	3.797	4	ast1	4.114	5	3.9357	5
ald	**3.1875**	**1**	**3.4689**	**1**	ald	**3.1268**	**1**	**3.3568**	**1**
India					**Indonesia**				
snorm	**2.9749**	**1**	**3.1279**	**1**	snorm	3.1434	2	**3.2237**	**1**
std	3.471	3	3.5809	3	std	3.7022	4	3.7748	6
sstd	3.4754	4	3.5924	4	sstd	3.5699	3	3.6646	3
ast	3.8811	5	3.8616	5	ast	3.8107	5	3.7608	4
ast1	3.8811	5	3.8616	5	ast1	3.8107	5	3.7608	4
ald	3.1082	2	3.3593	2	ald	**3.1199**	**1**	3.3717	2
Malaysia					**South Korea**				
snorm	**3.5613**	**1**	**3.7291**	**1**	snorm	3.3377	3	3.426	2
std	4.2176	2	4.2573	4	std	3.3855	4	3.5337	4
sstd	4.0857	3	4.142	3	sstd	3.3033	2	3.4421	3
ast	4.9669	5	4.6225	5	ast	3.8355	5	3.7959	5
ast1	4.9669	5	4.6225	5	ast1	3.8355	5	3.7959	5
ald	3.7296	2	3.948	2	ald	**2.9583**	**1**	**3.2284**	**1**
Russia					**Turkey**				
snorm	3.1632	2	3.2346	2	snorm	**2.916**	**1**	**3.0118**	**1**
std	3.4788	4	3.491	4	std	3.4358	4	3.495	4
sstd	3.445	3	3.4376	3	sstd	3.2811	3	3.391	3
ast	3.9856	5	3.7836	5	ast	3.8907	5	3.8118	5
ast1	3.9856	5	3.7836	5	ast1	3.8907	5	3.8118	5
ald	**2.9384**	**1**	**3.197**	**1**	ald	2.9737	2	3.2127	2

Table 3.3 (Cont.)

Eurozone and Global Financial Crises periods: 19/4/2011 to 7/6/2013									
	$\alpha = 1\%$		$\alpha = 2.5\%$			$\alpha = 1\%$		$\alpha = 2.5\%$	
South Africa	***MAE***	***Rank***	***MAE***	***Rank***	**Taiwan**	***MAE***	***Rank***	***MAE***	***Rank***
snorm	3.2767	2	3.4229	2	snorm	**3.299**	**1**	**3.4071**	**1**
std	3.5123	4	3.5893	4	std	3.8108	4	3.8382	4
sstd	3.3524	3	3.5004	3	sstd	3.7946	3	3.79	3
ast	3.869	5	3.7718	5	ast	4.305	5	4.0323	5
ast1	3.869	5	3.7718	5	ast1	4.305	5	4.0323	5
ald	**2.9552**	**1**	**3.2084**	**1**	ald	3.3833	2	3.6053	2
Post-crisis period: 22/7/2017 to 19/2/2019									
Brazil					**Chile**				
snorm	3.4654	2	3.3923	2	snorm	4.0034	3	4.1076	3
std	3.7783	4	3.6558	6	std	4.1892	4	4.3267	4
sstd	3.4789	3	3.4207	3	sstd	3.9683	2	4.1013	2
ast	3.7186	5	3.5145	4	ast	5.5801	5	4.9784	5
ast1	3.7186	5	3.5145	4	ast1	5.5801	5	4.9784	5
ald	**3.1954**	**1**	**3.3179**	**1**	ald	**3.8464**	**1**	**4.0473**	**1**
Mexico					**China**				
snorm	3.8824	4	3.8266	2	snorm	3.6054	3	3.7332	3
std	3.8507	2	3.8881	4	std	3.7989	4	3.8681	4
sstd	3.8730	3	3.8757	3	sstd	3.5876	2	**3.3737**	**1**
ast	3.9232	5	3.8944	5	ast	3.927	5	3.8899	5
ast1	3.9232	5	3.8944	5	ast1	3.927	5	3.8899	5
ald	**3.3897**	**1**	**3.6049**	**1**	ald	**3.3497**	**1**	3.6219	2
India					**Indonesia**				
snorm	3.5975	3	3.7616	2	snorm	3.4349	2	**3.5576**	**1**
std	3.9709	4	4.0831	4	std	3.8822	6	3.8838	6
sstd	3.5907	2	3.7719	3	sstd	3.7812	5	3.801	5
ast	4.2145	5	4.1632	5	ast	3.6858	3	3.6474	3
ast1	4.2145	5	4.1632	5	ast1	3.6858	3	36474	3
ald	**3.5121**	**1**	**3.7586**	**1**	ald	**3.3779**	**1**	3.5965	2
Malaysia					**South Korea**				
snorm	**3.9946**	**1**	**4.0746**	**1**	snorm	3.995	5	3.9596	5
std	4.6639	4	4.6066	4	std	4.0831	6	4.0637	6
sstd	4.4845	3	4.4549	3	sstd	3.9317	4	3.9478	4
ast	4.9791	5	4.728	5	ast	3.7236	2	**3.6645**	**1**
ast1	4.9791	5	4.728	5	ast1	3.7236	2	**3.6645**	**1**
ald	4.0999	2	4.3	2	ald	**3.6214**	**1**	3.7949	3
Russia					**Turkey**				
snorm	3.4105	2	**3.4038**	**1**	snorm	4.0116	5	3.702	4
std	3.9187	4	3.8218	4	std	3.8813	4	3.7219	5
sstd	3.7707	3	3.7015	3	sstd	4.2028	6	3.8511	6
ast	4.3137	5	4.0686	5	ast	3.4312	2	**3.3484**	**1**
ast1	4.3137	5	4.0686	5	ast1	3.4312	2	**3.3484**	**1**
ald	**3.3996**	**1**	3.4991	2	ald	**3.2892**	**1**	3.3819	3
South Africa					**Taiwan**				
snorm	3.575	3	3.5551	3	snorm	4.321	3	4.1728	3
std	3.5382	2	3.5779	4	std	4.3809	4	4.2641	4
sstd	3.5683	4	3.5506	2	sstd	4.2646	2	4.1679	2
ast	3.7178	5	3.6378	5	ast	4.652	5	4.3702	5
ast1	3.7178	5	3.6378	5	ast1	4.652	5	4.3702	5
ald	**3.1252**	**1**	**3.3436**	**1**	ald	**3.9**	**1**	**3.9686**	**1**

Note: Best models are in boldface. We have chosen to write the model names in lower case to simplify the table.

It is apparent that the remaining models are either rejected (or accepted) as correctly specified by one of the three tests at varying levels of significance. Given the perceived robustness of the dynamic quantile, the results show how it rejects many models even if they are highly accepted by either unconditional coverage or correct conditional coverage, or both. Among others, Braione and Scholtes (2016) attribute the robustness of dynamic quantile to it taking into account a more general temporal dependence between the series of violations. As in many studies this study also support the robustness of the dynamic quantile test. Going forward and for 1% (VaR, ES) forecasts models are chosen further analysis if they are correctly specified by at least one of unconditional coverage, correct conditional coverage, and dynamic quantile. Where neither of three tests accept as correctly specified it is omitted from continuous analysis into spatial risk comparison.

Even though not one of the objects of this study, a model comparison between the two percentile requirements of Basel III is deemed appropriate. This was achieved via quantile loss ratios between 1% and 2.5% (VaR, ES) model forecasts obtained from the back testing results. For each market in Table 3.3 the ratio $Quantile\ Loss\ Ratio = Quantile\ Loss_{1\%}/Quantile\ Loss_{2.5\%}$ is calculated in the last column. If $Quantile\ Loss\ Ratio < 1$, the model at 1% outperforms that of 2.5% and vice versa (Ardia et al., 2016c).

It is clear from the quantile loss ratios that in the EZC-GFC episodes the 1% models do better than the 2.5% models in the range of 18% - 77% for all markets except Turkey (14%) in favour of the latter models. The Post-crisis period follows a similar pattern but with the 2.5% models out performing 1% in some markets, namely; Brazil (26%), Russia (41%), Turkey (15.2%), Malaysia (6.3%), and Taiwan (23%). The remaining go to 1% (VaR, ES) models between 9% and 74%. In the same period the 1% and 2.5% (VaR, ES) models perform equally for Chile. These further corroborate the election of the 1% (VaR, ES) models for spatial risk analysis in Section 3.4.4.

These outcomes bring to question whether the 99% or the 97.5% confidence level is appropriate for capital requirement and risk quantification. It is obvious that by moving from VaR to ES and using 97.5% Basel III seeks capital requirement that captures both a longer tails as well as losses beyond the VaR. The Basel Committee also recognise the prominence of ensuring that regulatory capital requirement is sufficient in periods of significant market stress where capital is most crucial to absorb losses. However, given that for internal models of emerging markets equities, the 99% tail risk models seem to outperform those of 97.5% across different market episodes of stress and tranquility, what confidence level will be used by the BIS? It is also interesting to note that it is rather in the relatively calm Post-crisis market period that the 97.5% models are perform better. Perhaps this is only the case with the (VaR, ES) model which draws on information from both VaR and ES. Having said that, it may be suggested that the relatively new robust elicitable (VaR, ES) models can be factored into subsequent revision of regulatory capital requirement. Im light of the elicitability feature which helps in comparative back testing, the case for this has been made by researchers such as Patton et al. (2019) and Fissler et al. (2015).

Table 3.4: Back testing results of selected univariate GAS (VaR, ES) models

Market	Distribution	α	UC	CC	DQ	QL	QL ratio	QL ratio
Eurozone and Global Financial Crises periods: 19/4/2011 to 7/6/2013								
Brazil	ald	1%	3.09 (0.08)	3.11 (0.21)	101.61 (0.00)	0.035758		69.81
	snorm	2.5%	5.92 (0.015)	6.05 (0.05)	184.36 (0.00)	0.118433	0.301924	
Chile	ald	1%	5.78 (0.02)	5.78 (0.06)	85.24 (0.00)	0.055979		67.32
	ald	2.5%	0.70 (0.4)	1.14 (0.56)	342.62 (0.00)	0.171281	0.326828	
Mexico	ald	1%	3.09 (0.08)	3.11 (0.21)	136.94 (0.00)	0.049568		68.29
	ald	2.5%	4.36 (0.04)	4.54 (0.10)	235.62 (0.00)	0.156341	0.317052	
China	ald	1%	3.09 (0.08)	3.11 (0.21)	183.01 (0.00)	0.06908		48.94
	ald	2.5%	5.92 (0.01)	6.05 (0.05)	159.51 (0.00)	0.135294	0.510592	
India	snorm	1%	5.78 (0.02)	5.78 (0.06)	104.60 (0.00)	0.068456		33.60
	snorm	2.5%	20.98 (0.00)	20.96 (0.00)	53.21 (0.00)	0.103101	0.663968	
Indonesia	ald	1%	3.09 (0.08)	3.11 (0.21)	124.99 (0.00)	0.092661		56.38
	snorm	2.5%	7.82 (0.01)	7.91 (0.02)	143.55 (0.00)	0.212443	0.43617	
Malaysia	snorm	1%	1.46 (0.23)	1.49 (0.47)	226.77 (0.00)	0.072898		51.80
	snorm	2.5%	4.36 (0.04)	4.54 (0.10)	253.88 (0.00)	0.151255	0.481953	
South Korea	ald	1%	5.78 (0.02)	5.78 (0.06)	50.45 (0.00)	0.035885		75.23
	ald	2.5%	4.36 (0.04)	4.51 (0.10)	239.53 (0.00)	0.144898	0.247658	
Russia	ald	1%	0.51 (0.48)	0.56 (0.75)	268.23 (0.00)	0.116734		43.00
	ald	2.5%	1.29 (0.26)	1.65 (0.44)	286.92 (0.00)	0.204788	0.570021	
Turkey	snorm	1%	1.46 (0.23)	1.49 (0.47)	186.19 (0.00)	0.198591		-14.06*
	snorm	2.5%	12.94 (0.00)	12.97 (0.002)	101.17 (0.00)	0.174113	1.140583	
South Africa	ald	1%	5.78 (0.02)	5.78 (0.06)	70.11 (0.00)	0.040661		68.74
	ald	2.5%	5.92 (0.01)	6.05 (0.05)	188.86 (0.00)	0.13006	0.312635	
Taiwan	snorm	1%	3.09 (0.08)	3.11 (0.21)	181.94 (0.00)	0.120612		18.25
	snorm	2.5%	7.82 (0.01)	7.91 (0.02)	139.35 (0.00)	0.147538	0.817498	
Post-crisis period: 22/7/2017 to 19/2/2019								
Brazil	ald	1%	4.77 (0.03)	4.77 (0.09)	103.82 (0.00)	0.304885		-26.27*
	ald	2.5%	7.93 (0.004)	7.99 (0.02)	64.23 (0.00)	0.241452	1.262715	
Chile	ald	1%	2.32 (0.13)	2.33 (0.31)	150.69 (0.00)	0.145619		0.00**
	ald	2.5%	4.20 (0.04)	4.35 (0.11)	148.57 (0.00)	0.145619	1	
Mexico	ald	1%	0.92 (0.34)	0.96 (0.62)	287.31 (0.00)	0.143451		23.25
	ald	2.5%	5.86 (0.02)	5.96 (0.05)	151.09 (0.00)	0.186918	0.767451	
China	ald	1%	4.77 (0.03)	4.77 (0.09)	84.63 (0.00)	0.054487		73.75
	sstd	2.5%	0.03 (0.87)	0.93 (0.63)	349.06 (0.00)	0.20759	0.262475	
India	ald	1%	9.99 (0.002)	9.99 (0.01)	4.98 (0.66)	0.035121		70.33
	ald	2.5%	10.51 (0.001)	10.54 (0.01)	101.30 (0.00)	0.118363	0.296723	
Indonesia	ald	1%	0.92 (0.34)	0.96 (0.62)	148.76 (0.00)	0.161379		20.93
	snorm	2.5%	2.88 (0.09)	3.08 (0.21)	220.52 (0.00)	0.204085	0.790744	
Malaysia	snorm	1%	0.20 (0.65)	0.27 (0.87)	218.89 (0.00)	0.227853		-6.28
	snorm	2.5%	7.93 (0.005)	7.99 (0.02)	123.27 (0.00)	0.214395	1.06277	
South Korea	ald	1%	0.92 (0.34)	0.96 (0.62)	204.50 (0.00)	0.213014		42.24
	ast	2.5%	0.02 (0.90)	0.61 (0.74)	237.12 (0.00)	0.368781	0.577616	
Russia	ald	1%	4.77 (0.03)	4.77 (0.09)	103.86 (0.00)	0.332661		-40.10*

Table 3.5 (Cont.)

Market	Distribution	α	UC	CC	DQ	QL	QL ratio	QL ratio
Eurozone and Global Financial Crises periods: 19/4/2011 to 7/6/2013								
	snorm	2.5%	18.08 (0.00)	18.08 (0.00)	51.62 (0.00)	0.23745	1.400973	
Turkey	ald	1%	0.74 (0.39)	10.14 (0.01)	275.41 (0.00)	0.529278		-15.19
	ast	2.5%	0.51 (0.47)	1.04 (0.59)	309.82 (0.00)	0.459501	1.151853	
South Africa	ald	1%	0.20 (0.65)	0.27 (0.87)	267.05 (0.00)	0.202594		19.37
	ald	2.5%	1.07 (0.30)	1.36 (0.51)	218.34 (0.00)	0.251253	0.806335	
Taiwan	ald	1%	2.32 (0.13)	2.33 (0.31)	189.25 (0.00)	0.407695		-23.33*
	ald	2.5%	1.85 (0.17)	4.40 (0.11)	134.35 (0.00)	0.330563	1.233334	

*Note: *Negative percentage indicate the 2.5% (VaR, ES) model outperforms the 1% (VaR, ES) model. **There is no difference in the 1% and 2.5% (VaR, ES) models. UC - Unconditional Coverage, CC - Correct Conditional Coverage, DQ - Dynamic Quantile, and QL - Quantile Loss.*

As a function emanating from both VaR and ES, the (VaR, ES) is intuitively important for empirical risk modelling because it can provide a better risk measure by drawing information from two tail measures. The plots of all three tail risk measures are assessed to provide empirical perspectives on their relationships for the selected models. These are presented in Figures 3.10A and 3.10B. A close observation of the plots reveal a rather unexpected pattern of (VaR, ES) forecasts. At the any $\alpha < 0.50$ Taylor (2019) indicates that (VaR, ES) forecast values are all expected to be negative, however, we find positive (VaR, ES) values in the plots. It is also counter-intuitive given that these are supposed to be loss values. Even more disconcerting is that these positive (VaR, ES) forecast values occur at the backdrop of carefully cleaned data and negative values for both VaR and ES. Moreover, a pattern seems to emerge that the positive (VaR, ES) forecast values occur at points where VaR and ES both show smaller negative values. On top of these the values are not only positive they are very large as well (to the extent of being extreme outliers). Nonetheless, it may be too early to raise sound alarm since the (VaR, ES) model and elicitable loss functions are still in their early research stages. Also, apart for Taylor (2019) the rather limited empirical literature has not made explicit claims as to the expected values of (VaR, ES) model forecasts, however, obvious that they have to be negative. To that end characteristic

(VaR, ES) model forecast obtained from the unconditional first moments may be interpreted with caution until elaborate literature become available to decipher the consequences of this. This is because the location parameters are usually influenced by the extreme positive values.

3.4.3 Characteristic (VaR, ES) estimates for 1% univariate GAS models

In this sub-section single (VaR, ES) model forecast values are estimated. This task in necessary to answer the main question of this study (i.e. how do investors make a choice for emerging markets when their time-varying risks are juxtaposed with spatial time-invariant risks?). For the 12 market equities the characteristic (VaR, ES) forecast values are estimated from the unconditional[39] location parameters from the respective distribution for 1% out-of-sample (VaR, ES) forecasts. As tail risk estimates (and jointly sharing features with VaR and ES) and as loss functions, smaller values are preferred to larger ones. Thus, as displayed in Table 3.4 in the "Rank" column the (VaR, ES) values are ranked according to their magnitudes in an ascending order. The least negative (VaR, ES) forecast value is ranked 1 and the most negative 12.

To put it in perspective, the (VaR, ES) forecast values in Table 3.4 indicate the riskiness, tail risk, and capital requirement inherent in the respective equities. We argue, as did Patton et al. (2019), that besides the mathematical and theoretical strength of the (VaR, ES) gained by drawing information from two tail measures (VaR and ES) it is intuitively important for empirical risk modelling because it can provide a better risk measure than either separately. We also surmise that given a potential portfolio investor of EMEs equities the selection would follow these rankings for

[39]Conditional parameters are the case in which the scale parameter is set to be time-varying in the typical GAS models used for (VaR, ES) estimation and forecasting. The unconditional parameters have not time-varying assumptions.

EZC-GFC and Post-crisis periods subject to financial resource constraints. This assumption is in line with a rational investor's quest to maximise utility while at the same time minimising risk.

Table 3.6: Characteristic (VaR, ES) forecast values for selected distributional innovations

Market	Innovation	EZC-GFC	Rank	Market	Innovation	Post-crisis	Rank
Turkey	snorm	-2.2366	1	Turkey	ald	-2.8266	1
India	snorm	-2.4644	2	Brazil	ald	-3.2134	2
Taiwan	snorm	-2.9880	3	South Africa	ald	-3.2418	3
Russia	ald	-3.1362	4	Malaysia	snorm	-3.2756	4
South Africa	ald	-3.1362	4	Russia	ald	-3.4021	5
Malaysia	snorm	-3.1411	6	South Korea	ald	-3.4678	6
Brazil	ald	-3.1481	7	Mexico	ald	-3.5140	7
South Korea	ald	-3.1520	8	China	ald	-3.5305	8
China	ald	-3.3102	9	Indonesia	ald	-3.5402	9
Indonesia	ald	-3.3463	10	Taiwan	ald	-3.5404	10
Mexico	ald	-3.3586	11	India	ald	-3.5653	11
Chile	ald	-3.4038	12	Chile	ald	-3.9501	12

It is it worthwhile to place these tail risk levels in perspective for better understanding. From Table 3.4 we observe that the risk level or the capital required to absorb losses is least for the Turkish EM equity index for both EZC-GFC and Post-crisis periods but larger for the latter. That Post-crisis period risk is larger than EZC-GFC is ironic given that Post-crisis is considered a peaceful market era than both the EZC and GFC. On the other hand, the Turkish economy has been marked by domestic political instabilities during 2014-2015 which can contribute to risks in their financial markets as well (Tekin, 2015). Nonetheless, having the least risk profile of the 12 emerging markets equities is also an enviable feat since the economy has, in general, suffered a number of uncertainties relative to the rest in the bunch. Brazil ranking second in the Post-crisis era is also interesting to note at the backdrop of economy wide uncertainties stemming from corruption scandal involving both politicians and business executives since 2014. This has led to the oncebooming economy taking a fall; a situation that does not augur well for any emerging market equity index (Bray et al., 2018; Melo, 2016). These may bring to mind the question of how much of the happenings in an EME filter down to the risk profile of their respective equity indices.

The spots for India, Russia, and South Africa, respectively, do seem fair given that they are part of the BRICS bloc. In recent times the BRICS have been touted as being potentials to overtake the G7[40] in the long-run due to exchange rate appreciation, to foreign capital inflows, market size, trade openness, GDP growth rate, and macroeconomic stability among other things (Mahmood & Mostafa, 2015; Nasir et al., 2016; Shah & Ali, 2016). Similar analogies can be made for Malaysia and South Korea with respect to their positions on tail risk league table. However, for Taiwan and India the switch in capital requirement is hard to miss. The more worrying part being that they move from low risk to high risk from a risk-prone market setting to the relatively less risk-prone. That tail risks are time-varying and regular updating of risk profiles in EMEs cannot be overemphasised.

Chile placed last in both periods in direct contrast with Turkey. This is not be surprising because a tighter market integration to breed support during crisis only began in May 2011 as the Latin American Integrated Market (MILA, after Spanish initials). The MILA comprises Chile, Colombia, and Peru (Bolaños et al., 2015). The other perceived benefits of this integration are yet to show in the equity index which may lower the risks. However, Bolaños et al. (2015) indicate the volatility of the integrated market has shown downward trend.

[40] These are Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States.

China's 9th (EZC-GFC) and 8th (Post-crisis) spots also do not seem out of place because despite its highly coveted growth rate over the last decade, being the world's largest investor and biggest contributor to global economic growth by significant margins for many years and still counting, it has equally significant downsides (Carpenter et al., 2015). For instance, Carpenter et al. (2015) document that its stock market rewards globally diversified investors with high alpha yet on the heels of inflated cost of equity capital which constraints investments and liquidity. Further, China's stock market is well-known for extremely high volatility in addition to very low return correlation with other large integrated markets. These together could explain its deservedly high equity index's tail risk.

Mexico's spots of 11th (EZC-GFC) and 7th (Post-crisis) are not as enviable but considering the general impact of the taper tantrum on EMEs equities it has done quite well. An unconventional post-GFC monetary policy measure by the Federal Reserve was Quantitative Easing to stabilise its financial system; the sheer signal of unwinding the same in May 2013 sent fears of crisis in almost all EMEs which came to be referred to as the taper tantrum (Estrada et al., 2016). They note the only Latin American economy that experienced a decline of less than 1% was Mexico. Other EMEs that had resilience on their equity fronts were hit via the exchange rates against the United States dollar; examples are India and South Korea (Estrada et al., 2016; Lee, Asuncion & Kim, 2016).

Indonesia's10th (EZC-GFC) and 9th (Post-crisis) positions also spell a good level of resilience in that it is one country prone to natural disasters (Lee et al., 2018). By studying natural disasters around the world (including Indonesia), Koerniadi et al., (2015) find that the overall stock market returns are negative in the long-term. However, they also suggest investors could benefit by taking long positions in the construction and material industry and/or a short position in non-life insurance and travel industries and thus boost confidence in the equity markets. This is plausible because the composition of the emerging markets equity index cuts across different industries and could explain why Indonesian is not the riskiest EME to invest in.

3.4.4 Spatial risks, autocorrelations, and portfolio strategies

Though tail risks are ranked in Table 3.4, it will be inappropriate to make portfolio selection solely on that. It is likely to be flawed since these equities have spatial characteristics that pose various risks which can impact the fabric of their financial system. These spatial risks can be revealed in their being grouped as one market class (which is accompanied by similar macroeconomic and financial features), that geographically some are proximate to each other, and psychological predispositions. Perhaps the most important aspect of the spatial analysis relevant for this study is the premise of the Moran's I statistic. It is based on the null hypothesis of spatial randomness in the variable (i.e. that each value is equally likely to occur at any location). Applied in this context implies that the distribution of the statistic is such that the aggregate of the GLIs for each EM equity per sub-sample is equally likely to be for any other EM. In this sub-section spatial risk autocorrelation results are explored and contrasted with how portfolio selection should be made.

As a first step neighbours are presented in Table 3.5 based on the distance weight function. The neighbours are same for both EZC-GFC and Post-crisis periods since they are calculated independent of the respective GLI aggregates. Centroid denotes each country and neighbours are the countries closest to them as determined by the distance weight function.

Table 3.7: EMEs and their neighbours according distance weight function

Centroid	Neighbours	Centroid	Neighbours
Brazil	Mexico, Chile	South Korea	Taiwan, Russia, Malaysia, Indonesia, India, China
Chile	Brazil	Malaysia	Taiwan, Russia, South Korea, Indonesia, India, China
China	Taiwan, Russia, Malaysia, South Korea, Indonesia, India	Russia	Taiwan, Malaysia, South Korea, Indonesia, India, China
India	Taiwan, South Africa, Turkey, Russia, Malaysia, South Korea, Indonesia, China	Turkey	India
Indonesia	Taiwan, Russia, Malaysia, South Korea, India, China	South Africa	India
Mexico	Brazil	Taiwan	Russia, Malaysia, South Korea, Indonesia, India, China

Note: Neighbours are determined by geographical distance weightings based on Local Indicators of Spatial Association (LISA) framework (Anselin, 2010). Centroid indicates a country serving as point of reference to calculate distance weights. They are generated from the GeoDa software. They are generated from the GeoDa software.

3.4.4.1 Composite spatial autocorrelation (EZC-GFC period)

As mentioned earlier to find the overall spatial autocorrelation among the 12 economies the Moran's I is used in Figure 3.1. The Moran's I is computed from the scatterplot of GLI against lagged GLI. The latter is the weighted average of the aggregate GLIs in neigbouring locations. In effect Moran's I is the slope of the regression of $\sum_j w_{ij z_j}$ on z_i in (3.15). One unique feature of the Moran scatter plot is its ability to categorise spatial autocorrelation into four classes shown by four quadrants. Having standardised the GLIs with plot centred on the mean, points to the right of the mean are $z_i > 0$ and those to the left have $z_i < 0$, referred to as high-high and low-low, respectively. In the same manner values above lagged GLI are high as opposed to those below being low. It follows that the lower-left and upper-right quadrants have positive spatial autocorrelations which implies there are similar values at the neighbouring locations. The remaining two quadrants show negative spatial autocorrelations with dissimilar values at neighbouring locations. With the intention to minimise risks by investors would prefer negative spatial autocorrelated GLIs to the former.

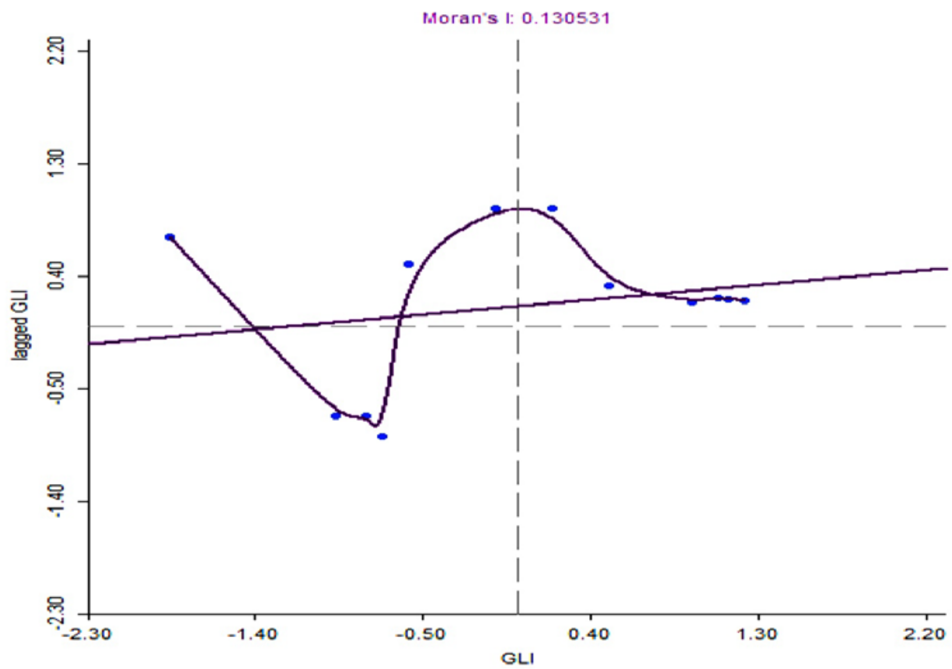


Figure 3.1: Composite Moran's I for EZC-GFC period (31/3/2007 – 31/12/2013)
*Note: Moran's I autocorrelation value is indicated at the top as **0.130531.***

From Figure 3.1 the slope 0.130531 indicating a positive spatial autocorrelation in all 12 EMEs. This is also preempted by both the positively sloping straight line and the locally weighted scatterplot smoothing (LOWESS) fitted to the plot. For the latter, steepness in the curves suggest both strong positive and negative spatial autocorrelations in contrast with flat indicating no spatial autocorrelation. In this case the positive autocorrelations seems to be larger than the negative ones yielding the positive Moran's I. The alternating positive and negative spatial autocorrelations in the scatter plot engender sub-setting the data for further Moran's I analysis as performed subsequently in sub-section 3.4.4.2.

The overall positive spatial autocorrelation is not conducive for international portfolio diversification since financial risk proxied by GLI is similar in the selected EMEs. That means, apart from the spillover of liquidity risk from one market to the other being a possible threat, the build-up of systemic vulnerabilities in the respective financial systems are similar and investments in these markets could implode all at once. Thus, despite the geographical distances between the 12 EMEs being wide, *"financial distances"* on the other hand are quite shorter. This suggests a closer similarity in financial systems which mirrors both opportunities and risks, but more so of the latter. A case in point is that time-invariant risks emanating from GLIs do not correspond with time-varying tail risks as indicated by (VaR, ES) model forecasts. Therefore, emerging markets equities investors may not invest in all 12 markets at once or may not spread funds over the respective equities in the order in which (VaR, ES) model forecast values are arranged as a matter of crucial importance. This portrays the insufficiency of relying on time-varying tail risks alone to make international portfolio diversification decisions involving EMEs equities. Given that EMEs generally show similar financial and economic topographies the findings using half of them could fairly be generalised for all 24 EMEs for the period under study.

Nonetheless, the significance of Moran's I is not established at this point and careful interpretation is advised. This can be ascertained using randomisation. Randomisation performs permutations of the data set and provides pseudo p-values to test the null hypothesis of spatial autocorrelation. In order to make fairly reliable inference 999 permutations are chosen as displayed in Figure 3.2. The most extreme pseudo p-value is 0.137 which means about 14% of the permuted data sets yield a Moran's I larger than 0.130531 from the original data set. This suggest a good acceptance of the null hypothesis of equally like aggregate GLIs occurring at any the 12 EMEs which naturally explains the positive spatial autocorrelation.

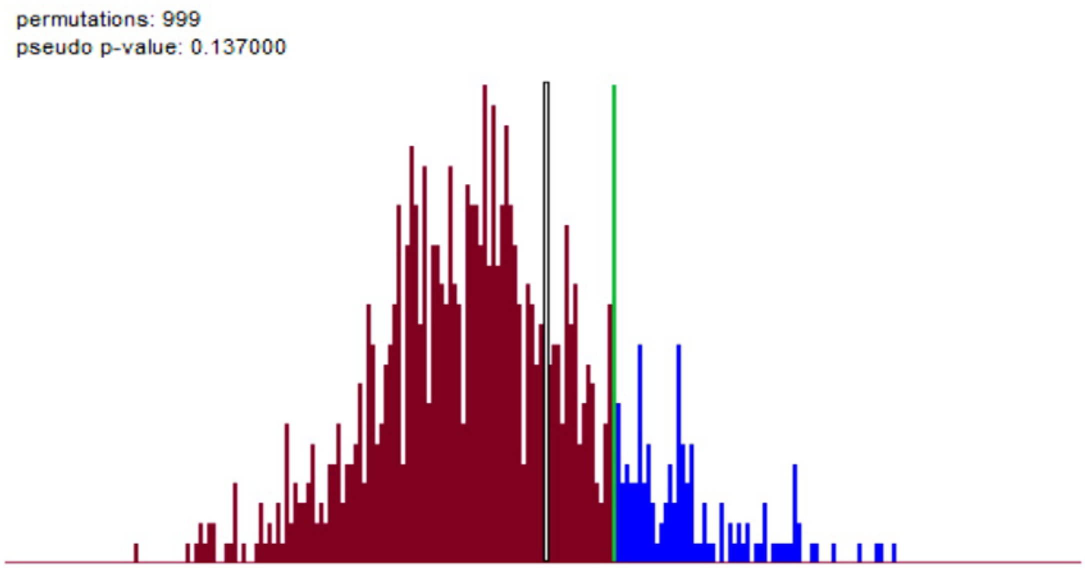


Figure 3.2: Randomisation test of the significance of Moran's I for EZC-GFC periods
*Note: pseudo p-value of **0.137000** corresponds to the green line and suggest significance of the Moran's I in Figure 3.1.*

This is depicted by the green line to the right of the centre of the distribution in Figure 3.2. In a nutshell, the Moran's I (0.130531) indicating overall positive spatial autocorrelation in the 12 GLIs is significant and thus practical implications of the analysis may be instructive. We note that since pseudo p-values are based on the number of permutations rather than analytically derived, the same number of permutations should be maintained for comparative significance assessment.

3.4.4.2 Regionalised spatial autocorrelations and portfolios for EZC-GFC

As hinted earlier interchanging positive and negative spatial autocorrelations in the scatter plot allow for testing spatial autocorrelation across different regions of the 12 EMEs. Munasinghe and Morris (1996) similarly evaluate regional measures of spatial autocorrelation for the localization of clusters of disease. Anselin (2010) refers to this as regionalised Moran's I test of spatial autocorrelation. In Figure 3.3, a map rendition of the 12 EMEs suggest three regions from left to right. These are *Region 1:* Mexico, Brazil, and Chile; *Region 2:* Turkey and South Africa; and *Region 3*: Russia, China, South Korea, Taiwan, India, Malaysia, and Indonesia. An exploration is performed by selecting each region at a time analysing the spatial autocorrelations. For every selected region (in rectangle) spatial autocorrelation is estimated for it on one side (denoted by *selected*) and for the remaining together on the other side (denoted by *unselected*) as in Figure 3.4.

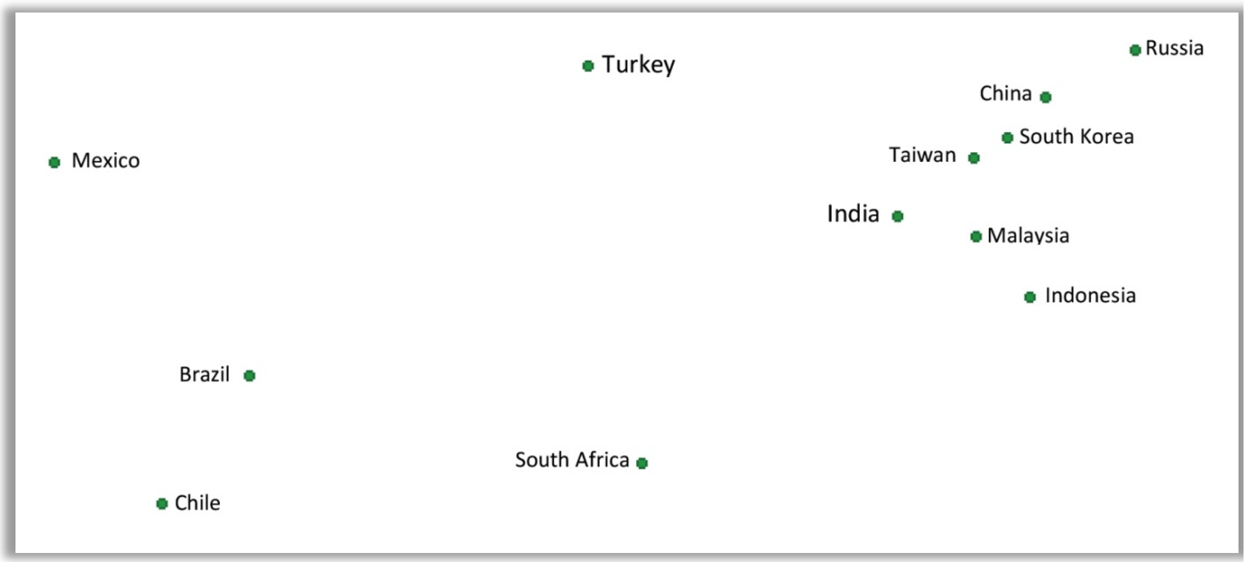


Figure 3.3: Spatial location map of the 12 EMEs

Note: This shows the GeoDa rendition of actual location of each of the 12 countries on a regular world map. It is useful in the regionalised spatial autocorrelation in this section. From left to right and from top to bottom: left three (Region 1): Mexico, Brazil, and Chile, middle two (Region 2): Turkey and South Africa, and right three (Region 3): Russia, China, South Korea, Taiwan, India, Malaysia, and Indonesia.

In Figure 3.4 where Region 1 is selected there is a negative spatial autocorrelation (-0.5786) and (-0.2013) in the unselected regions. Differing from the overall Moran's I of positive spatial autocorrelation (0.130531) is a sign of spatial heterogeneity in both the direction and magnitude of spatial autocorrelations. By analogy *regionalised* selection of emerging markets equity investment is preferred to all 12 markets. The spatial autocorrelations are negative for the two separate regions and are of fairly stronger magnitudes than the overall positive spatial autocorrelation. These imply that risk minimising diversification motives are better served given the time-invariant risk dynamics in the selected regions. Investors may, therefore, construct *portfolio A* (consisting of equities in Region 1) and *portfolio B*[41] (comprising equities in Regions 2 & 3) separately to avoid the risk of losing all investment in either scenario in case of financial system breakdown due to liquidity mismatch.

Barring spatial risk spillovers which may take time to materialise, investment strategies involving these two portfolios are shielded from systemic risk stemming from liquidity vulnerabilities in the respective regions. That is to say, regardless of how the equities are rated in terms of time-varying (VaR, ES) forecast values, their combinations as recommended by spatial autocorrelation in GLIs may take precedence. From the EZC-GFC period in Table 3.7, it is apparent that Brazil, Mexico, and Chile with rankings 7, 11, and 12, respectively (*portfolio A*) will not make the list of any prudent investor. However close *portfolio A*'s constituents are in terms of geographical location and time-varying risk, they are distant with respect to liquidity risk. *Portfolio B*, nonetheless, could be a good mix relative to *portfolio A* with a blurred feature of both long and short geographic and time-varying risk distances. But in terms spatial autocorrelation *portfolio B's* equities are more financially distant. These subtleties corroborate our initial submission that only time-varying risk assessment of equities solely based on tail behaviour of equities is not only inadequate but also dangerous. Intuitively, this makes sense from basic principles of systemic risks if the financial system is braced by liquidity vulnerabilities.

[41] In each instance portfolio A is the selected region while portfolio B is the unselected regions.

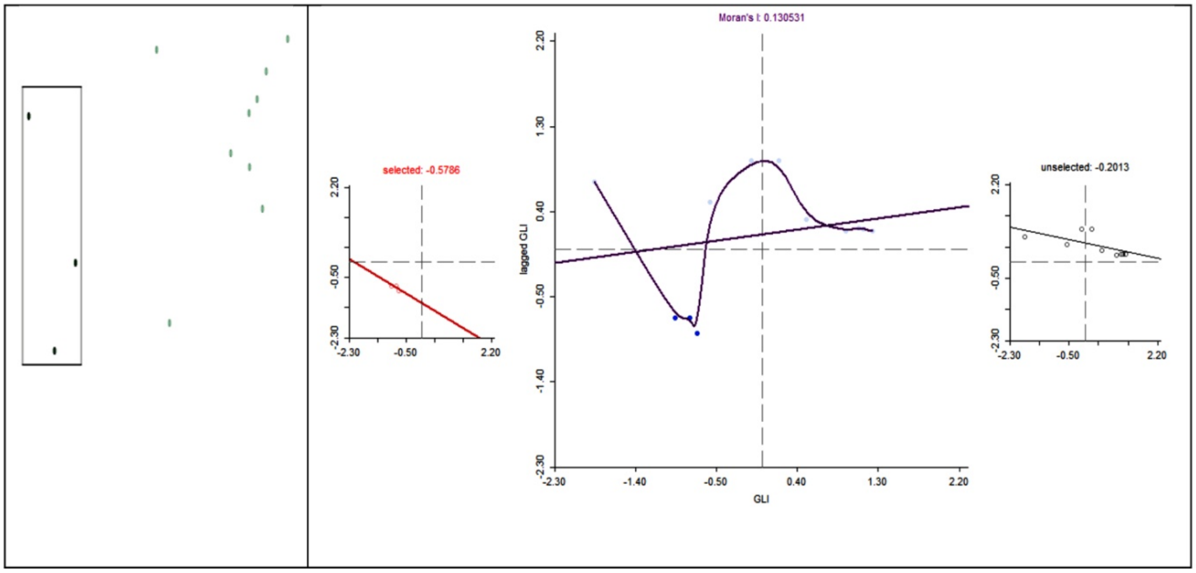


Figure 3.4: First portfolio strategy for EZC-GFC period. ***Portfolio A: Region 1, Portfolio B: Regions 2 & 3***

Note: Left pane, selected countries in rectangle (Region 1: Mexico, Brazil and Chile). Unselected countries (Regions 2 & 3): Unselected countries (Regions 2 & 3): Turkey, South Africa, Russia, China, South Korea, Taiwan, India, Malaysia, and Indonesia.

Unlike the previous scenario where *portfolios A* and *B* both provide diversification spatial risk minimisation, the situation is quite opposite under *portfolio A* (Region 2) and *portfolio B* (Regions 1 & 3). In the latter no spatial risk minimisation is expected from *portfolio A* since spatial autocorrelation is completely absent (0.000) whereas risk is being compounded with the construction of *portfolio B* with a positive spatial autocorrelation of 0.1291. The implications here are true in reverse for *Portfolio A* (Region 1) and *Portfolio B* (Regions 2 & 3) prior. Though this scenario (Region 2 selection) is not much desirable compared to the Region 1 and Region 3 selections, it seems prudent a strategy than a portfolio comprising all 12 emerging markets equities. At least the no spatial autocorrelation in *portfolio A* would mitigate the risks to some extent. Heterogeneity in the magnitude of the spatial autocorrelations is noted as well.

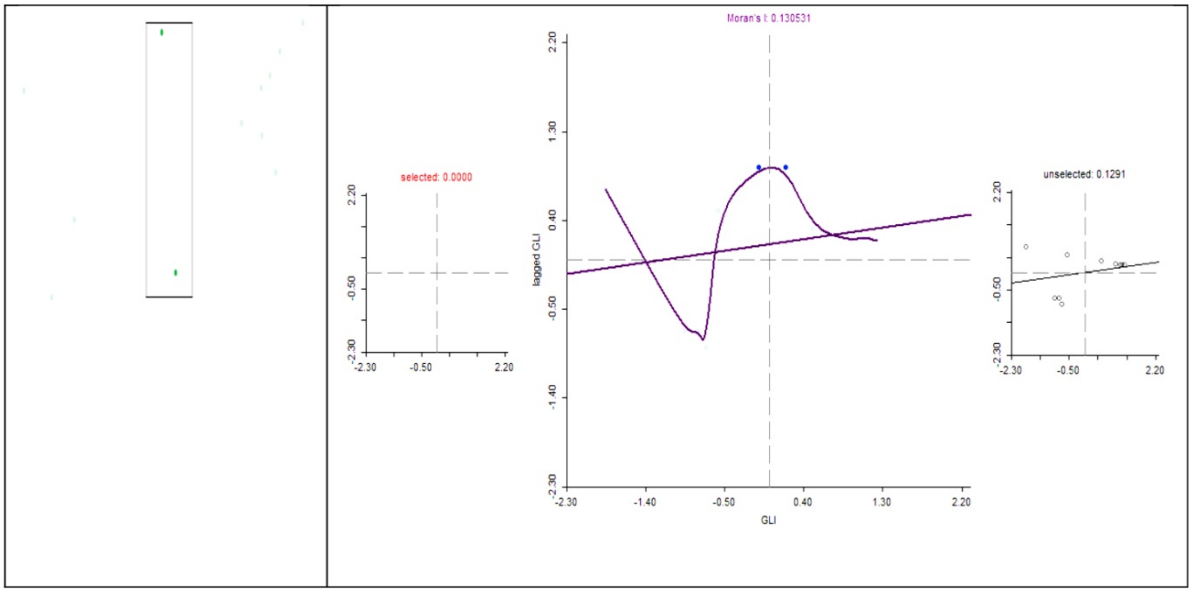


Figure 3.5: Second portfolio strategy for EZC-GFC period. ***Portfolio A: Region 2, Portfolio B: Regions 1 & 3***

Note: Left pane, selected countries in rectangle (Region 2: Turkey and South Africa). Unselected countries (Regions 1 & 3): Mexico, Brazil, Chile, Russia, China, South Korea, Taiwan, India, Malaysia, and Indonesia.

For the last strategy in Figure 3.8 where *portfolio A* comprises Region 3 equities and *portfolio B* is made up of Regions 1 & 2 equities there is a very close pattern the first strategy (*Portfolio A: Region 1, Portfolio B: Regions 2 & 3*). Therefore, similar analogies can be drawn for this. Although significance of these *regionalized* spatial autocorrelations are not readily available, a degree of reliability is fostered by the significance of the overall Moran's I which stays with the strategies in this sub-section (see for example, Figure 3.8).

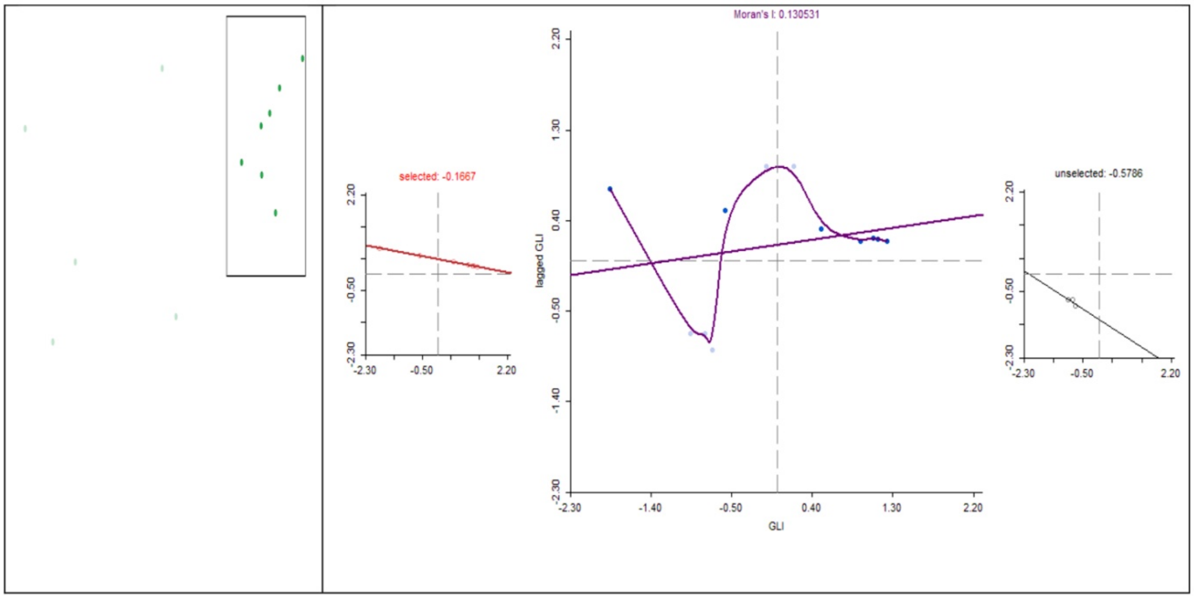


Figure 3.6: Third portfolio strategy for EZC-GFC period. ***Portfolio A: Region 3, Portfolio B: Regions 1 & 2***

Note: Left pane, selected countries in rectangle (Region 3: Russia, China, South Korea, Taiwan, India, Malaysia, and Indonesia). Unselected countries Regions 1 & 2: Mexico, Brazil, Chile, Turkey, and South Africa.

3.4.5 Composite spatial autocorrelation (Post-crisis period)

For the Post-crisis period overall spatial autocorrelation is depicted in Figure 3.7 where Moran's I is slope -0.105132. This this can also be seen from both the inversely sloping straight line and the locally LOWESS fitted to the plot. The composite slope negative slope in the LOWESS is larger than the positive steepness hence yielding an overall negative slope. Since some level of alternating positive and negative spatial autocorrelations exist at different region one can further exploit risk minimisation strategies via regionalised Moran's I as undertaken in the next sub-section.

The significance of Moran's I is also established with randomization using 999 permutations. A pseudo p-value of 0.463 as shown Figure 3.7 suggest about 46% of the permuted data sets yield a Moran's I larger than -0.105132 from the actual data set. This suggest a strong acceptance of the null hypothesis of equally like aggregate GLIs occurring at any the 12 EMEs which explains the negative spatial autocorrelation. That the spatial autocorrelation is significant can been seen by the green line to the left of the centre of the distribution in Figure 3.8.

In absolute terms, this is lower than that of the positive spatial autocorrelation in the EZC-GFC periods. However, in terms of implications for business the negative spatial autocorrelation is preferred. It implies an overall dissimilarity in the GLIs and hence systemic liquidity risk across all 12 EMEs. Thus, a portfolio consisting of equities in all 12 EMEs are unlikely to suffer significant loss from liquidity induced systemic risk in one market or a number of them.

It is important that the market period under study be put in perspective. A lot of insights can be drawn from the negative spatial autocorrelation as well as the smaller size of the same in the Post-crisis period. They imply that EMEs have learned their lessons in the aftermath of the GFC by reducing the levels of credit. Central Banks must have performed their duties well since the burden is on them of intervene is time of market stress. The IMF (2011) indicate the pressure on Central Banks to define liquidity risk as financial institutions continue to underprice it during good time. Maintaining prudent levels of liquidity is the key to prevent and predict systemic liquidity crisis. Cifuentes et al. (2005) implore regulators to employ a myriad of requirements of financial systems to maintain prudent levels of liquidity under a wide array of market conditions to enhance their resilience to shocks. They further indicate that at the systemic level, liquidity requirements can mitigate contagion, provide capital buffers in preventing systematic debacle. Under certain scenarios Cifuentes et al. (2005) opine that liquidity requirements may be more effective than capital buffers in curtailing systematic effects.

As global liquidity indicators pertaining to specific EMEs they are even more robust in preventing systemic failures. Bierut (2013), for instance, shows that global liquidity measures do better than domestic indicators to foretell warning signs of asset price booms whose eventual busts may cause financial stress.

The negative spatial autocorrelation could be a sign that post-GFC EMEs have avoided herding behaviour with each pursing its own prudent levels of liquidity. This action is critical in preventing contagion at different fronts to EMEs. For instance, Ahmed et al. (2017) deduce that the run-up in bank credit to the private sector is an important factor in the transmission of shock to financial markets in different EMEs leading to severe currency depreciation under stressed market conditions. Bruno and Shin (2018) also find emerging market firms’ United States dollar denominated borrowings render their economies vulnerable to a depreciation of the domestic currency against the dollar.

In another sense, since an increasing trend in global liquidity is a sign of deeper financial integration as pointed out by BIS (2011), both the negative and smaller spatial autocorrelation in the GLI could be a sign of a reverse trend.

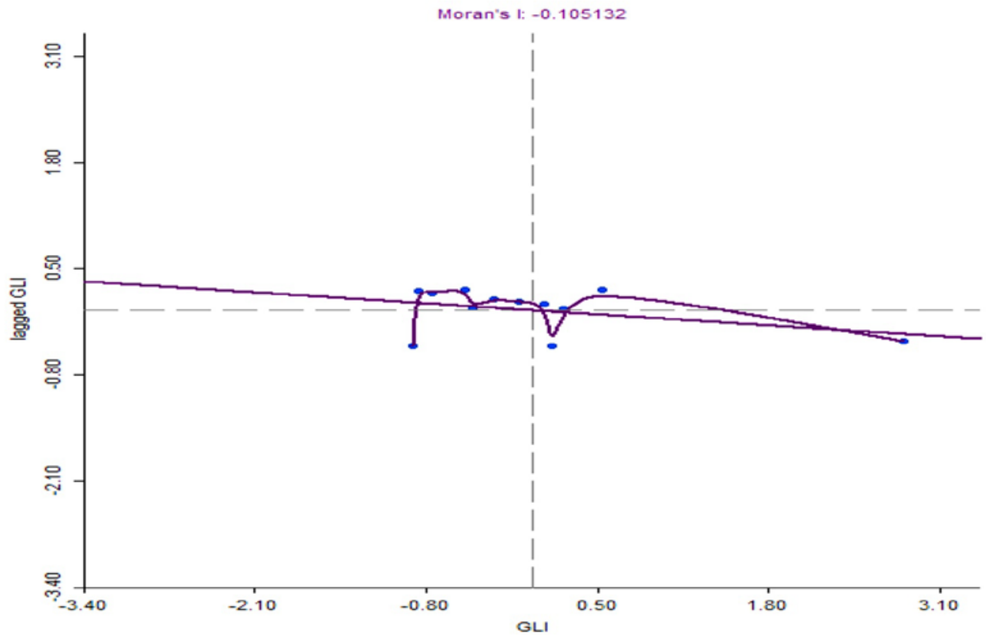


Figure 3.7: Composite Moran's I for Post-crisis period (31/3/2014 – 31/12/2018)
*Note: Moran's I autocorrelation value is indicated at the top as **-0.105132.***

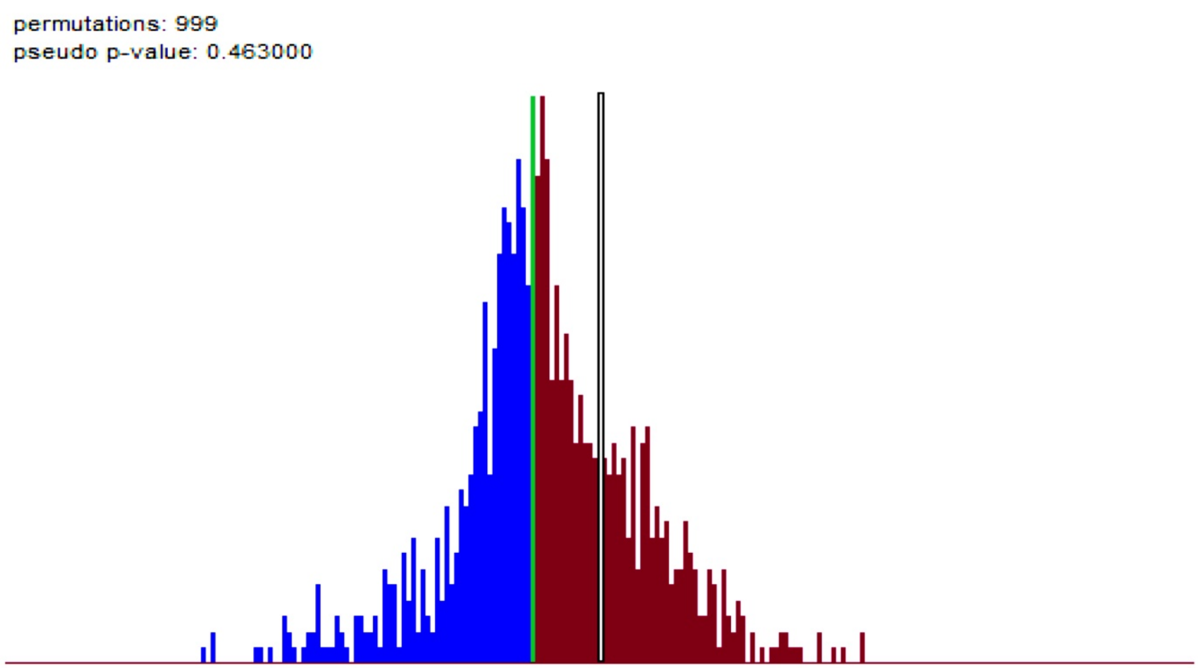


Figure 3.8: Randomisation test of the significance of Moran's I for Post-crisis period
*Note: pseudo p-value of **0.463000** corresponds to the green line and suggest significance of the Moran's I in Figure 3.7*

Though stronger financial ties may foster many benefits they could also enhance the adverse effects of contagion which is a close ally of interdependence. Having suffered the ravages of the GFC EMEs may have found it wise moderate the levels of interdependence in terms of liquidity.

Lastly, the lower magnitude of spatial autocorrelation can be inferred from the recent levels of GLI as reported by the BIS. The BIS (2019) indicate that the annual growth United States dollar credit to non-bank borrowers outside the United States slowed down to 3%, compared with its most recent peak of 7% at end-2017. The outstanding stock stood at $11.5 trillion at the end the September 2018. By December 2018 it had declined a fourth consecutive quarter. Despite credit to non-bank borrowers in emerging market and developing economies growing by 13% at the end of the third quarter in 2018, in the last quarter of 2018 this declined across all three major currencies.

All these implications of the negative spatial autocorrelation are not only beneficial for the EMEs but also for international portfolio investors interested in their equities. We further exploit this property through regionalisation of the EMEs as done under the EZC-GFC periods. *Portfolios A and B* are constructed in the same manner as done before and depicted in the Figures 3.9, 3.10, and 3.11, respectively.

In contrast with the EZC-GFC period the first strategy (Figure 3.9) in the Post-crisis period has negative spatial autocorrelation for *portfolio A* (-0.0601) and *portfolio B* (-0.1137). Thus, *portfolio B* with the larger number of EM equities is preferred to minimise systemic risk than the former.

These properties replicate in the last strategy Figure 3.11 where *portfolio A* (-0.1667) and *portfolio B* (-0.0601). It is clear that the former outperforms the latter in terms of spatial risk minimisation just as *portfolio B* in the former strategy with the larger number of constituents (9). *Portfolio A* has seven (7) equities in this strategy. This implies that during the Post-crisis period investment in more EMEs should be deemed appropriate that less. This provides an assurance to investors to bet on more EMEs equities regardless of the time-varying (VaR, ES) forecast rankings because of negative spatial autocorrelations.

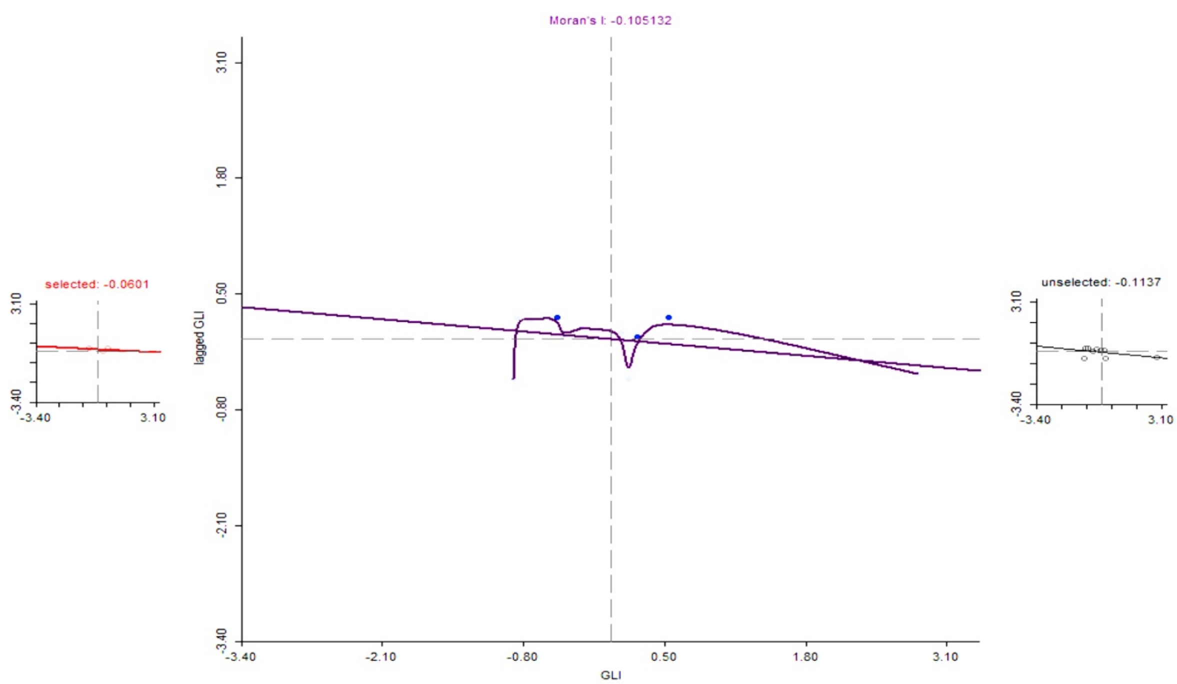


Figure 3.9: First portfolio strategy for Post-crisis period. *Portfolio A: Region 1, Portfolio B: Regions 2 & 3*

Note: Selected countries (Region 1): Mexico, Brazil, and Chile. Unselected countries (Regions 2 & 3): Turkey, South Africa, Russia, China, South Korea, Taiwan, India, Malaysia, and Indonesia.

This assurance is further strengthened by the second approach in Figure 3.10 with *portfolio A* (2 members) yielding no spatial autocorrelation and *portfolio A* (10 members) for a negative spatial autocorrelation of -0.1603. It is worth noting that many different combinations of portfolios (regionalisations) can be constructed to assess their interplay of spatial autocorrelations measuring *"financial distance"* as proxy for time-invariant risk vis-à-vis time-varying risks quantified by (VaR, ES) model forecasts in emerging markets equities.

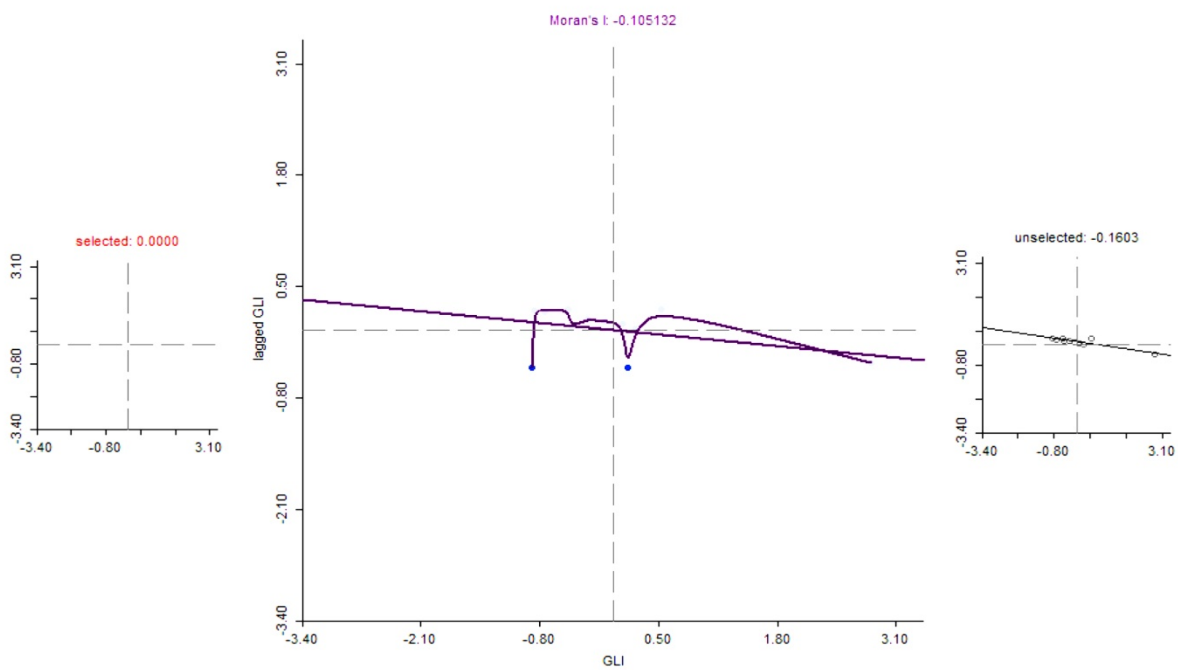


Figure 3.10: Second portfolio strategy for Post-crisis period. *Portfolio A: Region 2, Portfolio B: Regions 1 & 3*

Note: Selected countries (Region 2): Turkey and South Africa. Unselected countries (Regions 1 & 3): Mexico, Brazil, Chile, Russia, China, South Korea, Taiwan, India, Malaysia, and Indonesia.

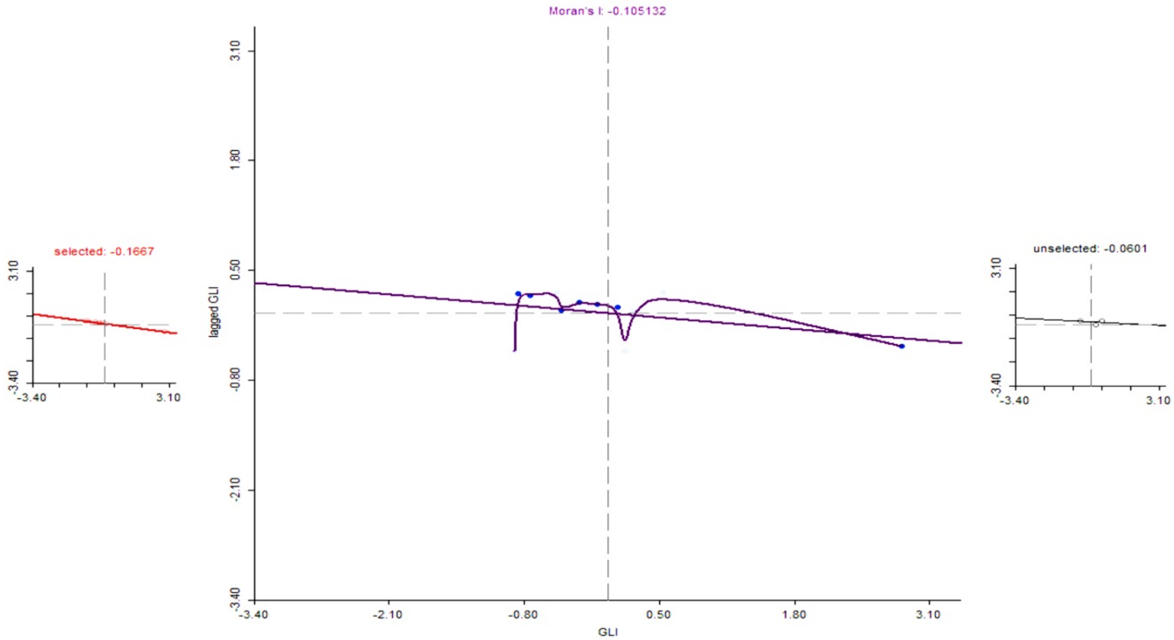


Figure 3.11: Third portfolio strategy for Post-crisis period. ***Portfolio A: Region 3, Portfolio B: Regions 1 & 2***

Note: Selected countries (Region 3): Russia, China, South Korea, Taiwan, India, Malaysia, and Indonesia. Unselected countries (Regions 1 & 2): Mexico, Brazil, Chile, Turkey, and South Africa.

3.5 Conclusions and recommendations

This paper intended to make a case for the use of both time-varying and time-invariant risk techniques in assessing emerging markets equities for robust risk-minimising construction of portfolios. This exercise entailed the use of the (VaR, ES) model for tail risk as a representation for time-varying risk for daily log-returns of emerging markets equities. For time-invariant risk *"financial distance"* measure through spatial analysis was performed with GLIs of 12 EMEs. The study period spanned 5/1/2007 through to 19/2/2019 sub-sampled into two different market conditions of EZC-GFC and Post-crisis.

Drawing on both VaR and ES, the (VaR, ES) model provides a rich measure of tail risk which is conducive for comparative back testing of competing forecasting models via ranking according to a consistent scoring function. Thanks to the elicitability feature of (VaR, ES) models and the FZL scoring function, internal models of financial institutions are also comparable to standardised capital requirement approach by regulatory bodies such as the BIS. As Nolde and Ziegel (2017) explain, the FZL function provides a statistically justifiable basis for comparing different methods when assessing a new forecasting procedure with existing ones or when defending internal models against some standard procedure. Applicable to financial institutions' risk management comparative back testing using consistent scoring function motivates risk managers to strive for accurate forecasting models to adequately quantify tail risks since the function penalises more severely for inaccuracies as opposed to traditional back testing which gives a *"yes"* or *"no"* answer to the question of whether a forecasting model is acceptable or not (Gneiting, 2011; Fissler et al., 2015; Nolde & Ziegel, 2017). Six different asymmetrical distributions were applied to the univariate GAS framework to better capture both heavy-tailedness and volatility clustering that characterise EMEs equity returns.

Further, we use Tobler's first law of geography to perform non-parametric spatial analysis on GLIs to ascertain the autocorrelation among EMEs systemic risks stemming from liquidity vulnerabilities. In the process, we proposed *"financial distance"* dimension as an extension of the CAGE distance framework. This undergirds the argument that market-wide risk measures should, perhaps, take preponderance over VaR, ES, and (VaR, ES) model or other asset-specific time-varying tail risk measures in emerging markets equity investments or cross-border portfolio flows.

Empirically, in order to rank tail risk model a typical out-of-sample forecasting procedure was undertaken and a battery of back testing techniques applied to the selected models to assess their adequacies. To contrast with GLIs 12 emerging markets equities were ranked as per their unconditional (VaR, ES) forecast values for EZC-GFC and Post-crisis periods. Spatial autocorrelations were estimated on the 12 EMEs GLIs altogether and by three different regions according to geographical proximities considered as portfolios.

For the EZC-GFC periods we find an overall significant positive spatial autocorrelation in the EMEs which suggest the markets have ties in terms of liquidity vulnerabilities. That puts in jeopardy any portfolio constructed with the 12 emerging markets equities ranked by the (VaR, ES) forecast values. The EMEs themselves are also at risk of contagion since this signals deeper levels of financial integration (BIS, 2011). However, by regionalising portfolios we find zero, negative, and positive spatial autocorrelations. For risk-minimising objectives the latter is less preferable to the former and hence emerging markets equities can be selected for those markets regardless of their placements on the time-varying risk league table.

However, for the Post-crisis period overall spatial autocorrelation tends to be negative and smaller in magnitude as compared to the prior period. For international portfolio investors this seems all good news because all 12 emerging markets equities can be combined into one portfolio without fear of implosion originating from liquidity susceptibilities of the respective EMEs. Further exploitation of this desirable features was possible through regionalisation of portfolios. At worst there was a zero spatial autocorrelation between Turkey and South Africa (being the least number of constituents of a portfolio) and we find that larger portfolios better minimised risk than smaller ones in the Post-crisis period.

At the EMEs levels we can infer that they may have learnt bitter lessons in the wake of the GFC by reducing credit and "un-herding" from each other in credit needs and liquidity policies and regulations. Central Banks must have been keen in protecting their economies knowing the pressure on them as the last intervening factor in time of market stress. Among others, the call on regulators to maintain prudent levels of liquidity to forestall systemic failures by Cifuentes et al., (2005), Ahmed et al. (2017), and Bruno and Shin (2018) may have heeded.

With specific reference to the CAGE distance framework our results, based on GLIs *"financial distance"* dimension contrast with the main assumption of the CAGE framework that markets are distant in these dimensions. We opine that *"financial distance"* can be included in the framework for further analysis since we find that financial market conditions, to some extent, could determine the magnitude of distance between two or more economies. We find that during stressed market conditions like the EZC-GFC periods EMEs were closer financially as opposed to the quiet Post-crisis era. This implies that distance dimensions may be "time-varying" and conditional on whether a market is in stressed or tranquil conditions. This extension is crucial not only for international equity investments in EMEs but also for international trade purposes as originally intended in the CAGE framework. There is enough research to support the fact that financial crisis equally adversely affect international trade or more generally that financial crisis can cause economic crisis (see for example, Ariu, 2016; Ikejiaku, 2017; Kenourgios & Dimitriou, 2015; Khalid et al., 2019). If *"financial distance"* is short and liquidity vulnerabilities materialise into full blown financial system breakdowns, the significant CAGE distance dimensions cannot offer any solace to neither MNCs nor governmental trade partnership deals.

The outcomes of this study may leave some questions to be answered with respect to the elicitable tail risk models such as the (VaR, ES) scored by the FZL function. We find that 99% level models for the (VaR, ES) almost consistently outperformed those of 97.5% under all three market eras. It does seem to appear that the (VaR, ES) model model is affected by the confidence level specified for its estimations. Given that BIS's recommendation of 97.5% to calibrate stressed market and the desirable feature of the (VaR, ES) model for comparative back testing and model ranking, how should this be resolved? Perhaps further research is needed to fully unravel the dynamics of the (VaR, ES) and FZL function given their newness albeit promising features for tail risk modelling and quantification. Nolde and Ziegel (2017) reiterate that further research is needed to shed more light on the empirical estimates and their interpretations of the (VaR, ES) models as well as forecasting and back testing. For instance, issues like the circumstances and explanations for why both negative VaR and ES estimates yield positive (VaR, ES) forecast values (and extreme ones for that matter) need clarifications in empirical settings.

Appendix 3.1: Descriptive statistics, emerging markets equities and GLIs plots and 1% VaR, ES, and (VaR, ES) forecast plots

Table 3.8: Summary statistics of emerging markets equities

EME	Brazil	Chile	Mexico	China	India	Indonesia	Malaysia	South Korea	Russia	Turkey	South Africa	Taiwan
						EZC-GFC period						
In-sample												
Observations	1117	1117	1117	1117	1117	1117	1117	1117	1117	1117	1117	1117
Mean ($x10^{-4}$)	5.00	0.00	1.00	3.00	3.00	6.00	4.00	3.00	-2.00	3.00	2.00	1.00
Variance ($x10^{-4}$)	8.00	2.00	4.00	5.00	5.00	5.00	2.00	6.00	9.00	7.00	5.00	3.00
Skewness	-0.34	0.10	0.02	0.03	0.19	-0.20	-0.76	-0.13	-0.40	-0.12	-0.26	-0.20
Kurtosis	7.39	4.15	6.46	5.02	6.89	5.96	7.54	17.11	13.79	3.86	4.31	2.40
Normtest.W*	0.90	0.95	0.91	0.94	0.94	0.93	0.94	0.86	0.85	0.96	0.95	0.96
Out-of-sample												
Observations	559	559	559	559	559	559	559	559	559	559	559	559
Mean ($x10^{-4}$)	-8.00	2.00	1.00	-3.00	-4.00	1.00	2.00	-2.00	-7.00	0.00	-3.00	-1.00
Variance ($x10^{-4}$)	3.00	3.00	2.00	2.00	2.00	2.00	1.00	3.00	3.00	3.00	3.00	2.00
Skewness	-0.40	-0.37	-0.53	-0.08	0.03	-0.84	0.11	-0.25	-0.48	-0.71	-0.08	-0.17
Kurtosis	2.82	2.01	3.79	2.90	1.33	6.53	4.83	2.46	2.64	4.20	1.56	1.93
Normtest.W*	0.97	0.97	0.96	0.96	0.98	0.93	0.94	0.97	0.96	0.95	0.98	0.97
						Post-crisis period						
In-sample												
Observations	740	740	740	740	740	740	740	740	740	740	740	740
Mean ($x10^{-4}$)	-3.00	1.00	-2.00	2.00	2.00	-1.00	-4.00	1.00	-2.00	-5.00	1.00	2.00
Variance (x10-4)	4.00	1.00	2.00	2.00	1.00	2.00	1.00	1.00	4.00	4.00	3.00	1.00
Skewness	0.18	-0.24	-0.60	-0.17	-0.51	-0.13	0.20	-0.16	-0.03	-0.09	-0.25	-0.15
Kurtosis	1.82	1.55	4.97	3.07	4.22	3.78	3.86	1.45	7.26	2.46	2.94	2.31
Normtest.W*	0.98	0.98	0.96	0.96	0.95	0.94	0.96	0.98	0.93	0.97	0.97	0.97
Out-of-sample												
Observations	368	368	368	368	368	368	368	368	368	368	368	368
Mean ($x10^{-4}$)	4.00	1.00	-3.00	3.00	1.00	1.00	1.00	1.00	1.00	-6.00	-2.00	0.00

Variance (x10^{-4})	3.00	1.00	2.00	1.00	1.00	1.00	0.00	1.00	2.00	4.00	3.00	1.00
Skewness	-1.26	-0.05	-0.57	-0.12	-0.37	-0.29	-0.84	-0.36	-1.82	-1.44	-0.22	-0.96
Kurtosis	12.68	1.48	3.08	0.57	0.87	1.85	3.89	1.71	17.03	9.48	1.21	6.98
Normtest.W*	0.92	0.98	0.97	0.99	0.99	0.97	0.95	0.98	0.91	0.91	0.99	0.93

Note: EZC-GFC periods: 31/3/2007 – 31/12/2013 (In-sample: 5/1/2007 – 18/4/2011, Out-of-sample: 19/4/2011 – 7/6/2013). Post-crisis period: 31/3/2014 – 31/12/2018 (In-sample: 21/11/2014 – 14/7/2017, Out-of-sample: 22/7/2017 – 19/2/2019). Normtest.W indicate that normality assumption is rejected at all conventional levels of significance.*

Table 3.9: Summary statistics of emerging markets GLIs

EME	Brazil	Chile	Mexico	China	India	Indonesia	Malaysia	South Korea	Russia	Turkey	South Africa	Taiwan
EZC-GFC periods												
Observations	28	28	28	28	28	28	28	28	28	28	28	28
Minimum	106395.2	37239.69	101005	17726.8	28396.2	15486	23397.15	74318.58	75376.01	77583.39	7528	26932.1
Maximum	203781.2	79781.18	185805.1	603359.6	81955.72	109001.9	32906.13	125249.7	140240.9	145485.3	24977.73	56634.42
Range	97385.98	42541.49	84800.12	585632.8	53559.52	93515.86	9508.98	50931.09	64864.92	67901.96	17449.73	29702.32
Sum	4279579	1567036	3779417	7101798	1629241	1409382	781510	2975296	2874485	2850162	406039	1178051
Mean	152842.1	55965.56	134979.2	253635.6	58187.18	50335.08	27911.07	106260.6	102660.2	101791.5	14501.39	42073.24
Post-crisis period												
Observations	20	20	20	20	20	20	20	20	20	20	20	20
Minimum	177600	73602.82	191788.9	492819.9	79965.33	114180.2	31239.95	114753.2	94857.43	155340.3	23564.6	44976.41
Maximum	216039.6	104228.2	271598.3	689583.4	109203.3	179379.9	41153.81	127907.3	248783	198351	44532.17	62487.09
Range	38439.62	30625.33	79809.42	196763.5	29237.94	65199.74	9913.858	13154.16	153925.6	43010.7	20967.57	17510.68
Sum	3907355	1776520	4740171	11354960	1912562	2926834	736700.5	2405824	3489657	3680177	630251.1	1057045
Mean	195367.8	88826.01	237008.5	567748	95628.08	146341.7	36835.03	120291.2	174482.9	184008.8	31512.55	52852.24

Note: All values are in billion USD. The sum for each market is the amount used in the spatial autocorrelation analysis referred to as aggregate. EZC-GFC periods: 31/3/2007 – 31/12/2013 and Post-crisis period: 31/3/2014 – 31/12/2018.

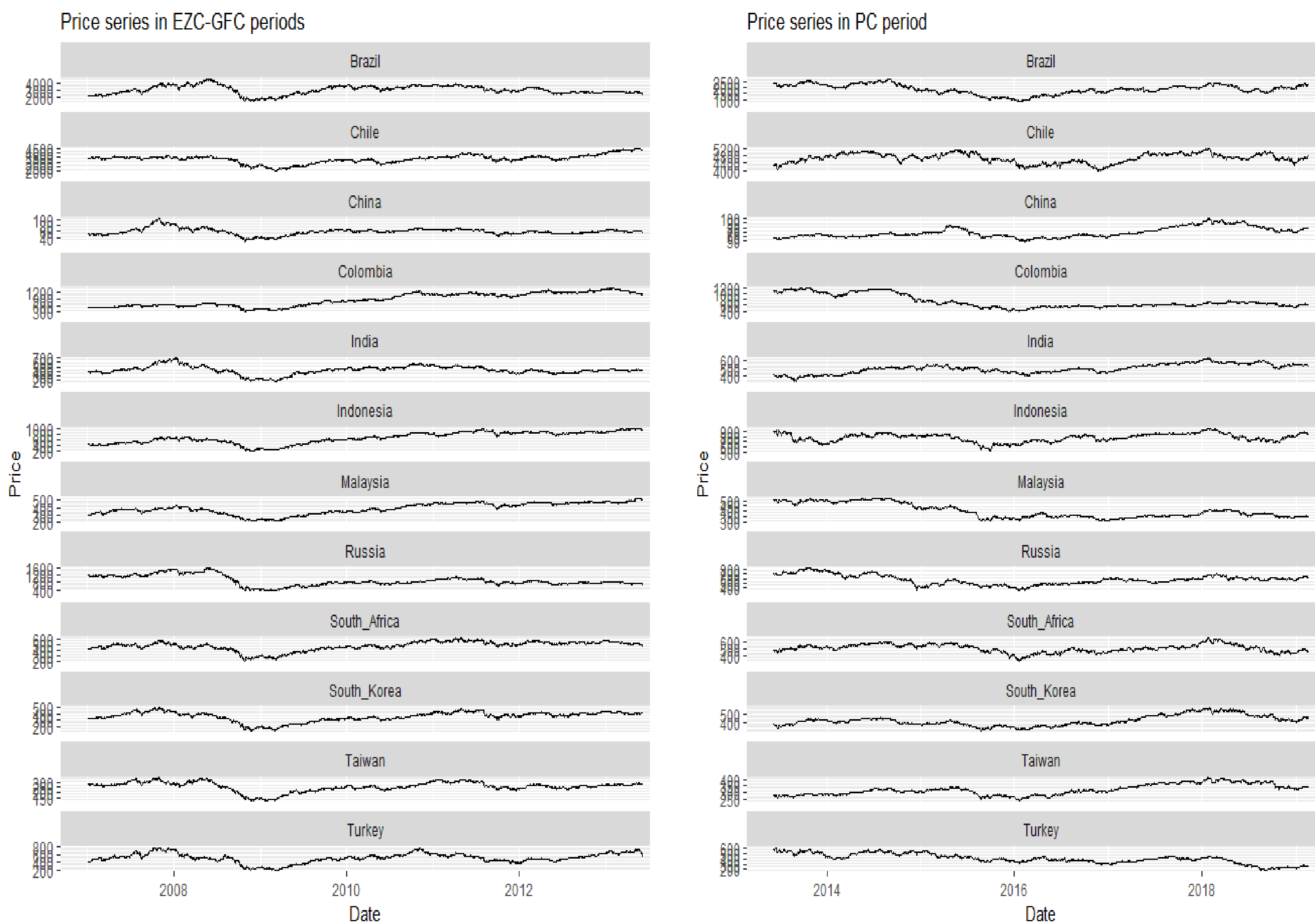


Figure 3.12: Price plots of the emerging markets equities

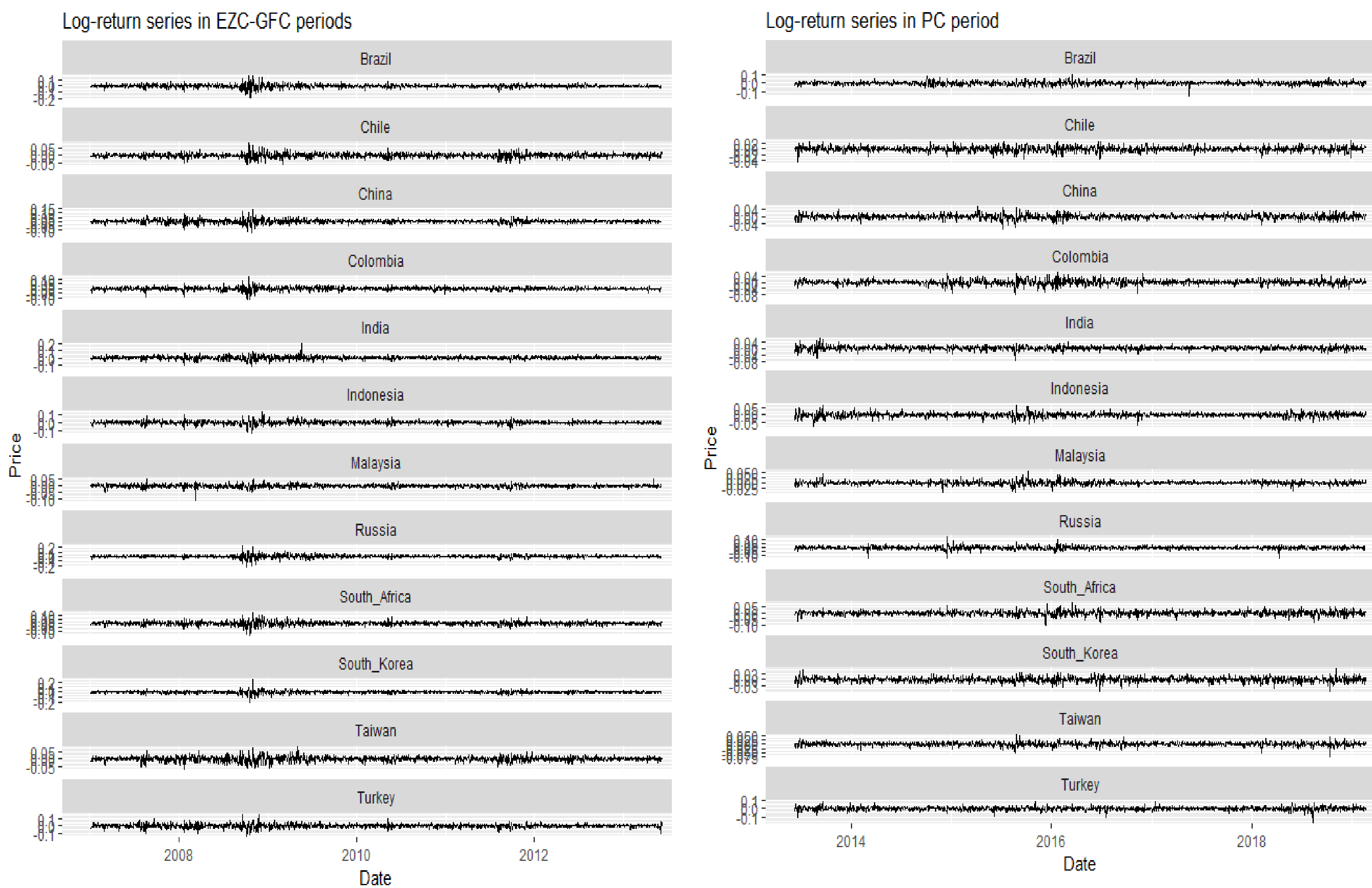


Figure 3.13: Log-returns plots of emerging markets equities

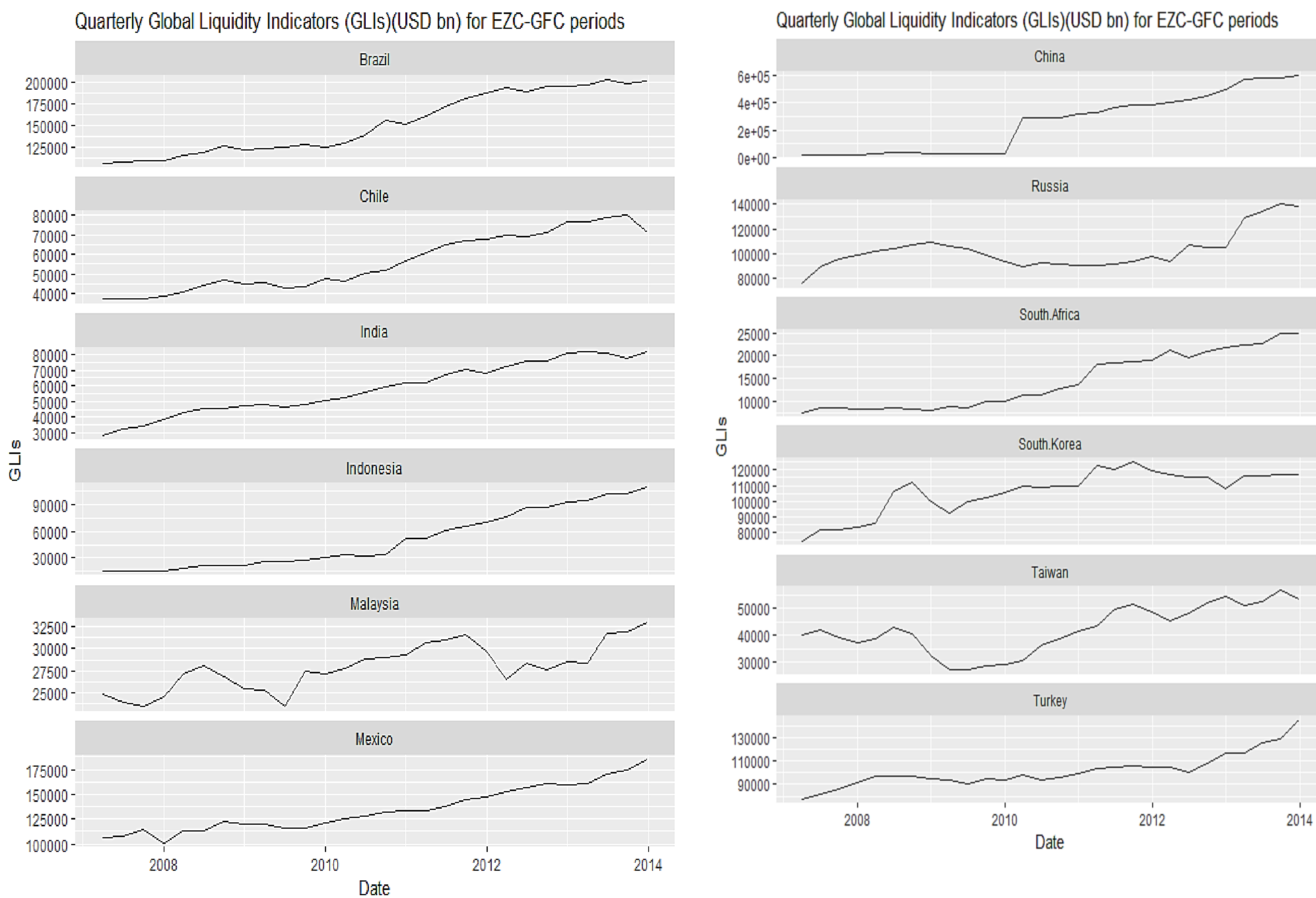


Figure 3.14: Quarterly Global Liquidity Indicators (in billion USD) plots for EZC-GFC periods from 31/3/2007 to 31/12/2013

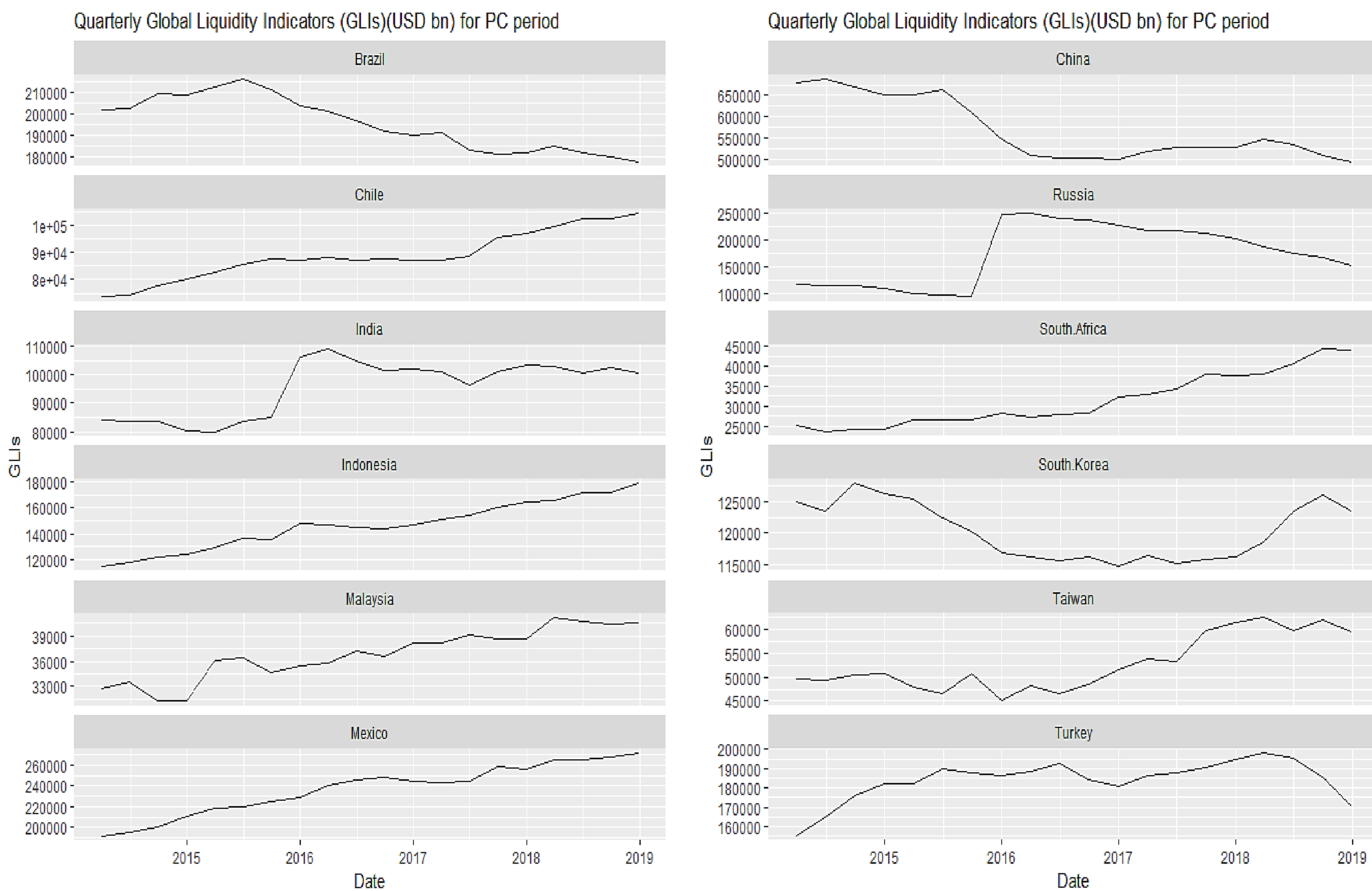
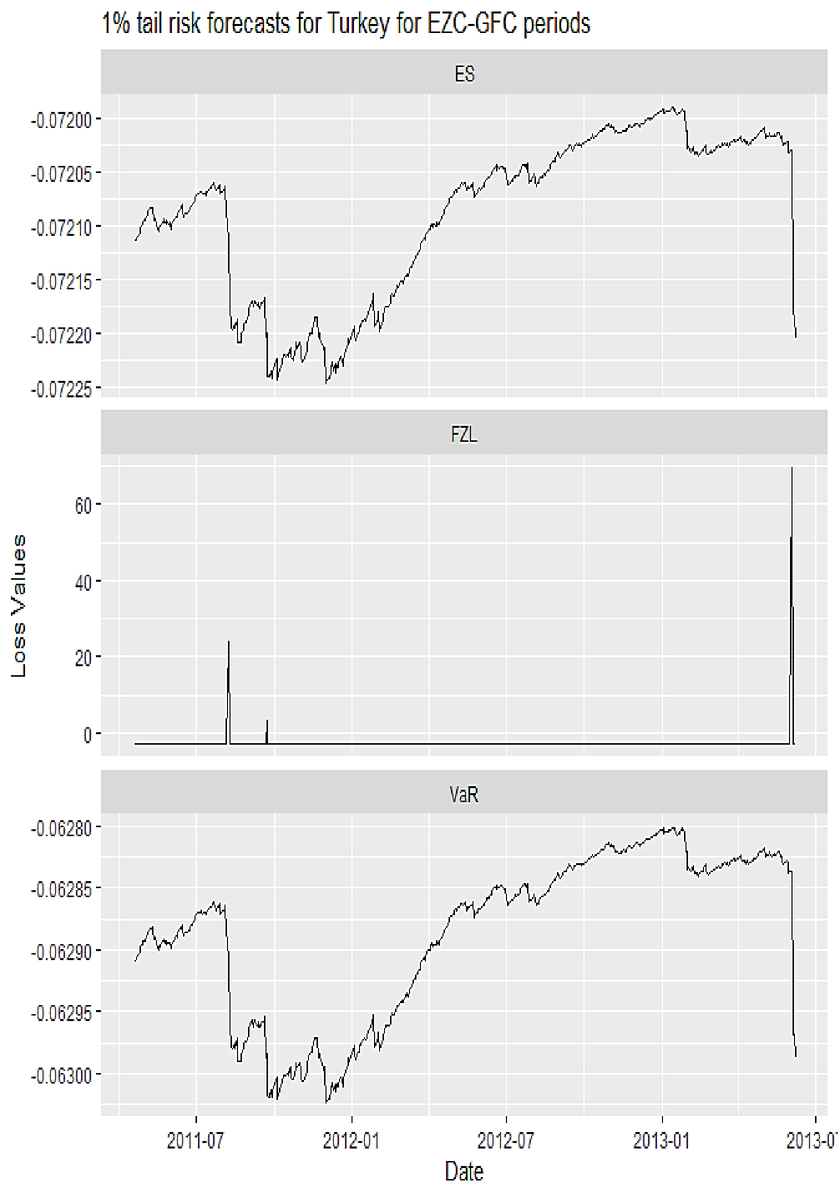
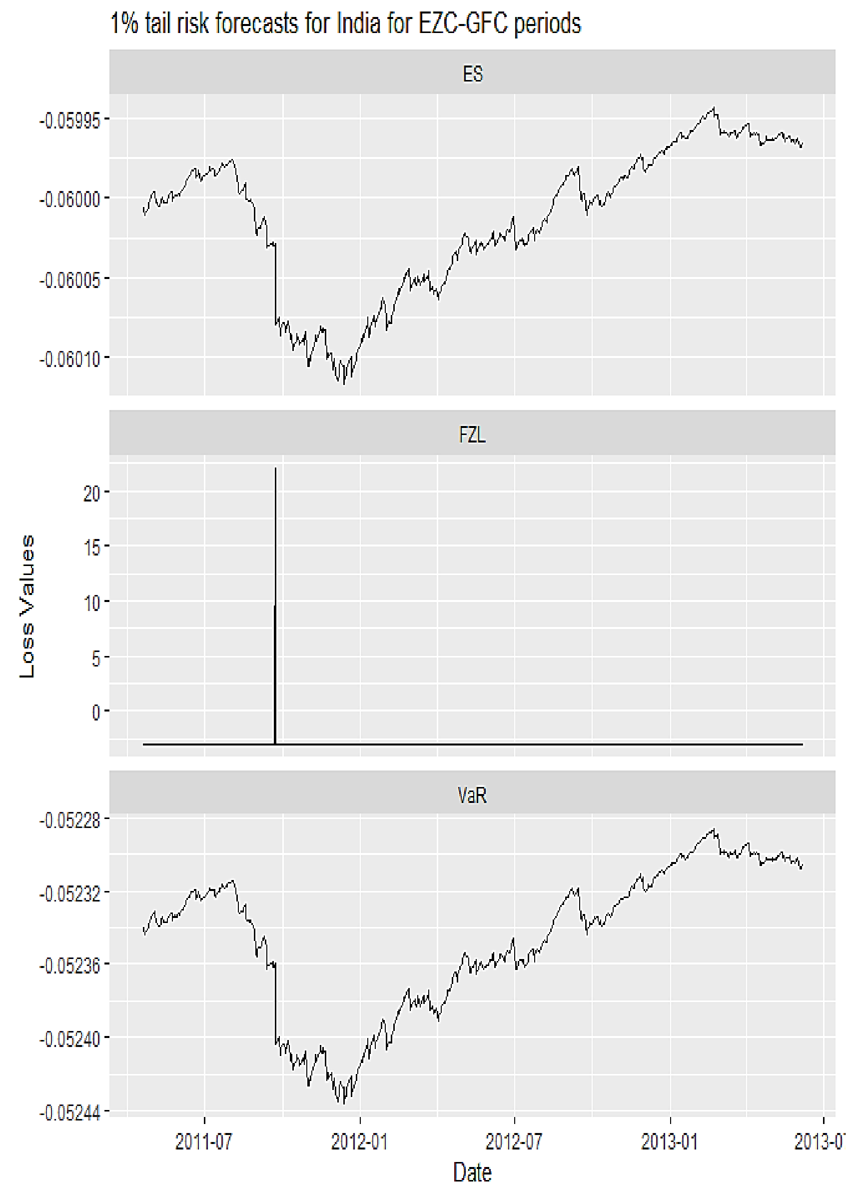
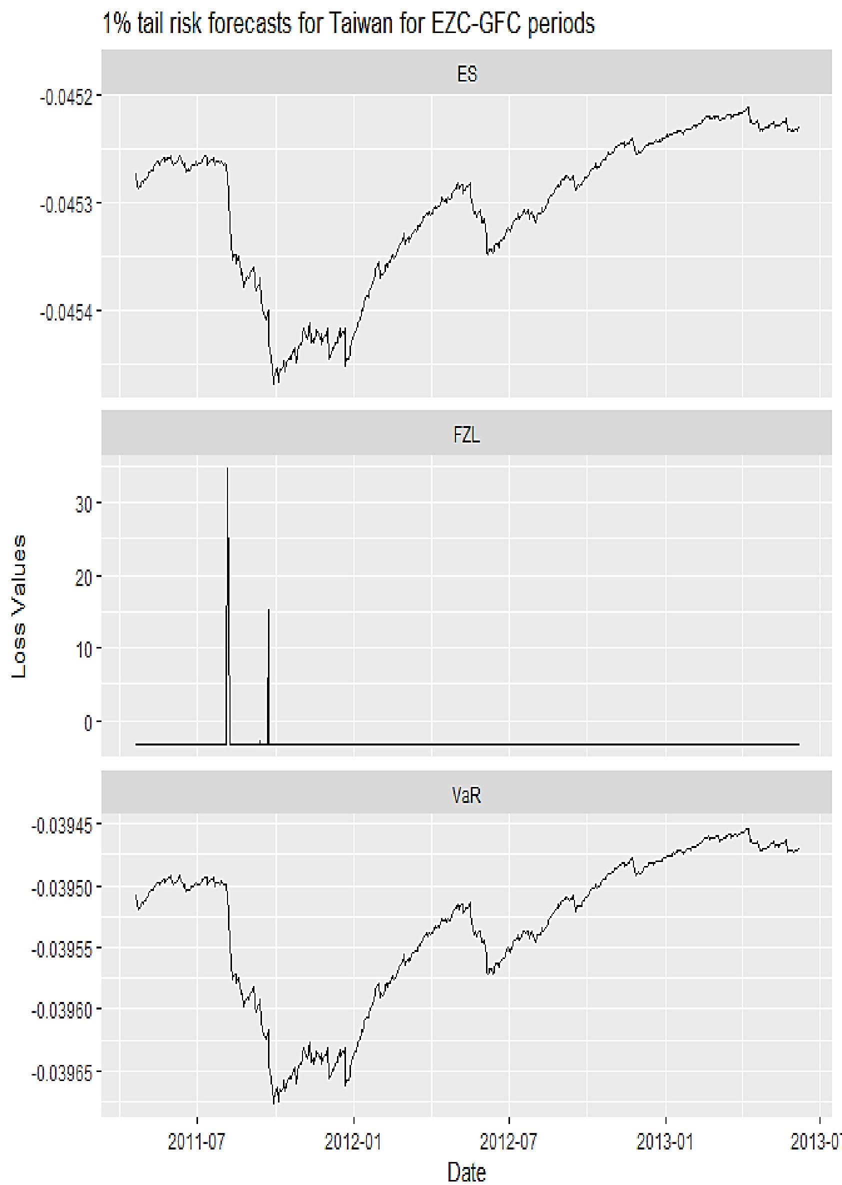
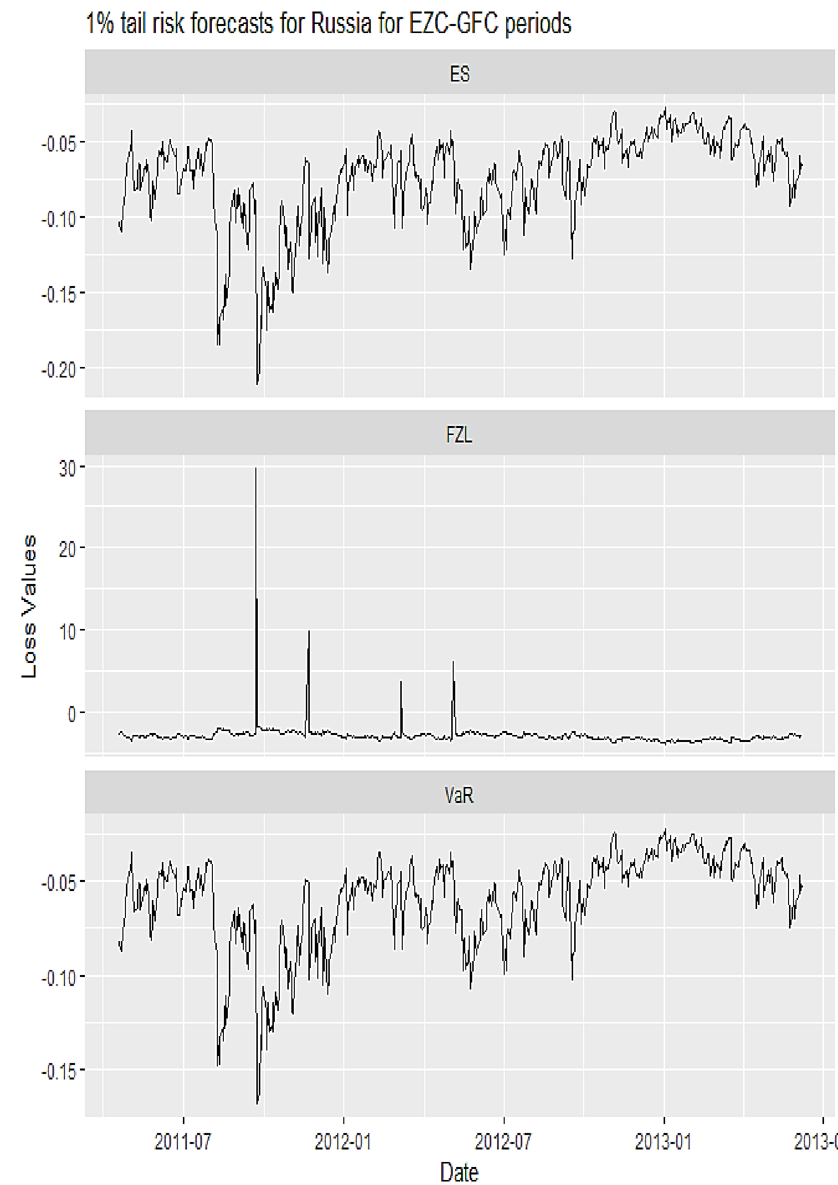


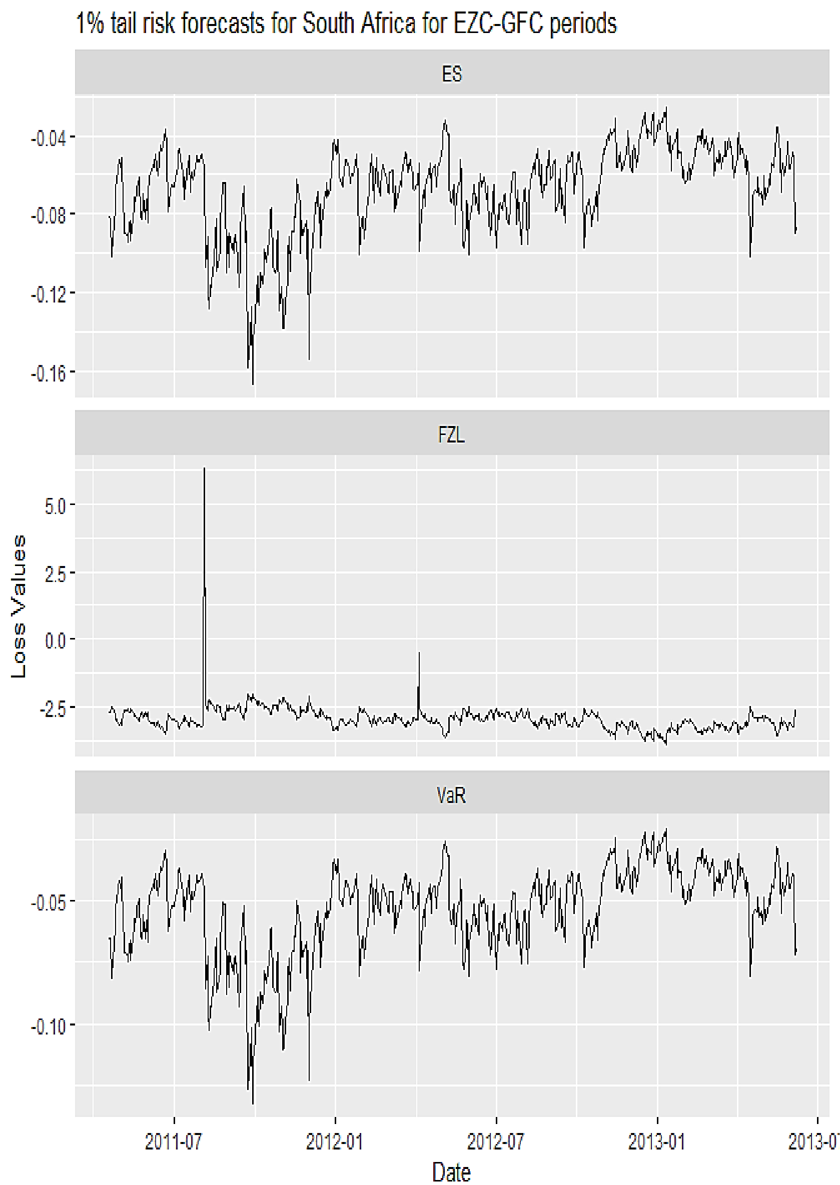
Figure 3.15: Quarterly Global Liquidity Indicators (in billion USD) plots for Post-crises periods from 31/3/2014 to 31/12/2018

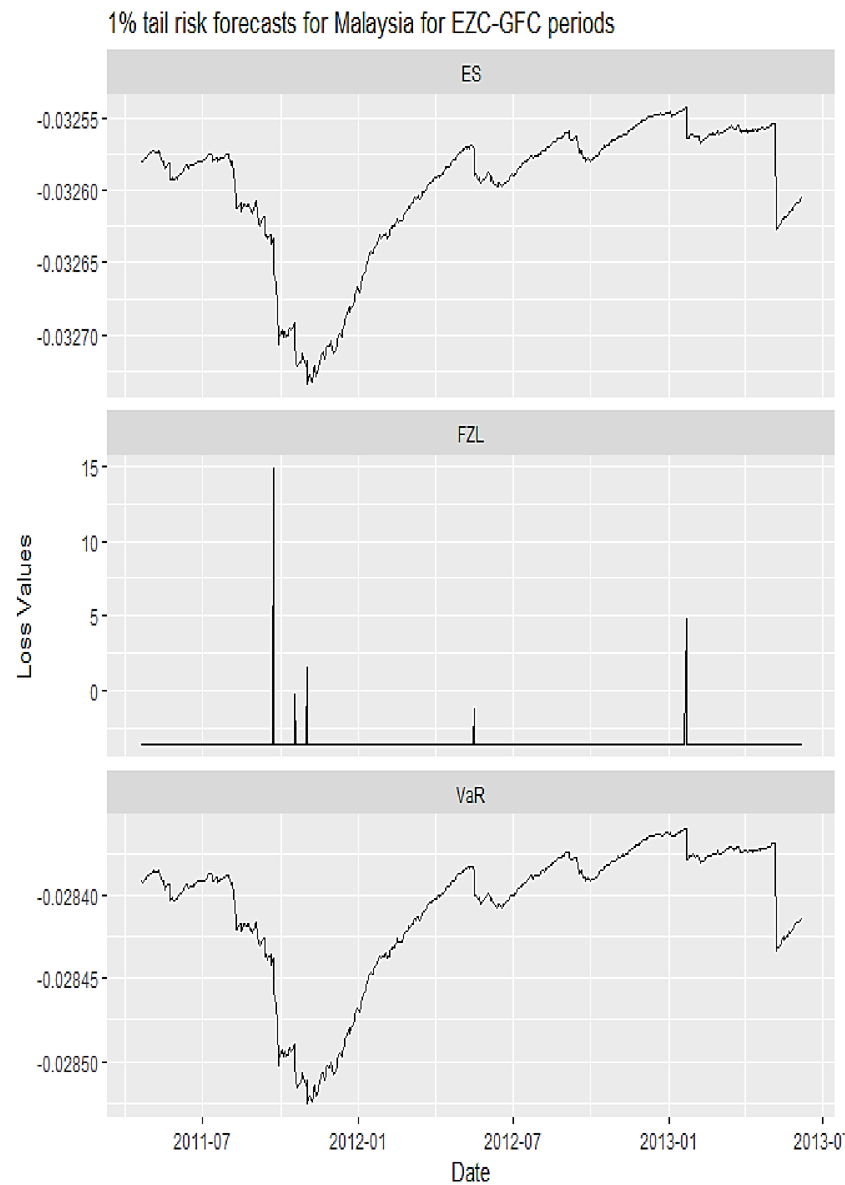

1% tail risk forecasts for Turkey for EZC-GFC periods
ES
-0.07200
-0.07205
-0.07210
-0.07215
-0.07220
-0.07225
FZL
60
40
20
0
VaR
-0.06280
-0.06285
-0.06290
-0.06295
-0.06300
Loss Values
2011-07
2012-01
2012-07
2013-01
2013-0
Date

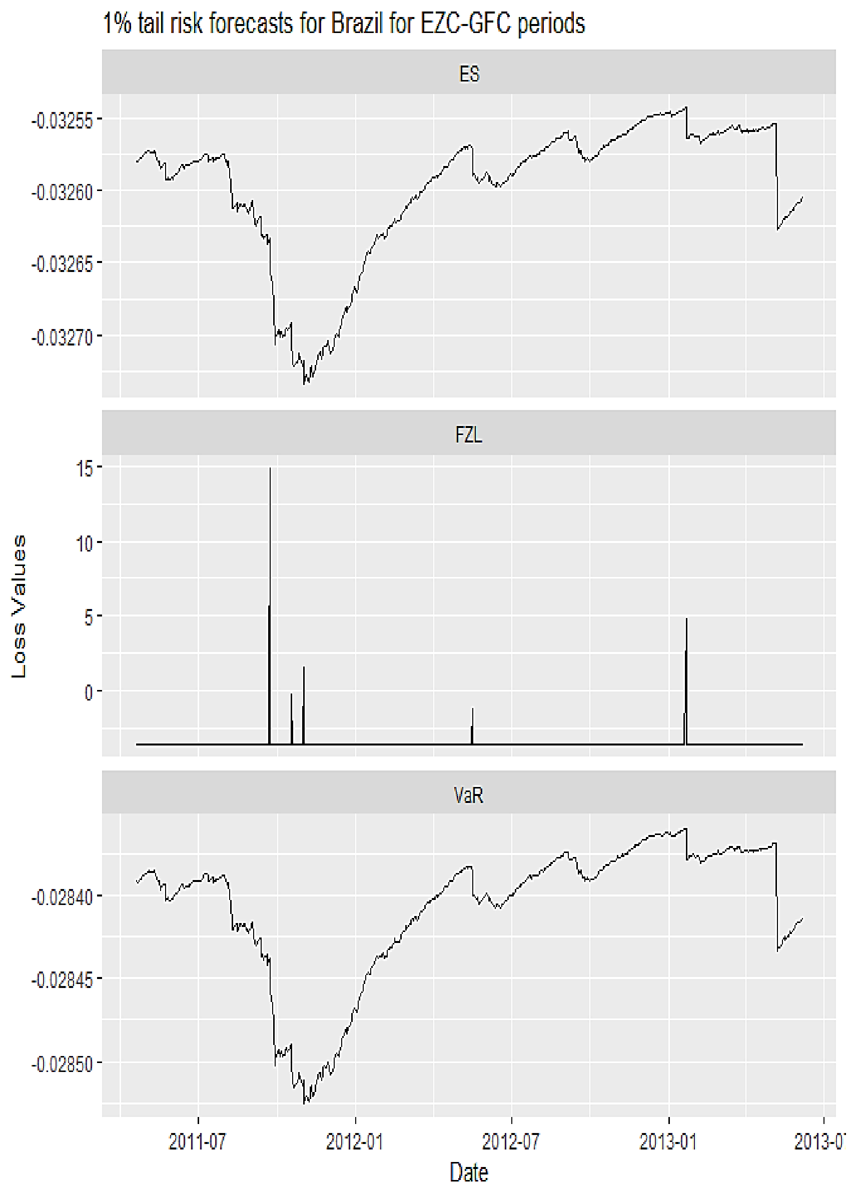

1% tail risk forecasts for India for EZC-GFC periods
ES
-0.05995
-0.06000
-0.06005
-0.06010
FZL
20
15
10
5
0
VaR
-0.05228
-0.05232
-0.05236
-0.05240
-0.05244
Loss Values
2011-07
2012-01
2012-07
2013-01
2013-0
Date

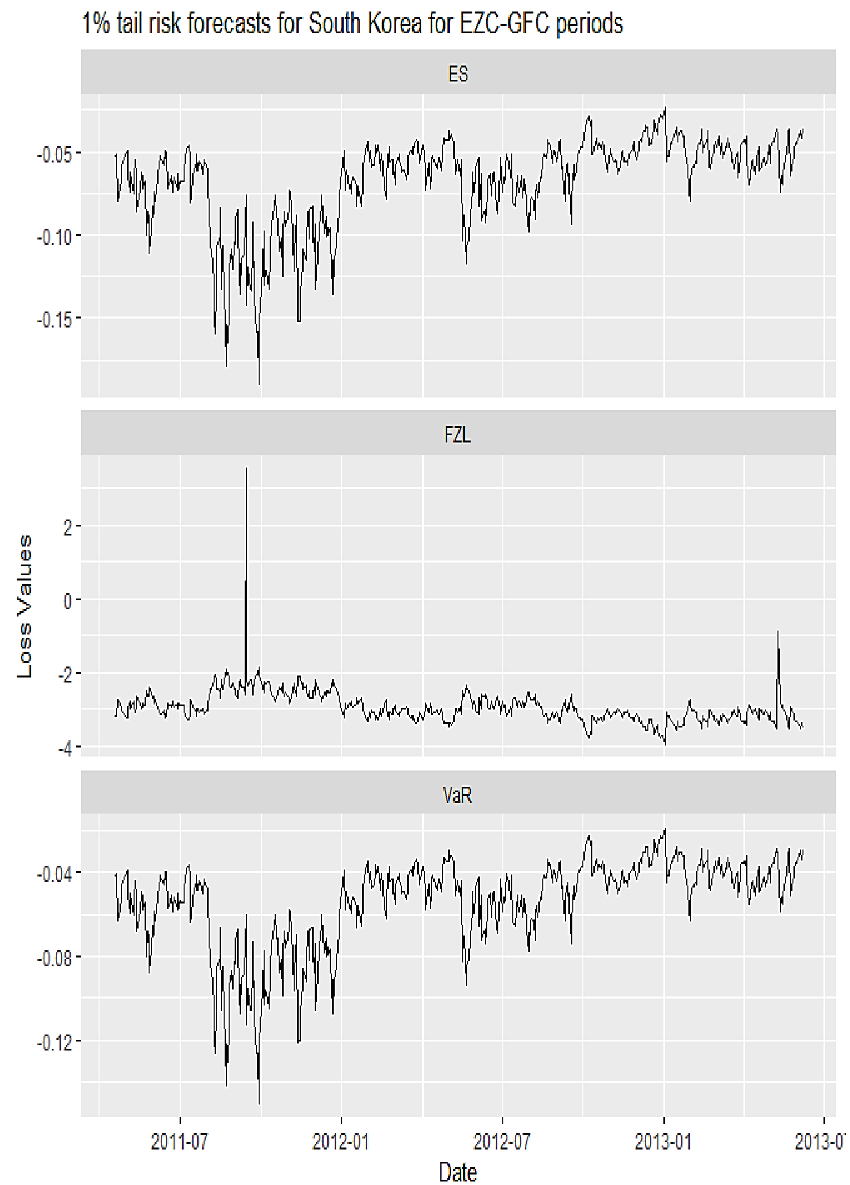

1% tail risk forecasts for Taiwan for EZC-GFC periods
ES
-0.0452
-0.0453
-0.0454
FZL
30
20
10
0
VaR
-0.03945
-0.03950
-0.03955
-0.03960
-0.03965
Loss Values
2011-07
2012-01
2012-07
2013-01
Date

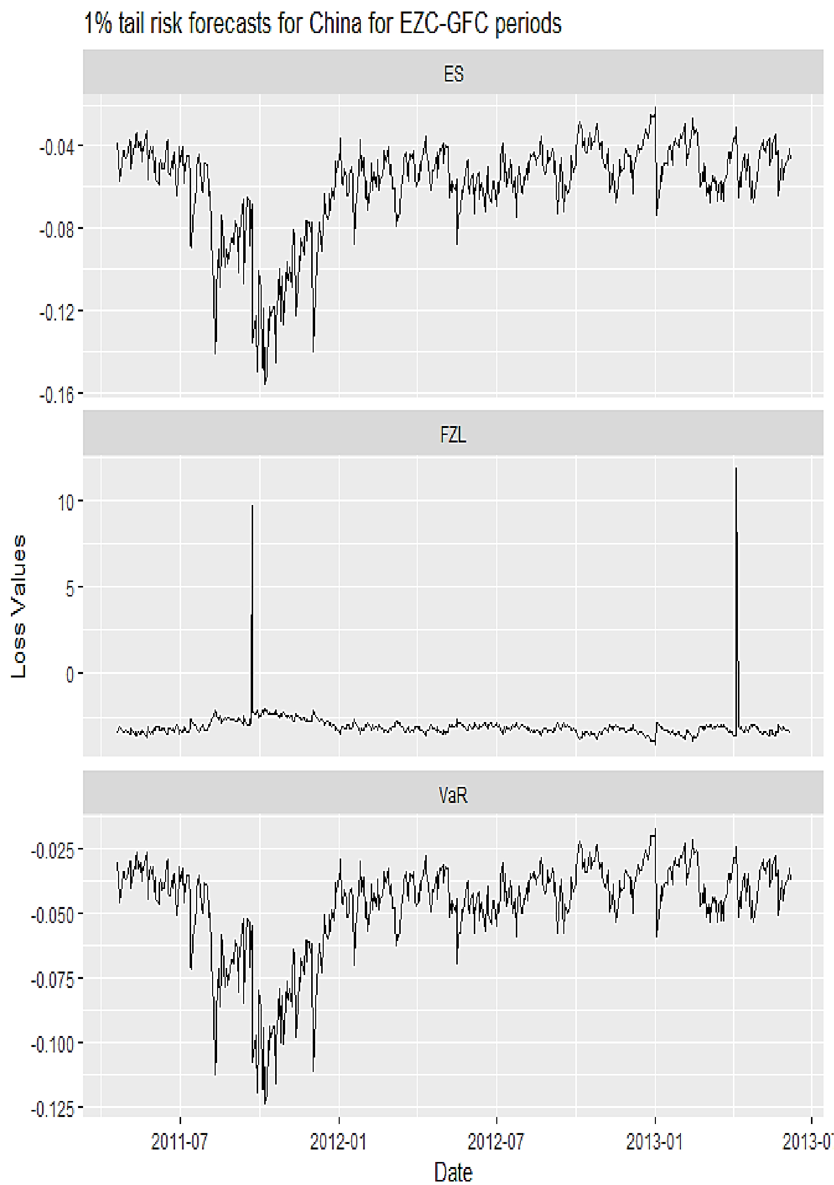

1% tail risk forecasts for Russia for EZC-GFC periods
ES
-0.05
-0.10
-0.15
-0.20
FZL
30
20
10
0
VaR
-0.05
-0.10
-0.15
Loss Values
2011-07
2012-01
2012-07
2013-01
Date

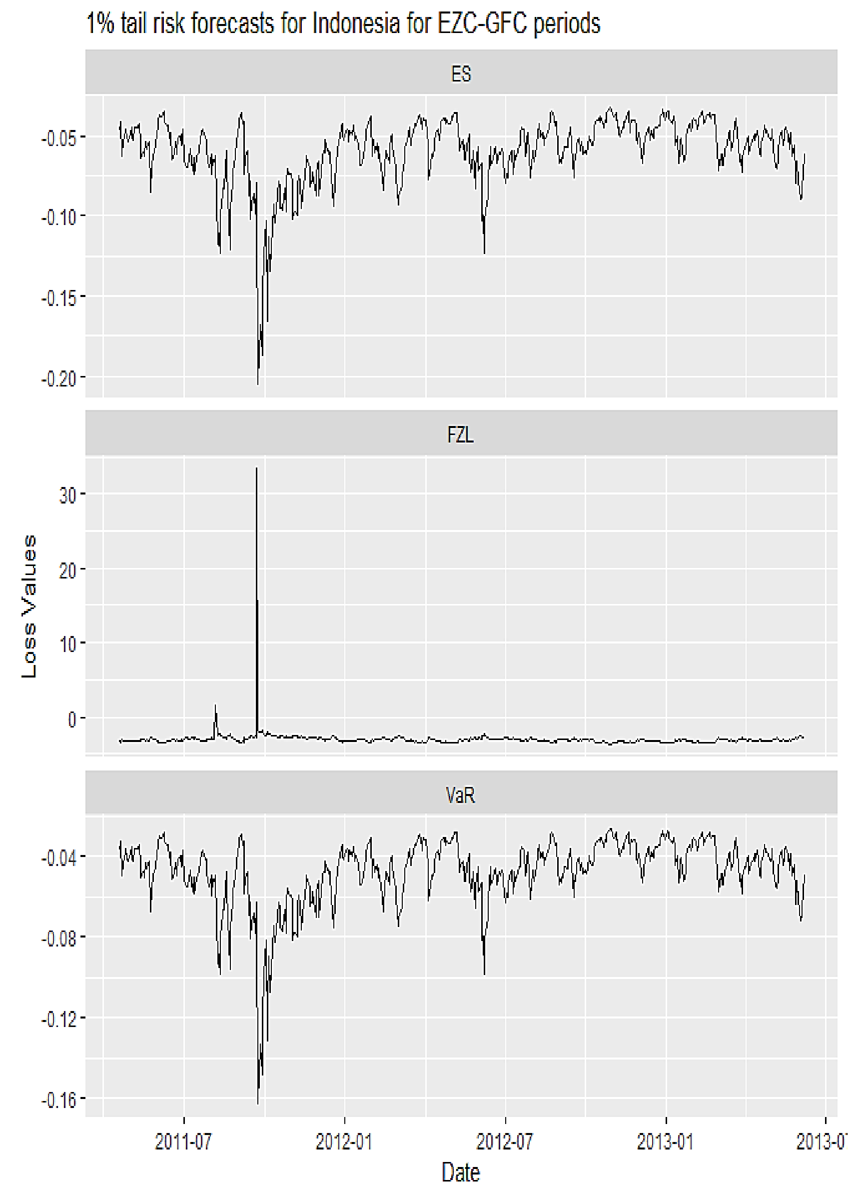

1% tail risk forecasts for South Africa for EZC-GFC periods
ES
FZL
VaR
Loss Values
Date


1% tail risk forecasts for Malaysia for EZC-GFC periods
ES
FZL
VaR
Loss Values
Date


1% tail risk forecasts for Brazil for EZC-GFC periods
ES
FZL
VaR
Loss Values
Date
2011-07
2012-01
2012-07
2013-01


1% tail risk forecasts for South Korea for EZC-GFC periods
ES
FZL
VaR
Loss Values
Date
2011-07
2012-01
2012-07
2013-01


1% tail risk forecasts for China for EZC-GFC periods
ES
FZL
VaR
Loss Values
Date
-0.04
-0.08
-0.12
-0.16
10
5
0
-0.025
-0.050
-0.075
-0.100
-0.125
2011-07
2012-01
2012-07
2013-01
2013-07


1% tail risk forecasts for Indonesia for EZC-GFC periods
ES
FZL
VaR
Loss Values
Date
-0.05
-0.10
-0.15
-0.20
30
20
10
0
-0.04
-0.08
-0.12
-0.16
2011-07
2012-01
2012-07
2013-01
2013-07

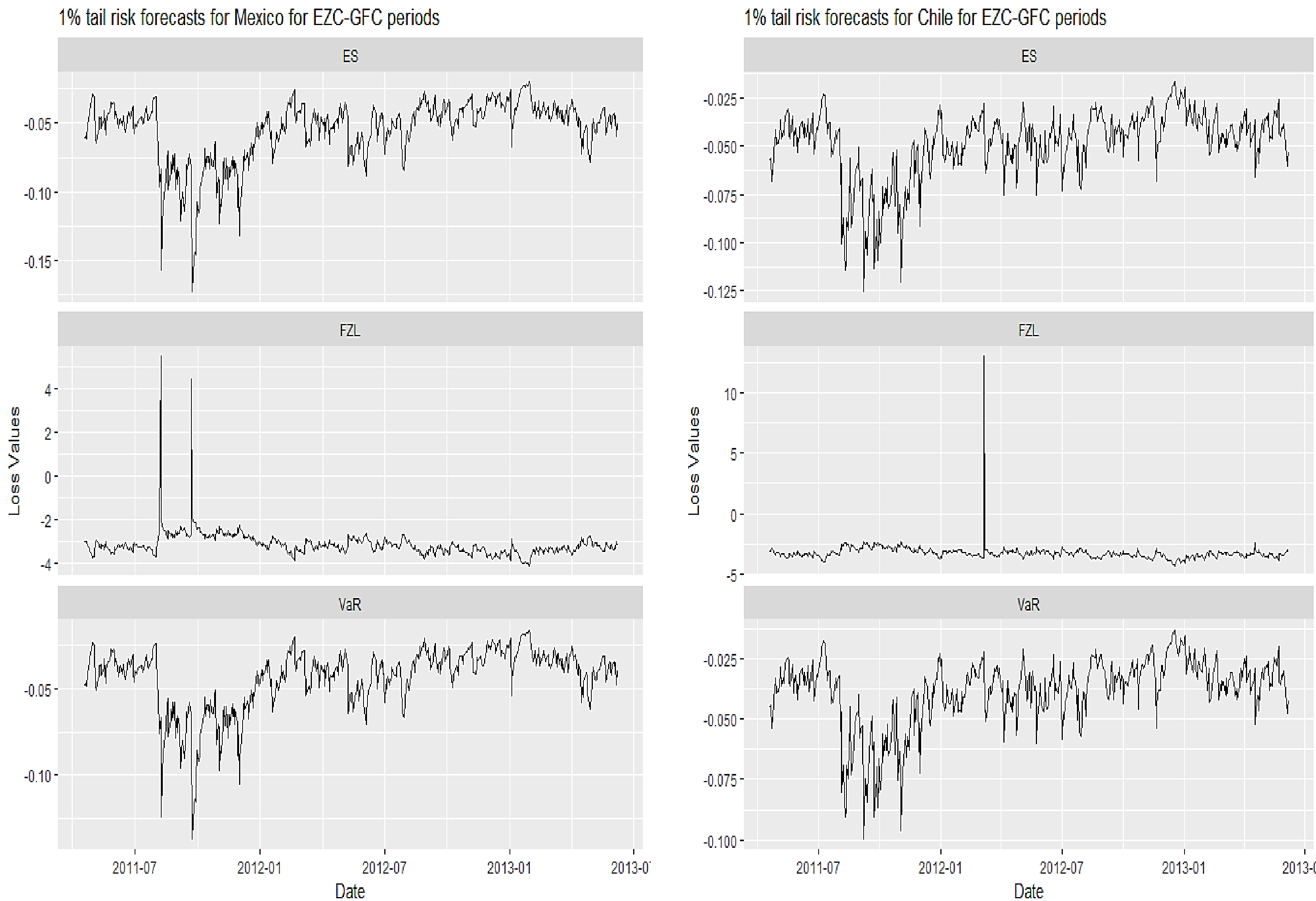
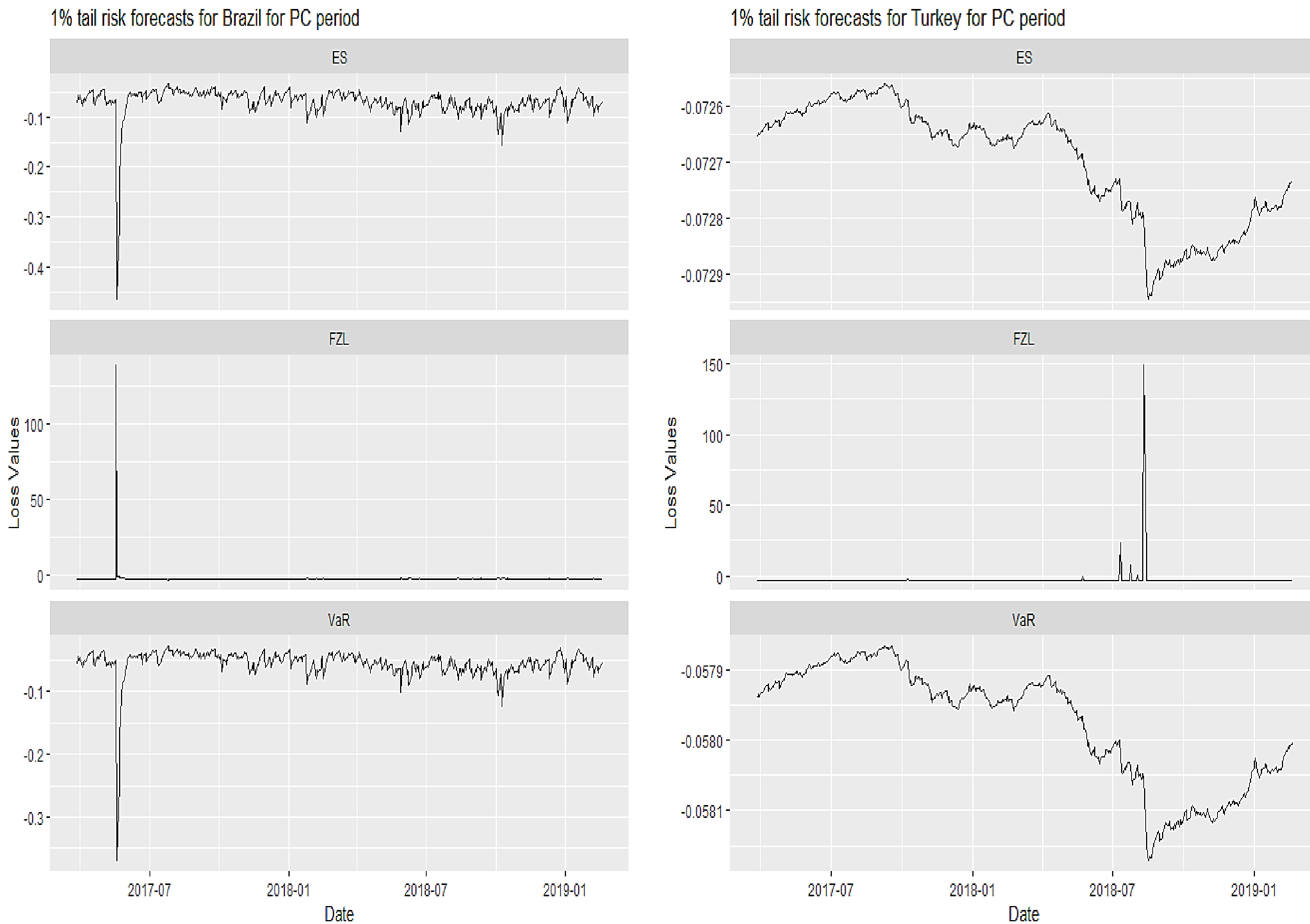
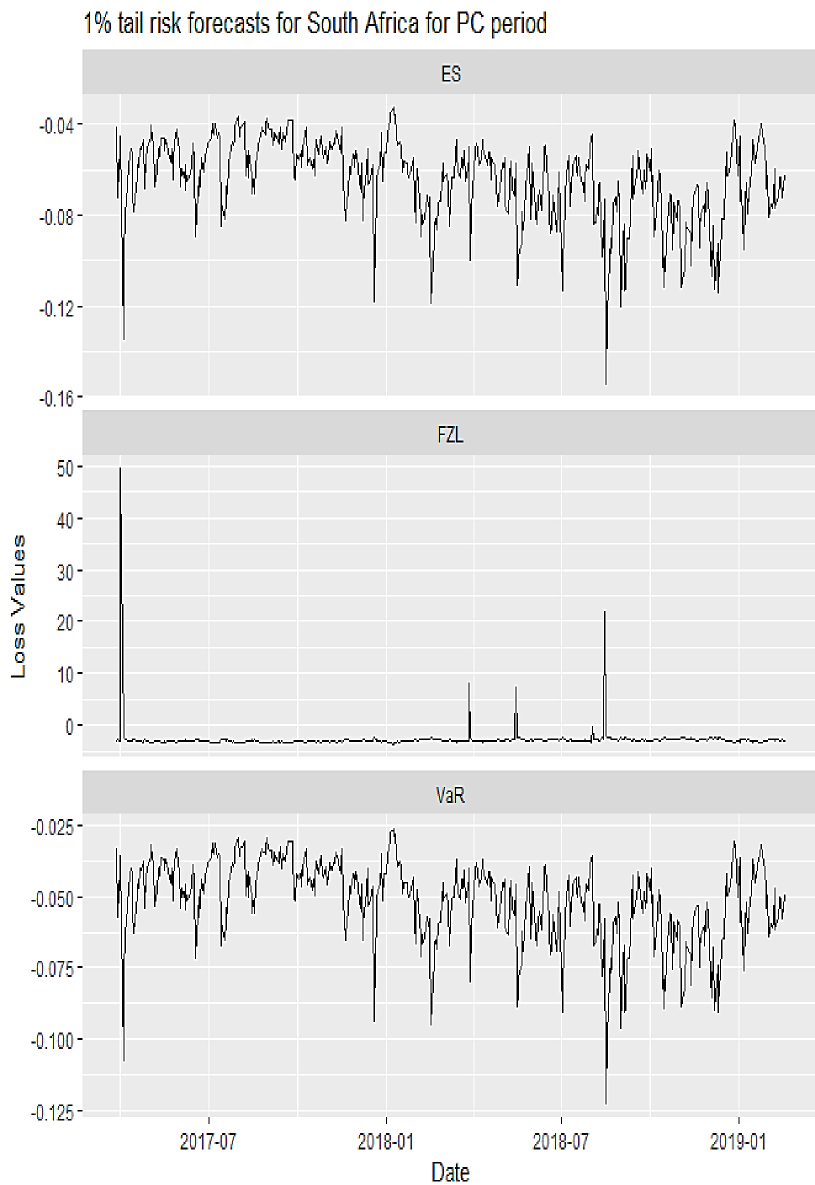
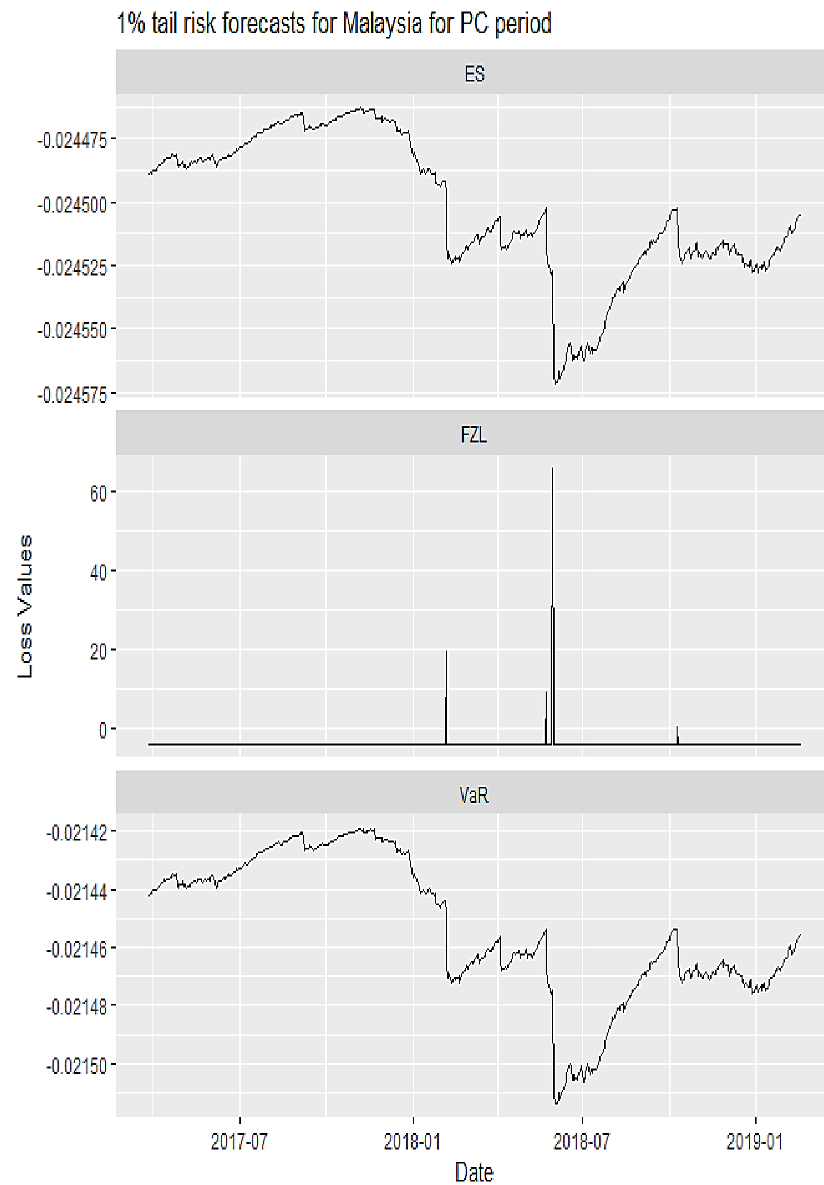
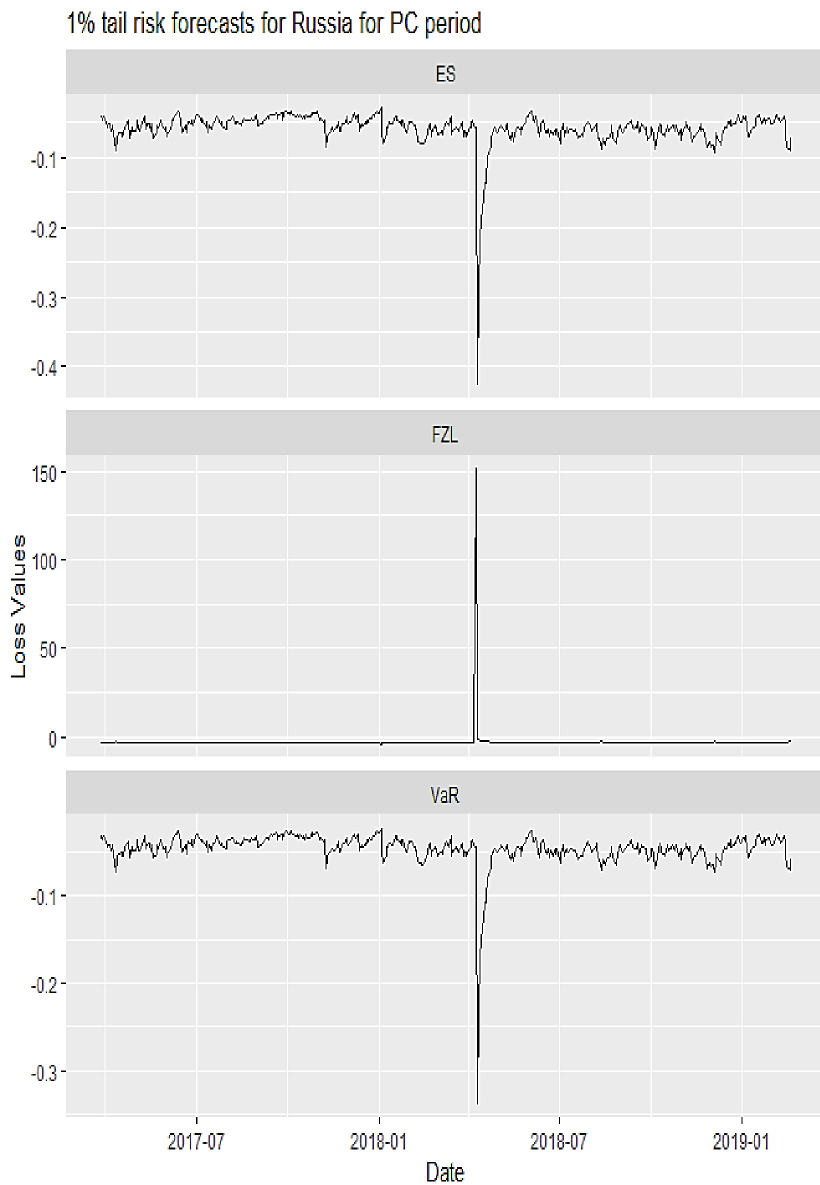


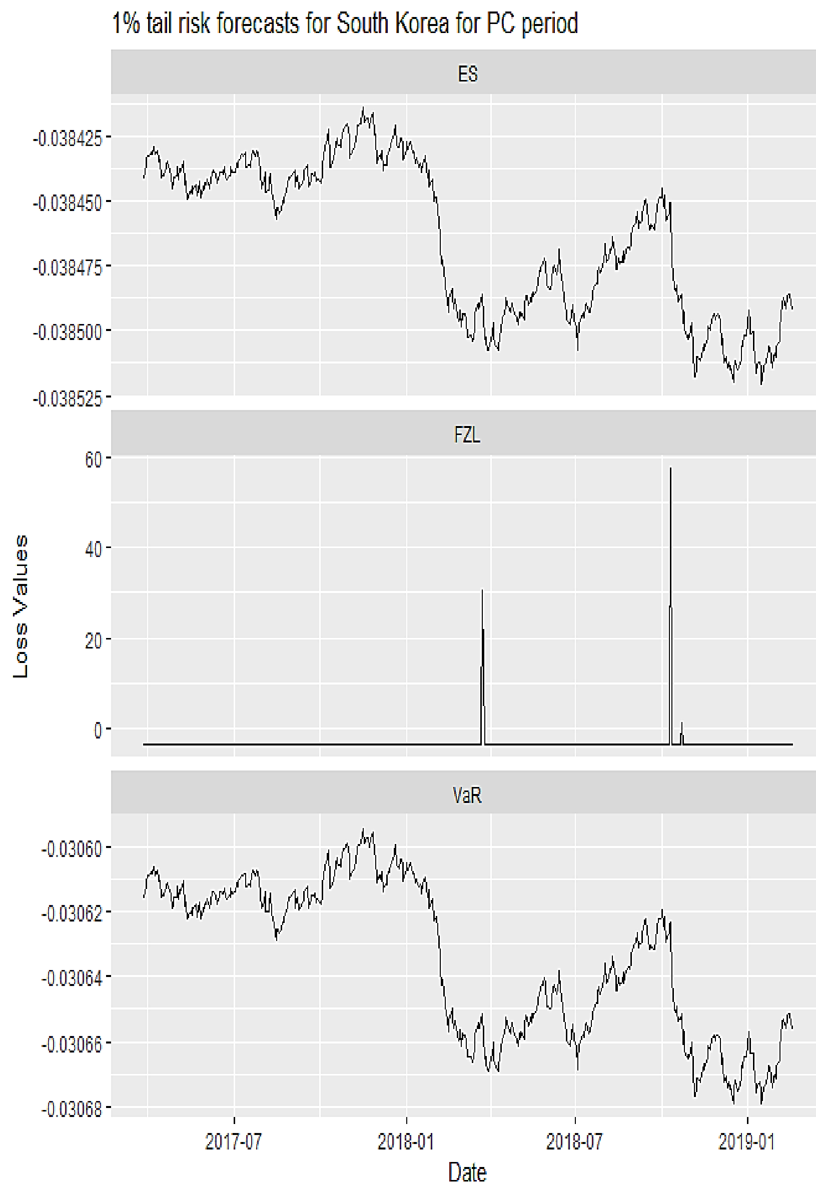
Figure 3.16: 1% tail risk forecasts series plots for emerging markets equities for EZC-GFC periods from 19/4/2011 to 7/6/2013

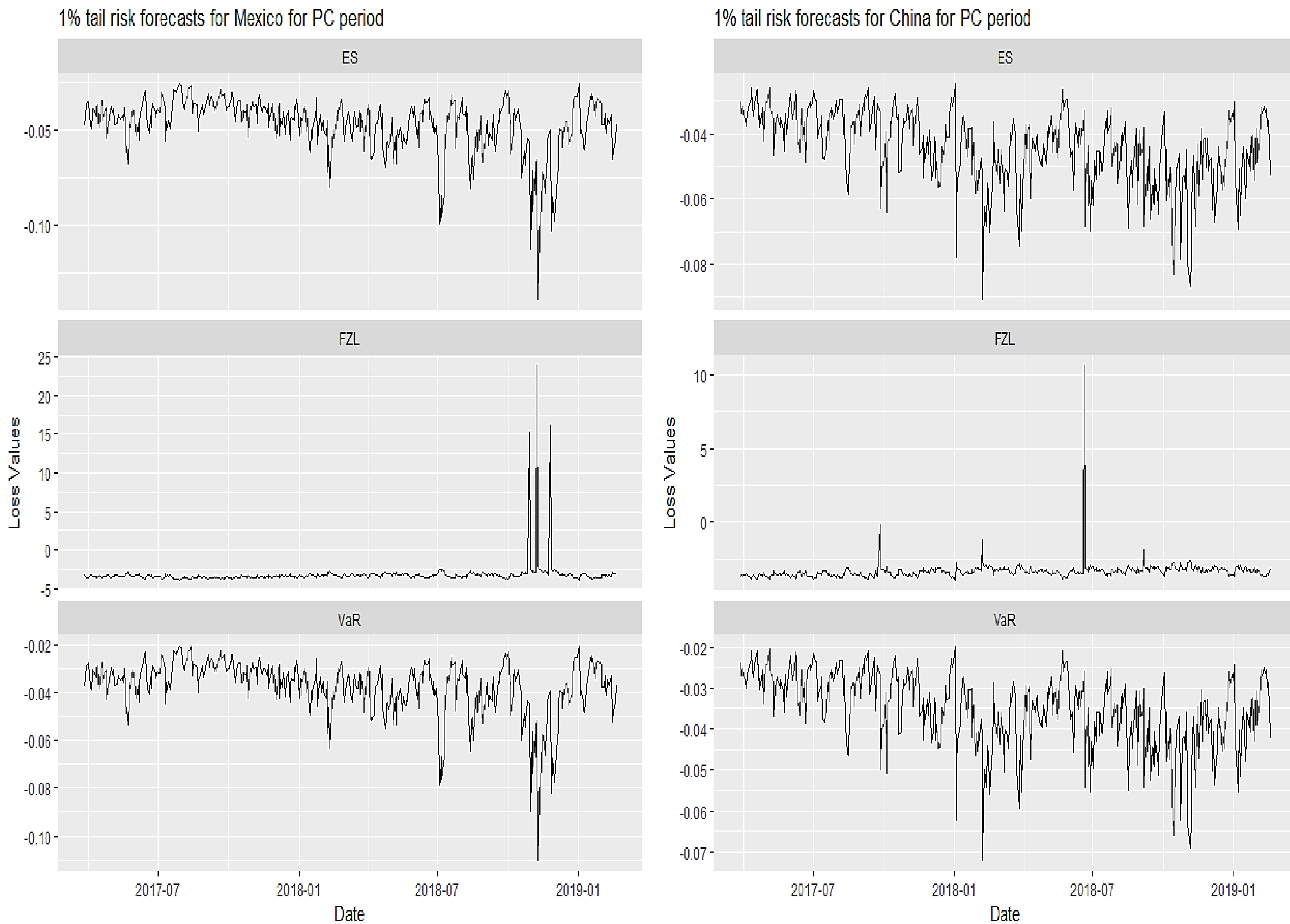

1% tail risk forecasts for Brazil for PC period
ES
FZL
VaR
Loss Values
Date
2017-07
2018-01
2018-07
2019-01
1% tail risk forecasts for Turkey for PC period
ES
FZL
VaR
Loss Values
Date
2017-07
2018-01
2018-07
2019-01

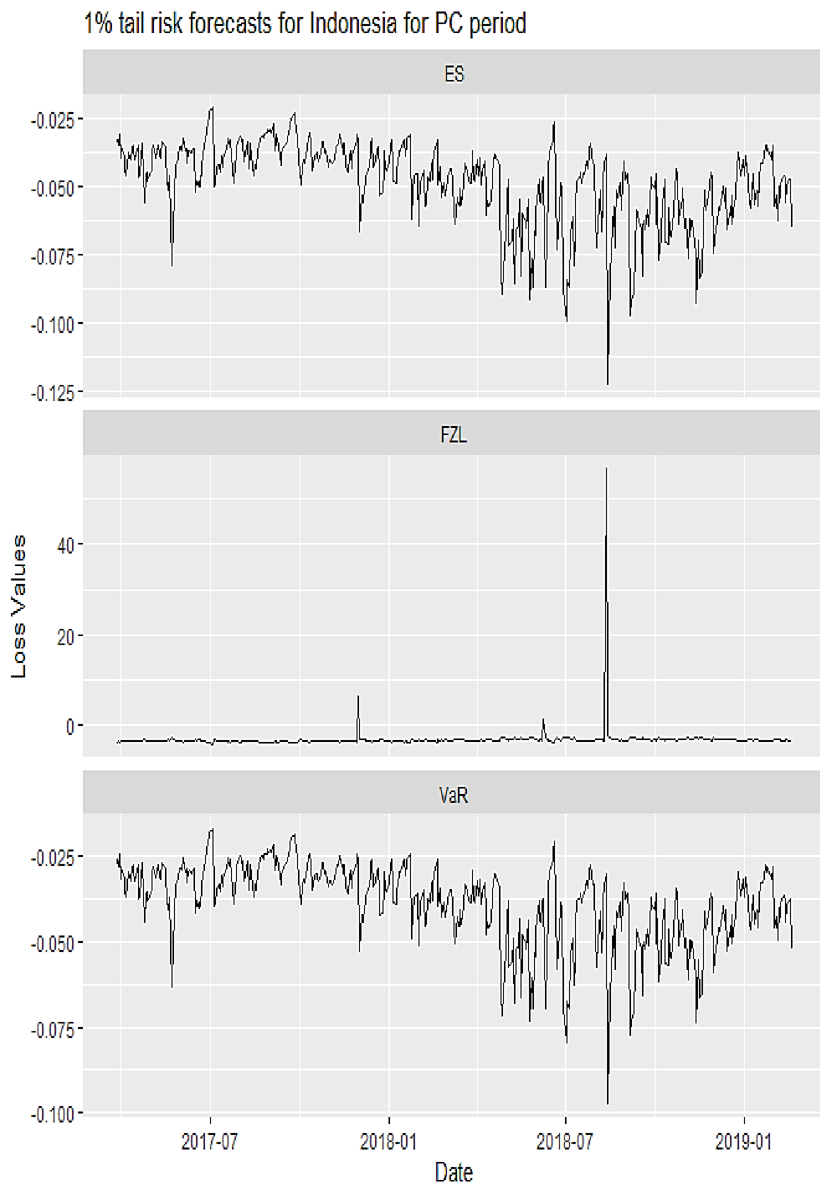

1% tail risk forecasts for South Africa for PC period
ES
-0.04
-0.08
-0.12
-0.16
FZL
50
40
30
20
10
0
VaR
-0.025
-0.050
-0.075
-0.100
-0.125
Loss Values
2017-07
2018-01
2018-07
2019-01
Date

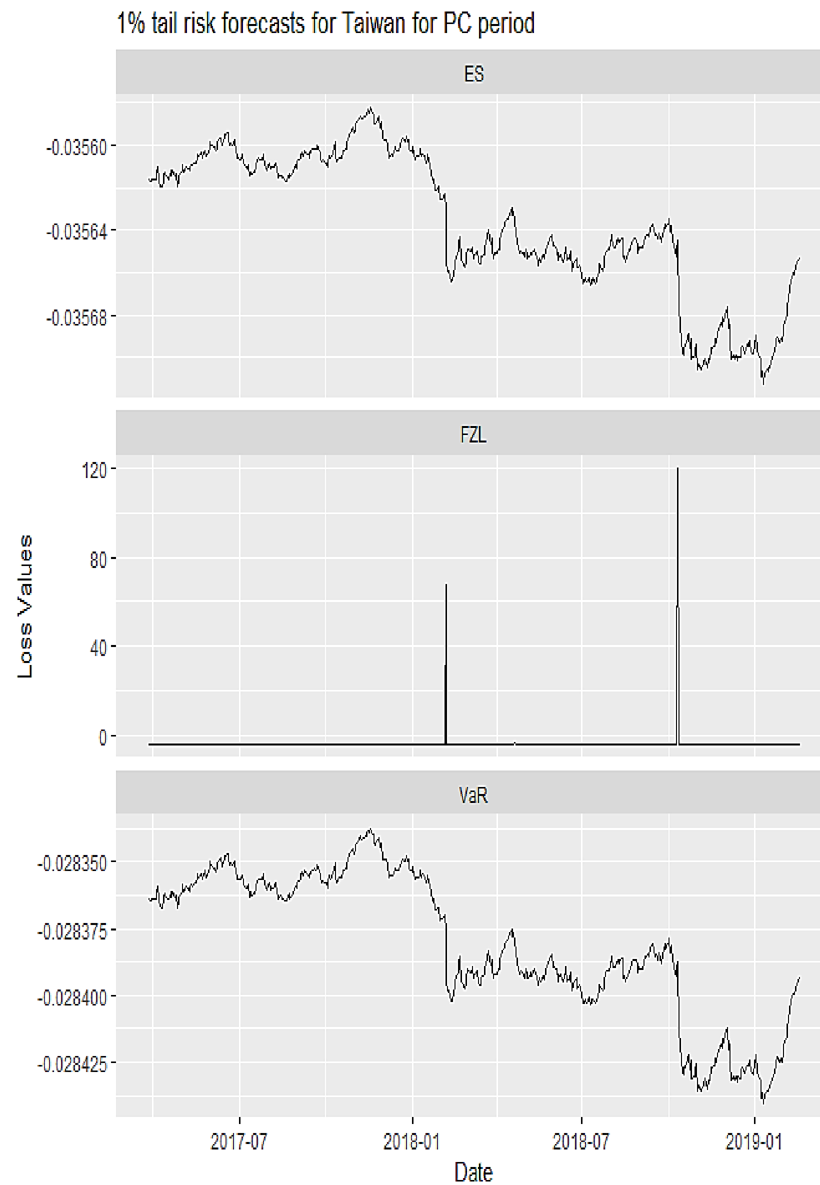

1% tail risk forecasts for Malaysia for PC period
ES
-0.024475
-0.024500
-0.024525
-0.024550
-0.024575
FZL
60
40
20
0
VaR
-0.02142
-0.02144
-0.02146
-0.02148
-0.02150
Loss Values
2017-07
2018-01
2018-07
2019-01
Date


1% tail risk forecasts for Russia for PC period
ES
FZL
VaR
Loss Values
Date
2017-07
2018-01
2018-07
2019-01


1% tail risk forecasts for South Korea for PC period
ES
FZL
VaR
Loss Values
Date
2017-07
2018-01
2018-07
2019-01


1% tail risk forecasts for Mexico for PC period
ES
-0.05
-0.10
FZL
25
20
15
10
5
0
-5
VaR
-0.02
-0.04
-0.06
-0.08
-0.10
Loss Values
2017-07
2018-01
2018-07
2019-01
Date
1% tail risk forecasts for China for PC period
ES
-0.04
-0.06
-0.08
FZL
10
5
0
VaR
-0.02
-0.03
-0.04
-0.05
-0.06
-0.07
Loss Values
2017-07
2018-01
2018-07
2019-01
Date


1% tail risk forecasts for Indonesia for PC period
ES
-0.025
-0.050
-0.075
-0.100
-0.125
FZL
40
20
0
VaR
-0.025
-0.050
-0.075
-0.100
Loss Values
2017-07
2018-01
2018-07
2019-01
Date


1% tail risk forecasts for Taiwan for PC period
ES
-0.03560
-0.03564
-0.03568
FZL
120
80
40
0
VaR
-0.028350
-0.028375
-0.028400
-0.028425
Loss Values
2017-07
2018-01
2018-07
2019-01
Date

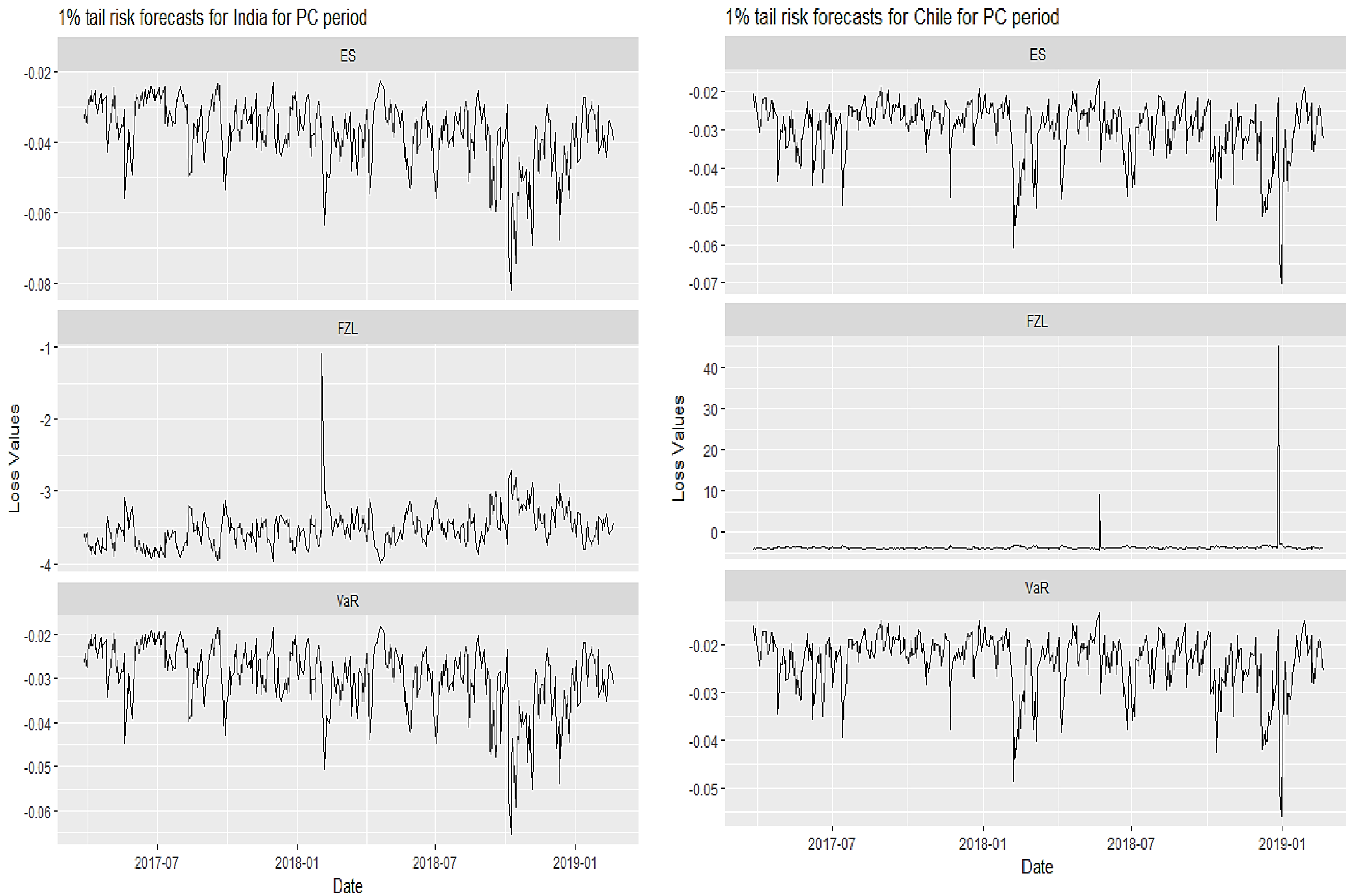


Figure 3.17: 1% tail risk forecasts series plots for emerging markets Post-crisis period from 22/7/2017 to 19/2/2019
Note: PC indicate Post-crisis and FZL indicate (VaR, ES) model.

CHAPTER FOUR

ON THE ELICITABILITY AND RISK MODEL COMPARISON OF EMERGING MARKETS EQUITIES

4.1 Introduction

Value-at-Risk (VaR) and Expected Shortfall (ES) have been the two main regulatory bank capital requirements and portfolio risk measures for a long time. However, both of them suffer practical and coherent risk weaknesses (Burzoni et al., 2017; Cont et al., 2013; Fissler & Ziegel, 2016; Fissler et al., 2015; Nolde & Ziegel, 2017). Though ES may have been espoused as a better measure of risk, it is sensitive to tails and can lead to greater periodic capital charges unlike VaR (Chang et al., 2019). Large ES values also tend to be more sensitive towards regulatory arbitrage and parameter misspecification (Kellner & Rösch, 2016). But more importantly, it is the lack of elicitability of the ES that poses concerns (Fissler & Ziegel, 2016; Nolde & Ziegel, 2017).

On the other hand, modelling the tail risks of financial assets continue to be a daunting task for risk managers. There are a myriad of distributional innovations to choose from in the quest to address stylised facts of assets returns. The last decade has seen a proliferation of competing models (Bernardi & Catania, 2016), at the disposal of both econometricians and internal risk managers of financial firms. In the family of volatility models alone, the Autoregressive Conditional Heteroscedasticity (ARCH) models (Engle, 1982; Bollerslev, 1986), for instance, is perhaps the most wide-ranging of all econometric inventions (Moosa, 2017). Non-linear state space stochastic volatility models have also been explored by Taylor (1994), Harvey and Shephard (1996), and Gallant et al. (1997). The Generalised Autoregressive Score (GAS) model of Harvey (2013) and Creal et al. (2013) has also become popular in recent times (Bernardi & Catania, 2016).

Hence, the objective of risk managers is to find set of ordered superior models instead of a single best model (Hansen et al., 2011).

Nonetheless, choosing a set of risk models should not only be an internal affair, but it should be in line with regulatory framework. The Basel III framework requires VaR and ES models to be comparable to their standardised approach known as comparative back testing. While VaR models are elicitable, ES lacks this property. However, at the higher level, the joint (VaR, ES) is elicitable. This property offers the possibility to rank competing risk models based on a consistent scoring function. Elicitable risk measures, therefore, serve as the bridge between internal models of financial institutions and standardised regulatory approaches. In essence, modelling tail risk with the (VaR, ES) and FZL support the agenda of Basel III to reduce regulatory arbitrage. This has resulted in renewed interest in financial risk modelling and selection which is in direct agreement with regulatory standards. While risk modelling of emerging markets equities abound in the literature, studies on model ranking and selection meant to eliminate regulatory arbitrage are largely missing. In this study, we seek to examine tail risk selection and ranking behaviour of sampled emerging markets equities using the (VaR, ES) and FZL function mainly because they align with the current regulatory framework. In so doing, we further employ Hansen et al.'s (2011) Model Confidence Set (MCS) procedure in ranking and selection of Superior Set Models (SSMs) of the (VaR, ES) model forecasts.

In the EMEs literature, several studies have used the Akaike, Consistent Akaike, Bayesian, and Hannan-Quinn Information Criteria; AIC, BIC, and HQIC, respectively, for risk model ranking and selection in the univariate case. Yet, others include the Log-likelihood, root mean squared error (RMSE), and mean absolute error (MAE). (Blazsek & Hernández, 2018; Gong et al., 2019; Troster et al., 2019). However, these approaches have important shortcomings. First, they do not rank all models concurrently as a set. Model criteria values are compared after they have been estimated independent of each other. This approach plays down on the interdependence that may exist in the competing risk models (Han & Hausman, 1990). Second, the criteria do not possess any consistent scoring function to allow for model ranking. Ranking based on only the magnitudes of model errors is almost sure to be inadequate.

Testing procedures for "best" fitting models include; Reality Check (White, 2000), Stepwise Multiple Testing (Romano & Wolf, 2005), Superior Predictive Ability (Hansen & Lunde, 2005), and Conditional Predictive Ability (Giacomini & White, 2006), are among the recent ones in the literature. These approaches lack a consistent scoring function such as the FZL function. Even though, the studies of Barendse (2017), Dimitriadis and Bayer (2017), and Couperier and Leymarie (2019) employ a consistent scoring function, their regressions require the specification of covariates which may be arbitrary or complicate the models. Lastly, Taylor (2019)'s study is limited to only the asymmetric Laplace distribution. In this study, we employ the Model Confidence Set (MCS) technique of Hansen et al (2011) to construct a "superior" set of competing (VaR ES) models based on the FZL function of emerging markets (EMs) equities. The MCS follows a sequence of tests to perform the dual task of creating a SSM and ranking the models therein. The null hypothesis of equal predictive ability (EPA) (Diebold & Mariano, 1995) is used to arrive at the SSM. We use the 95% confidence level in selecting SSMs in the MCS procedure.

This study makes important contributions to the literature on emerging markets equities risk analysis. First, this is the first study to model tail risks in emerging markets equities with the joint (VaR, ES) model based on FZL function, hence, conforming to the current regulatory framework (i.e. Basel III). The number of available risk models has never been greater and this intensifies the dilemma of risk managers to ascertain the "best" model while adhering to regulatory requirements. Moreover, it remains a concern for both internal risk managers and regulators to quantify tail risks to safeguard financial catastrophes that may result from inaccurate estimates and forecasts. We offer some novel insights to perform this task using emerging markets equities.

Second, we surmise that risk modelling and selection that are consistent with regulatory standards may bolster confidence in international investor concerning emerging markets equities. One can imagine the prospects of capital flows into EMEs under the circumstance. Third, given that EMEs are prone to episodes of turbulent market dynamics (structural breaks), this study is particularly useful since we perform the analysis across three different market conditions. Emerging markets crises (EMC) period from 3/6/1997 to 10/11/1999, EZC and GFC periods from 5/1/2007 to 7/6/2013, and Post-crisis period from 10/6/2013 to 19/2/2019. The selected sub-samples are supported in the literature as the probable time frames which capture these market dynamics (see Dimitrakopoulos, et al., 2010; Mollah & Mobarek, 2016; Mollah et al., 2016; Mollah et al., 2016). This provides a time-varying assessment of emerging markets risk dynamics and mitigates the problem of model misspecification. Further, we use different distributional innovations to fit the risk models to sidestep single model misspecification tendency as well as improve forecasting performance (Bernardi & Catania, 2016).

Fourth, the study affords an opportunity to classify emerging markets equities portfolios as well diversified or otherwise. It can be inferred from the MCS procedure that equities which exhibit a large SSM size are homogeneous and those with small SSM sizes are heterogeneous. In the context of this study, we define homogeneity (or heterogeneity) as the difference between the models in the initial set of models and the SSM. We take SSMs with at least one half of the initial set of models to be homogeneous. Similarly, we take SSMs with less than one half of the initial set of models to be heterogeneous. Empirically, homogeneity in the SSM is suggestive of well diversified portfolios. This knowledge is useful to inform international investors in asset selection and risk management decision making (see Bernardi & Catania, 2016).

The empirical results show that, about one-third of the equities contain all six (6) initial models in the SSM between percentiles and across the three sub-sample periods. Hence, they exhibit homogeneous risk models, their tail risk models are time-invariant, and percentile-independent. The remaining equities show less homogeneity in the models with SSM of size ranging between five (5) and three (3). These SSMs are also time-varying across the different market episodes as well as percentile-dependent. The Chinese equity stands out as the most heterogeneous as per the SSM sizes, time-varying, and percentile-dependent. These imply that modelling the tail risk of the Chinese equity may be more difficult than the rest and thus makes diversification involving this equity less plausible. In general, the least number of members in the SSM recorded is three and hence indicates a mid-way between homogeneity and heterogeneity in the risk models. Finally, we find that model ranks differ for many markets in the different sub-periods. These suggests the need to be mindful of market dynamics in modelling tail risk when the specific order of model superiority is of importance.

4.2 Theoretical models and empirical methodology

The techniques we have selected appeal to the elicitability of the joint (VaR, ES) model (Gneiting, 2011; Weber, 2006). They allow for model selection, estimation, forecast comparison, and forecast ranking, among others (Fissler et al., 2015). We build the MCS procedure on the same GAS and FZL specifications as presented in Chapter Three. The reader can refer to these specifications accordingly.

4.2.1 The MCS procedure

Because of elicitability of the (VaR, ES) model, the FZL function permits the MCS procedure to construct a SSM and ranks them based on a loss function that satisfies generic weak stationarity conditions (Bernardi & Catania, 2016). Given that more than two models are employed in this study, the MCS benefits from multivariate version of Diebold and Mariano (1995), Mariano and Preve (2012) (MDP) as well as West (1996) to test the null hypothesis of equal predictive ability (EPA).

In formal terms let $r_t, \hat{r}_{i,t}$ denote the log-returns at time t and the output of model i at time t, respectively. Then the loss function

$$\mathcal{L}_{i,t} = \mathcal{L}\big(r_t, \hat{r}_{i,t}\big), \tag{4.1}$$

can be defined as the difference between $\hat{r}_{i,t}$ and r_t. Following González-Rivera et al., (2004) and Bernardi et al., (2017), the FZL loss function (under MCS) can be defined as

$$\ell(r_t, FZL_t^{\tau}) = (\tau - d_t^{\tau})(r_t - FZL_t^{\tau}), \tag{4.2}$$

where FZL_t^{τ} denotes the τ-level predicted FZL at time t, in the filtration $\mathcal{F}_{t-1}$, and $d_t^{\tau} = \mathbb{I}(r_t < FZL_t^{\tau})$ is the τ-level FZL loss function. The MCS algorithm begins with an all-encompassing initial set of alternative models of m −dimension, M^0 at a confidence level α. It then builds $m^* \leq M^0$ set models called the superior set model (SSM). The SSM, $\widehat{M}^*_{1-\alpha}$ contains all models with superior predictive ability as per the selected loss function.

For the model selection, let

$$d_{ij,t} = \ell_{i,t} - \ell_{j,t}, \qquad i,j = 1, \dots, m, \qquad t = 1, \dots, n \tag{4.3}$$

denote the loss differential between models i and j at time t. Also let

$$d_{i.,t} = (m-1)^{-1} \sum_{j \in M} d_{ij,t} \quad i = 1, \dots, m, \tag{4.4}$$

denote the simple loss of model i relative of another model j at time t and M is the number of models. The hypothesis for EPA can be formulated as

$$\begin{gathered} H_{o,M} = c_{i,j} = 0, \qquad \forall\ i,j = 1, \dots, m, \\ H_{A,M} = c_{i,j} \neq 0, \qquad for\ some\ \ i,j = 1, \dots, n, \end{gathered} \tag{4.5}$$

where $c_{i,j} = \mathcal{Z}(d_{i,j})$ is assumed to be finite and time independent. The required the test statistic is

$$t_{i,j} = \frac{\bar{d}_{ij}}{\sqrt{\widehat{var}(\bar{d}_{ij})}}, for\ i,j \in M, \tag{4.6}$$

where $\bar{d}_{ij} = m^{-1} \sum_{t=1}^{m} d_{ij,t}$ denotes the relative sample loss between the ith and jth models, and $\widehat{var}(\bar{d}_{ij})$ is the bootstrapped estimate of $var(\bar{d}_{ij})$. We use the MCS package in R (Bernardi & Catania, 2014) to perform a block-bootstrap with 5000 re-samples. Significant parameters are obtained by fitting an autoregressive ($AR(p)$) process on all $d_{i,j}$ terms with a maximum block length p. Lastly, $H_{o,M}$ naturally fit into the test statistic (Hansen et al., 2011):

$$T_{R,M} = \max_{i,j \in M} |t_{ij}| \tag{4.7}$$

For a complete description of the MCS procedure one may refer to (Bernardi & Catania, 2014, 2016; Hansen & Lunde, 2005; West, 1996; White, 2000).

We follow the empirical evidence that financial returns are skewed and heavy-tailed with-varying variances or volatility clustering (Cajueiro & Tabak, 2005; McNeil & Frey, 2000; McNeil et al., 2015) to select distributions. We use six different asymmetric distributions of fit (VaR, ES) in the GAS model. These are skewed-Gaussian (SNORM), student-t (STD), skewed-student-t (SSTD) (Fernández & Steel, 1998); asymmetric student-t with two tail decay parameters (AST), asymmetric student-t with one tail decay parameter (AST1) (Zhu & Galbraith, 2010, 2011); and asymmetric Laplace distribution (ALD) (Kotz et al., 2012). These distribution have been proven to work in the baseline GAS framework (Benardi & Catania, 2014). For brevity reasons we refer the reader to Chapter Three (sub-section 3.2.3) and the references therein.

4.3 Data, samples periods, and preliminary analysis

We use the daily log-returns ($r_t = lnP_t - lnP_{t-1}$) of all 24 constituents[42] as per the MSCI emerging markets indices from 3/6/1997 to 19/2/2019. The analyses are sub-sampled into three periods, namely; EMEs crises (EMC) from 3/6/1997 to 10/11/1999 involving Asia (1997 - 1998), Russia (1998) and Brazil (1999); Eurozone crisis and GFC (EZC-GFC) between 5/1/2007 and 7/6/2013; and Post-crisis period from 10/6/2013 to 19/2/2019. These represent both stressed (EMC and EZC-GFC) and tranquil (Post-crisis) market periods. The selected sub-samples are supported in the literature (see Dimitrakopoulos et al., 2010; Mollah & Mobarek, 2016; Mollah et al., 2016). Due to the availability of data the coverage for Egypt begins from 1998 while those of Greece start

[42] The list of countries are provided in Appendix 4.1 (Table 4.2).

from 2010. Additionally, Qatar and the United Arab Emirates (UAE) are from 2014. The price data were gleaned from the Bloomberg Terminal.

We choose the estimation and forecasting periods as follows: EMC has M = 386 (3/6/1997 – 15/1/1999) with H = 251 (25/11/1998 – 10/11/1999); EZC-GFC gets M = 1117 (5/1/2007 – 18/4/2011), H = 559 (19/4/2011 – 7/6/2013) while Post-crises has M = 740 (21/11/2014 – 14/7/2017), H = 368 (22/7/2017 – 19/2/2019). We note that M and H denote in-sample and out-of-sample forecast lengths, respectively. The out-of-sample is chosen such that it is a minimum of one year of current observations one-day actual profit or loss. The loss functions are also estimated at the 97.5 and 99 percentiles, as required by the Bank for International Settlements (BIS) (BIS, 2013).

4.3.1 Descriptive statistics

In Figures 4.1 and 4.2 (in Appendix 4.1) we show both the price and log-returns plots of three sub-samples. We see that the fluctuations in the plots are typical of high frequency financial data of daily periodicity. They exhibit varied levels of volatility across sub-sample periods. Log-returns also exhibit volatility clusters which conform to the price fluctuations as expected. Summary statistics show skewness and excess kurtosis values indicating non-normality and leptokurtic behaviour in the equity returns across the board. The mixture of positive (negative) skewness values indicate the possibility of positive (negative) returns to be more than negative (positive) for returns in the different equities between the in-sample and out-of-sample periods. Leptokurtosis also suggests the presence of extreme returns across the board but of different magnitudes. These do not only suggest non-normality in the equities, they also indicate time-varying dynamics.

Further, the Shapiro-Wilk test of normality corroborates these by rejecting the Gaussian assumption at all conventional levels of significance. These go to support the need to use time-varying and asymmetric distributional approaches in modelling the tail risks in the equities.

4.4 Empirical results

In Table 4.1 we present the SSM from Hansen et al. (2011)'s MCS algorithm for both 1% and 2.5% (VaR, ES) forecasts. Individual p-values can be interpreted as the level of belongingness in the SSM. Similarly, overall p-values[43] indicate that the SSM contains true models with a probability no less than $1-\alpha$ ($\alpha = 0.01$ for both 1% and 2.5% (VaR, ES) forecasts). It is interesting to note that the magnitude of p-values does not correspond with the size of SSMs. It implies that the number of true models does not have to be large for the respective equity risk to be sufficiently modelled.

Though the SSM presents both the number of models and their ranks, we focus on the size of the SSM. It provides insight into the extent of heterogeneity and/or homogeneity among the risk models for the respective equities. If SSM contains a larger portion of M^0 then the competing models are statistically significant as regard their forecast ability of (VaR, ES), and vice versa (Bernardi & Catania, 2016). It is worth noting that, the models in the SSM are those characterised by very strong nonlinear dynamics for the conditional volatility process.

Our SSMs reveal that some equities exhibit time- and percentile-invariant SSMs (with respect to the number of models in the SSM rather than the rank of the models) across the three sub-sample

[43] P-values were evaluated using 5000 bootstrap replications.

periods. That is, they have the same number of models in the SSM and is mostly large. The following equities contain the original set of models M^0 across the board; Brazil, Colombia, Mexico, Turkey, India, and Pakistan. We can view these equities to be robust different market conditions as they remain unchanged over the three sub-samples. We further note that they also exhibit the highest level of homogeneity in terms of risk models and that makes for less difficulty for risk managers.

All remaining equities exhibit varying levels of model homogeneity/heterogeneity and are both time- and percentile-dependent. For example, Chile, Russia, South Africa, Peru, Czech Republic, Hungary, Poland, Indonesia (5)[44], South Korea, and Taiwan (4) have SSMs of size six (6) in the EMC period, with very similar patterns in the EZC-GFC periods. Furthermore, in the Post-crisis period we find Czech Republic, Egypt, Greece, Hungary, Russia, South Africa (4), UAE (4), Indonesia (4), Malaysia, Taiwan, and Thailand equally have size 6 in their SSMs. But in the EMC period Philippines and Thailand show size 5 SSMs. These scenarios show slight differences in SSMs per equity amongst the sub-samples as well as between the two percentile levels.

However, a few equities exhibit some peculiar dynamics which are worth our attention. For instance, while risk models in Malaysia are homogeneous in the EZC-GFC and Post-crisis period, they are rather heterogeneous (SSM of size 3 (4 at 97.5% level) in the EMC period. This situation connotes some level of difficulty in sampling large models that can adequately forecast Malaysian equity risks when financial market crisis is limited to EMEs. A similar analogy can be made for Hungary, Russia, and South Africa in the EZC-GFC periods. For Poland, model homogeneity turns

[44] The number in parenthesis after the equity name is the size of the SSM at the 97.5 percentile.

from not so good in EZC-GFC periods to bad in Post-crisis period. Additionally, Egypt has SSM of size 4 in EZC-GFC period as compared to 6 in Post-crisis period. Again, this can be attributed to crisis effect as well. But Qatar (only captured in Post-crisis period) shows less homogeneity (i.e. size 4 SSM). Ironically, Chile and South Korea record their most heterogeneous model levels in the tranquil Post-crisis period. Lastly, China shows almost a consistent pattern of deviating from all other equities across the three market periods. However, it not have model homogeneity in the Post-crisis period at the 97.5% level. We record SSM sizes 5 (4), 4 (3), and 4 (6) during EMC, EZC-GFC, and Post-crisis periods, respectively, for China. Hence, we see a clear time-varying and percentile-dependent dynamics at work in the Chinese equity risk forecasting. However, time-varying, the SSMs are not hugely different in size across the sub-sample periods hence it is difficult to account for the cause of these phenomena. Nonetheless, it is clear that tail risk modelling in the Chinese equity may be the most difficult of all the equities in this study.

We surmise from the results that the ease/difficulty with which to model tail risk does not depend on the actual conditions of the financial markets for any particular equity except for those that are both time- and percentile-invariant and homogeneous. Bernardi and Catania (2016) found similar results in using the MCS algorithm to compare VaR models of four major global stock indices (i.e. Asia/Pacific 600, North America 600, Europe 600, and Global 1800). It follows that risk managers would prefer a SSM with a size closer to M^0 to those that are not. The latter shows that models are statistically equivalent in their (VaR, ES) forecasting abilities and thus reduce the task of finding the singular best model. Moreover, given that SSMs are ranked, risk manager are at ease of choosing the best ranked model for their equities.

Furthermore, that many of the SSMs are independent of market conditions is instructive for tail risk modelling for those equities. That is to say each EM equity may have to be subjected to the rigour of tail risk modelling, irrespective of the market condition. This brings to the fore an important difference and/or similarity amongst emerging markets. We evidence that despite the fact that EMEs are bracketed into one market class, the tail risks in their equities couldn't be more different. A fallout of this revelation is that portfolio diversifications benefits involving emerging markets equities are possible and that right combinations are likely to yield the needed results.

Empirically, the homogeneity in the SSM is suggestive of well diversified portfolios for the respective equity, given that different distributional assumptions are applied to the returns. This applies to all the equities with both time- and percentile-invariant and homogeneous risk models. Bernardi and Catania (2016) opine that, the fact that diversified portfolios are characterised by inversely related risks and returns properties, so does diversification mitigate against negative and positive tail events that affect conditional distribution and kurtosis of equity returns. Finally, given the mixture of both large and small markets, we do not find any pattern according to market size. Neither SSMs sizes nor ordering of models is market size dependent.

Table 4.1: SSM of univariate GAS (VaR, ES) model forecasts per market

Emerging markets crisis (EMC) period: 25/11/1998 to 10/11/1999

Model	**$Rank_{R,M}$**	**t_{ij}**	**p-$value_{R,M}$**	**$Rank_{max,M}$**	**t_i**	**p-$value_{max,M}$**	**Loss**	**Model**	**$Rank_{R,M}$**	**t_{ij}**	**p-$value_{R,M}$**	**$Rank_{max,M}$**	**t_i**	**p-$value_{max,M}$**	**Loss**
	Brazil 1%							**Brazil 2.5%**							
snorm	4	0.44	0.95	5	2.79	0.03	-2.62	snorm	4	0.44	0.95	5	2.79	0.03	-2.62
std	5	0.55	0.91	2	2.11	0.18	-2.60	std	5	0.55	0.91	2	2.11	0.18	-2.60
sstd	1	-5.53	1.00	1	-2.11	1.00	-2.74	sstd	1	-5.53	1.00	1	-2.11	1.00	-2.74
ast	3	-0.29	1.00	4	2.65	0.05	-2.64	ast	3	-0.29	1.00	4	2.65	0.05	-2.64
ast1	2	-0.29	1.00	3	2.28	0.18	-2.64	ast1	2	-0.29	1.00	3	2.28	0.18	-2.64
ald	6	1.63	0.23	6	4.68	0.00	-2.55	ald	6	1.63	0.23	6	4.68	0.00	-2.55
P-value	**0.234**							**P-value**	**0.271**						
	Chile 1%							**Chile 2.5%**							
snorm	2	-1.73	1.00	2	0.74	0.89	-3.38	snorm	2	-1.77	1.00	3	1.10	0.74	-3.56
std	1	-2.90	1.00	1	-0.74	1.00	-3.44	std	1	-3.60	1.00	1	-1.09	1.00	-3.63
sstd	3	-1.55	1.00	3	1.32	0.42	-3.37	sstd	3	-1.77	1.00	2	1.09	0.75	-3.56
ast	5	1.54	0.16	6	2.20	0.09	-2.96	ast	5	1.99	0.07	4	2.81	0.04	-3.22
ast1	6	1.54	0.16	5	2.20	0.17	-2.96	ast1	6	1.99	0.07	5	2.81	0.04	-3.22
ald	4	-0.14	1.00	4	1.94	0.17	-3.25	ald	4	-0.47	1.00	6	3.61	0.00	-3.48
P-value	**0.161**							**P-value**	**0.065**						
	Colombia 1%							**Colombia 2.5%**							
snorm	4	0.75	0.74	3	1.37	0.66	-2.46	snorm	4	0.28	0.97	2	1.46	0.44	-2.78
std	3	-0.64	1.00	4	1.46	0.46	-2.57	std	3	-0.97	1.00	4	1.96	0.21	-2.82
sstd	1	-1.77	1.00	2	0.85	1.00	-2.61	sstd	2	-1.89	1.00	3	1.51	0.44	-2.85
ast	6	1.28	0.40	6	1.57	0.40	-2.40	ast	5	2.36	0.05	5	2.42	0.07	-2.66
ast1	5	1.28	0.40	5	1.49	0.46	-2.40	ast1	6	2.36	0.05	6	2.42	0.07	-2.66
ald	2	-1.18	1.00	1	-0.85	1.00	-2.78	ald	1	-2.04	1.00	1	-1.46	1.00	-2.98
P-value	**0.400**							**P-value**	**0.049**						
	Mexico 1%							**Mexico 2.5%**							
snorm	3	-1.09	1.00	4	2.11	0.13	-2.69	snorm	4	-0.24	1.00	6	3.64	0.00	-2.89
std	2	-2.59	1.00	1	-0.34	1.00	-2.80	std	1	-3.35	1.00	1	-0.62	1.00	-3.00
sstd	1	-2.74	1.00	3	1.09	0.77	-2.76	sstd	2	-2.76	1.00	5	2.57	0.04	-2.96
ast	5	1.88	0.10	5	2.18	0.11	-2.45	ast	6	1.95	0.08	4	2.49	0.05	-2.77

Table 4.2 (Cont.)

Model	Rank$_{R,M}$	t_{ij}	p-value$_{R,M}$	Rank$_{max,M}$	t_i	p-value$_{max,M}$	Loss	Model	Rank$_{R,M}$	t_{ij}	p-value$_{R,M}$	Rank$_{max,M}$	t_i	p-value$_{max,M}$	Loss
ast1	6	1.88	0.10	6	2.18	0.11	-2.45	ast1	5	1.95	0.08	3	2.49	0.95	-2.77
ald	4	-0.78	1.00	2	0.34	0.99	-2.76	ald	3	-0.90	1.00	2	0.62	0.95	-2.96
P-value	**0.100**							**P-value**	0.085						
	Peru 1%							**Peru 2.5%**							
snorm	4	-0.54	1.00	6.00	3.27	0.01	-2.86	snorm	4	-0.31	1.00	6	3.18	0.01	-3.16
std	2	-2.04	1.00	2.00	0.02	1.00	-3.10	std	1	-2.64	1.00	1	-0.72	1.00	-3.38
sstd	1	-2.28	1.00	3.00	0.52	0.98	-3.06	sstd	2	-2.61	1.00	3	1.82	0.34	-3.28
ast	6	1.79	0.10	5.00	2.88	0.03	-2.28	ast	6	2.03	0.06	5	2.31	0.12	-2.80
ast1	5	1.79	0.10	4.00	1.95	0.98	-2.28	ast1	5	2.03	0.06	4	2.31	0.34	-2.80
ald	3	-1.59	1.00	1.00	-0.02	1.00	-3.10	ald	3	-2.17	1.00	2	0.72	0.96	-3.33
P-value	**0.099**							**P-value**	**0.064**						
	Czech Republic 1%							**Czech Republic 2.5%**							
snorm	4	-1.23	1.00	4	1.04	0.84	-2.84	snorm	4	-0.52	1.00	4	1.44	0.53	-3.05
std	2	-1.76	1.00	3	0.50	0.99	-2.85	std	1	-2.24	1.00	2	0.20	1.00	-3.14
sstd	1	-1.80	1.00	2	0.46	1.00	-2.87	sstd	3	-1.50	1.00	3	1.37	0.58	-3.09
ast	6	1.93	0.09	6	3.85	0.00	-2.23	ast	5	1.64	0.21	5	1.96	0.24	-2.75
ast1	5	1.93	0.09	5	2.00	0.84	-2.23	ast1	6	1.64	0.21	6	1.96	0.24	-2.75
ald	3	-1.75	1.00	1	-0.46	1.00	-2.94	ald	2	-1.75	1.00	1	-0.20	1.00	-3.15
P-value	**0.087**							**P-value**	**0.205**						
	Hungary 1%							**Hungary 2.5%**							
snorm	4	-0.49	1.00	3	0.87	0.86	-2.46	snorm	4	-0.02	1.00	3	1.44	0.47	-2.71
std	1	-3.75	1.00	2	0.16	1.00	-2.58	std	1	-4.78	1.00	1	-0.71	1.00	-2.93
sstd	2	-3.19	1.00	5	2.22	0.08	-2.53	sstd	2	-3.94	1.00	6	3.70	0.00	-2.87
ast	6	1.52	0.20	6	2.84	0.01	-1.75	ast	6	1.55	0.19	5	3.11	0.01	-2.44
ast1	5	1.52	0.20	4	2.02	0.86	-1.75	ast1	5	1.55	0.19	4	2.39	0.47	-2.44
ald	3	-1.35	1.00	1	-0.16	1.00	-2.61	ald	3	-1.30	1.00	2	0.71	0.91	-2.86
P-value	**0.197**							**P-value**	**0.189**						

Table 4.3 (Cont.)

Model	**Rank$_{R,M}$**	**t_{ij}**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t_i**	**p-value$_{max,M}$**	**Loss**	**Model**	**Rank$_{R,M}$**	**t_{ij}**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t_i**	**p-value$_{max,M}$**	**Loss**
	Poland 1%							**Poland 2.5%**							
snorm	2	-2.02	1.00	2	0.25	0.99	-2.75	snorm	3	-1.84	1.00	2	0.56	0.97	-2.97
std	1	-3.84	1.00	1	-0.25	1.00	-2.76	std	1	-3.75	1.00	1	-0.56	1.00	-2.98
sstd	3	-1.76	1.00	3	0.50	0.92	-2.75	sstd	2	-1.93	1.00	3	0.68	0.95	-2.97
ast	6	0.93	0.53	5	1.73	0.25	-2.60	ast	6	1.03	0.45	5	1.66	0.34	-2.85
ast1	5	0.93	0.53	4	1.56	0.92	-2.60	ast1	5	1.03	0.45	4	1.66	0.95	-2.85
ald	4	0.75	0.66	6	2.08	0.11	-2.61	ald	4	0.71	0.65	6	2.57	0.04	-2.87
P-value	**0.534**							**P-value**	**0.448**						
	Russia 1%							**Russia 2.5%**							
snorm	3	-1.64	1.00	2	0.58	0.96	-1.76	snorm	3	-1.50	1.00	1	-0.20	1.00	-2.09
std	2	-2.05	1.00	4	1.32	0.60	-1.66	std	2	-1.76	1.00	4	1.32	0.61	-2.03
sstd	1	-2.31	1.00	3	0.83	0.96	-1.71	sstd	1	-2.18	1.00	3	0.86	1.00	-2.05
ast	6	1.83	0.10	6	2.02	0.16	-1.27	ast	6	1.55	0.20	6	1.93	0.22	-1.88
ast1	5	1.83	0.10	5	2.02	0.60	-1.27	ast1	5	1.55	0.20	5	1.75	0.61	-1.88
ald	4	-1.37	1.00	1	-0.58	1.00	-1.84	ald	4	-1.00	1.00	2	0.20	1.00	-2.08
P-value	**0.097**							**P-value**	**0.202**						
	South Africa 1%							**South Africa 2.5%**							
snorm	4	0.01	1.00	6	2.69	0.02	-2.91	snorm	4	0.87	0.59	6	3.70	0.00	-3.07
std	1	-2.74	1.00	3	1.58	0.37	-3.02	std	2	-3.70	1.00	3	0.90	0.81	-3.23
sstd	2	-2.64	1.00	2	0.05	1.00	-3.05	sstd	1	-3.82	1.00	2	0.37	1.00	-3.24
ast	6	1.27	0.35	5	1.74	0.27	-2.70	ast	6	0.95	0.55	5	2.94	0.01	-3.07
ast1	5	1.27	0.35	4	1.74	0.37	-2.70	ast1	5	0.95	0.55	4	1.73	0.81	-3.07
ald	3	-1.10	1.00	1	-0.05	1.00	-3.06	ald	3	-1.31	1.00	1	-0.37	1.00	-3.27
P-value	**0.347**							**P-value**	**0.546**						
	Turkey 1%							**Turkey 2.5%**							
snorm	3	-1.48	1.00	2	0.55	1.00	-2.35	snorm	3	-1.74	1.00	3	1.33	0.54	-2.51
std	4	0.68	0.64	3	1.35	0.56	-1.78	std	4	-0.16	1.00	2	1.33	0.55	-2.25

Table 4.4 (Cont.)

Model	**Rank$_{R,M}$**	**t$_{ij}$**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t$_{i}$**	**p-value$_{max,M}$**	**Loss**	**Model**	**Rank$_{R,M}$**	**t$_{ij}$**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t$_{i}$**	**p-value$_{max,M}$**	**Loss**
sstd	2	-1.50	1.00	1	-0.55	1.00	-2.35	sstd	2	-1.85	1.00	1	-1.33	1.00	-2.52
ast	6	1.60	0.11	6	1.77	0.17	-1.30	ast	6	2.25	0.04	6	2.91	0.01	-1.91
ast1	5	1.60	0.11	5	1.77	0.51	-1.30	ast1	5	2.25	0.04	5	2.91	0.46	-1.91
ald	1	-1.52	1.00	4	1.41	0.51	-2.03	ald	1	-2.28	1.00	4	1.44	0.46	-2.34
P-value	**0.11**							**P-value**	**0.039**						
	China 1%							**China 2.5%**							
std	4	-0.21	1.00	4	0.23	0.98	-2.63	std	1	-0.52	1.00	1	-0.45	1.00	-2.84
sstd	1	-1.08	1.00	2	0.11	1.00	-2.64	sstd	2	0.04	1.00	4	0.54	0.87	-2.82
ast	3	-0.98	1.00	1	-0.11	1.00	-2.65	ast	3	0.33	0.89	2	0.45	0.91	-2.81
ast1	2	-0.98	1.00	3	0.16	0.99	-2.65	ast1	4	0.33	0.89	3	0.45	0.91	-2.81
ald	5	1.81	0.11	5	3.11	0.00	-2.50								
P-value	**0.106**							**P-value**	**0.893**						
	India 1%							**India 2.5%**							
snorm	3	-0.94	1.00	3	0.93	0.78	-3.01	snorm	2	-0.98	1.00	4	1.48	0.49	-3.15
std	1	-2.91	1.00	1	-0.93	1.00	-3.10	std	1	-3.27	1.00	1	-1.40	1.00	-3.23
sstd	2	-0.96	1.00	2	0.93	0.78	-3.01	sstd	3	-0.89	1.00	3	1.44	0.51	-3.15
ast	6	1.29	0.30	6	2.17	0.10	-2.76	ast	5	1.48	0.22	5	2.11	0.15	-2.94
ast1	5	1.29	0.30	5	1.95	0.78	-2.76	ast1	6	1.48	0.22	6	2.11	0.15	-2.94
ald	4	-0.43	1.00	4	0.96	0.78	-3.00	ald	4	-0.78	1.00	2	1.40	0.54	-3.15
P-value	**0.303**							**P-value**	**0.221**						
	Indonesia 1%							**Indonesia 2.5%**							
snorm	6	2.08	0.05	6	8.96	0.00	-1.83	std	1	-2.67	1.00	1	-1.13	1.00	-2.38
std	1	-3.88	1.00	1	-1.68	1.00	-2.24	sstd	2	-0.56	1.00	5	4.11	0.00	-2.31
sstd	2	-3.09	1.00	4	2.53	0.05	-2.15	ast	5	0.96	0.44	4	3.23	0.00	-2.23
ast	5	0.69	0.71	5	3.09	0.01	-1.95	ast1	4	0.96	0.44	3	1.56	0.66	-2.23
ast1	4	0.69	0.71	2	1.68	1.00	-1.95	ald	3	-0.29	1.00	2	1.13	0.66	-2.32
ald	3	-0.75	1.00	3	1.78	0.32	-2.11								
P-value	**0.049**							**P-value**	**0.438**						

Table 4.5 (Cont.)

Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss	Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss
	South Korea 1%							**South Korea 2.5%**							
snorm	2	-3.34	1.00	4	2.23	0.11	-2.43	snorm	2	-1.25	1.00	5	1.97	0.22	-2.58
std	1	-5.04	1.00	1	-0.96	1.00	-2.45	std	1	-3.31	1.00	1	-1.44	1.00	-2.61
sstd	3	-0.92	1.00	6	5.53	0.00	-2.41	sstd	3	0.21	0.98	6	4.77	0.00	-2.56
ast	4	-0.38	1.00	2	0.96	0.83	-2.41	ast	5	0.58	0.80	3	1.44	0.52	-2.55
ast1	5	-0.38	1.00	3	0.96	0.83	-2.41	ast1	4	0.58	0.80	2	1.44	1.00	-2.55
ald	6	2.44	0.01	5	4.02	0.00	-2.30	ald	6	0.59	0.79	4	1.86	0.26	-2.54
P-value	**0.014**							**P-value**	**0.788**						
	Malaysia 1%							**Malaysia 2.5%**							
std	3	2.00	0.04	2	2.00	1.00	-2.59	std	3	0.99	0.37	2	1.29	1.00	-2.74
ast	2	-2.00	1.00	3	2.71	0.02	-2.73	sstd	4	2.11	0.04	3	1.94	0.14	-2.70
ast1	1	-2.00	1.00	1	-2.00	1.00	-2.73	ast	2	-1.58	1.00	4	2.67	0.03	-2.84
								ast1	1	-1.58	1.00	1	-1.29	1.00	-2.84
P-value	**0.041**							**P-value**	**0.042**						
	Pakistan 1%							**Pakistan 2.5%**							
snorm	4	-0.95	1.00	1	-0.20	1.00	-2.37	snorm	4	-0.78	1.00	3	0.55	0.95	-2.61
std	2	-1.54	1.00	4	1.31	0.56	-2.09	std	2	-2.08	1.00	4	0.58	0.94	-2.60
sstd	1	-2.31	1.00	3	0.51	1.00	-2.20	sstd	1	-2.66	1.00	2	0.41	1.00	-2.62
ast	6	1.32	0.26	6	2.63	0.03	-0.92	ast	6	1.47	0.19	6	1.73	0.27	-1.91
ast1	5	1.32	0.26	5	1.53	0.56	-0.92	ast1	5	1.47	0.19	5	1.73	0.94	-1.91
ald	3	-1.26	1.00	2	0.20	1.00	-2.33	ald	3	-1.47	1.00	1	-0.41	1.00	-2.67
P-value	**0.258**							**P-value**	**0.193**						
	Philippines 1%							**Philippines 2.5%**							
std	1	-0.86	1.00	1	-0.16	1.00	-2.98	std	1	-0.69	1.00	1	-0.09	1.00	-3.14
sstd	4	-0.22	1.00	4	15.40	0.00	-2.93	sstd	4	0.05	0.99	5	8.20	0.00	-3.09
ast	3	-0.31	1.00	3	1.09	0.69	-2.95	ast	3	-0.28	1.00	3	1.44	0.42	-3.12
ast1	2	-0.31	1.00	2	0.16	1.00	-2.95	ast1	2	-0.28	1.00	2	0.09	1.00	-3.12
ald	5	1.99	0.05	5	22.70	0.00	-2.75	ald	5	1.33	0.20	4	6.82	0.00	-3.00

Table 4.6 (Cont.)

Model	$Rank_{R,M}$	t_{ij}	p-$value_{R,M}$	$Rank_{max,M}$	t_i	p-$value_{max,M}$	Loss	Model	$Rank_{R,M}$	t_{ij}	p-$value_{R,M}$	$Rank_{max,M}$	t_i	p-$value_{max,M}$	Loss
P-value	**0.048**							**P-value**	**0.197**						
	Taiwan 1%							**Taiwan 2.5%**							
snorm	3	-1.57	1.00	2	0.16	1.00	-2.90	snorm	2	-1.14	1.00	2	0.62	1.00	-3.09
std	1	-4.36	1.00	1	-0.16	1.00	-2.92	std	3	0.57	0.77	3	0.87	0.77	-3.04
sstd	2	-1.61	1.00	3	0.42	0.95	-2.90	sstd	1	-1.18	1.00	1	-0.62	1.00	-3.09
ast	5	2.51	0.02	5	3.34	0.00	-2.40	ald	4	1.20	0.35	4	1.28	0.51	-3.02
ast1	6	2.51	0.02	6	3.34	0.00	-2.40								
ald	4	-1.29	1.00	4	1.16	0.70	-2.82								
P-value	**0.019**							**P-value**	**0.348**						
	Thailand 1%							**Thailand 2.5%**							
snorm	5	2.25	0.02	5	769.31	0.00	-2.30	snorm	5	2.34	0.02	5	1342.78	0.00	-2.46
std	1	-3.42	1.00	1	-0.24	1.00	-2.50	std	1	-4.20	1.00	1	-0.59	1.00	-2.68
sstd	4	1.82	0.07	4	5.60	0.00	-2.32	sstd	4	1.57	0.13	4	5.49	0.00	-2.50
ast	3	-1.01	1.00	3	1.72	0.24	-2.48	ast	3	-0.81	1.00	3	2.47	0.04	-2.63
ast1	2	-1.01	1.00	2	0.24	1.00	-2.48	ast1	2	-0.81	1.00	2	0.59	1.00	-2.63
P-value	**0.021**							**P-value**	**0.021**						
Eurozone and Global Financial Crises (EZC-GFC) periods: 19/4/2011 to 7/6/2013															
	Brazil 1%							**Brazil 2.5%**							
snorm	2	-1.98	1.00	1	-1.20	1.00	-3.05	snorm	3	-1.43	1.00	2	0.06	1.00	-3.16
std	3	-1.50	1.00	2	1.20	0.74	-2.93	std	1	-2.56	1.00	1	-0.06	1.00	-3.16
sstd	1	-2.23	1.00	3	1.20	0.74	-2.97	sstd	2	-2.49	1.00	3	0.78	0.94	-3.13
ast	6	1.81	0.11	4	1.95	0.18	-2.51	ast	6	1.95	0.08	6	2.54	0.06	-2.89
ast1	5	1.81	0.11	5	1.95	0.18	-2.51	ast1	5	1.95	0.08	5	2.32	0.51	-2.89
ald	4	-1.12	1.00	6	4.05	0.00	-2.96	ald	4	-1.15	1.00	4	1.48	0.51	-3.13
P-value	**0.105**							**P-value**	**0.084**						
	Chile 1%							**Chile 2.5%**							
snorm	4	-0.60	1.00	4	2.04	0.20	-2.98	snorm	3	2.13	0.07	3	2.35	0.07	-3.21
std	1	-3.42	1.00	2	0.97	0.85	-3.15	std	2	-1.40	1.00	2	1.21	0.56	-3.32
sstd	3	-1.86	1.00	3	2.01	0.21	-3.00	sstd	4	2.87	0.01	4	2.76	0.03	-3.22
ast	6	2.89	0.01	6	3.44	0.01	-2.59	ald	1	-2.22	1.00	1	-1.21	1.00	-3.38

Table 4.7 (Cont.)

Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss	Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss
ast1	5	2.89	0.01	5	3.44	0.20	-2.59								
ald	2	-2.48	1.00	1	-0.97	1.00	-3.26								
P-value	**0.010**							**P-value**	**0.013**						
	Colombia 1%							**Colombia 2.5%**							
snorm	4	-0.85	1.00	6	2.99	0.01	-3.16	snorm	4	0.09	1.00	6	4.18	0.00	-3.32
std	2	-2.53	1.00	3	1.06	0.76	-3.23	std	2	-4.00	1.00	1	-0.46	1.00	-3.51
sstd	1	-3.52	1.00	1	-0.31	1.00	-3.29	sstd	1	-4.35	1.00	2	0.46	0.99	-3.50
ast	6	2.21	0.04	5	2.64	0.03	-2.67	ast	6	2.38	0.03	5	3.18	0.01	-3.08
ast1	5	2.21	0.04	4	2.64	0.76	-2.67	ast1	5	2.38	0.03	4	3.13	0.99	-3.08
ald	3	-1.83	1.00	2	0.31	1.00	-3.27	ald	3	-2.39	1.00	3	0.46	0.99	-3.48
P-value	**0.041**							**P-value**	**0.030**						
	Mexico 1%							**Mexico 2.5%**							
snorm	2	-1.32	1.00	1	-0.29	1.00	-3.17	snorm	4	-0.77	1.00	4	0.10	1.00	-3.32
std	4	0.13	1.00	4	1.17	0.71	-3.05	std	2	-1.17	1.00	1	-0.09	1.00	-3.33
sstd	1	-2.96	1.00	3	0.59	1.00	-3.13	sstd	1	-3.47	1.00	3	0.10	1.00	-3.32
ast	6	1.43	0.29	6	2.15	0.13	-2.93	ast	6	1.68	0.22	6	2.12	0.16	-3.21
ast1	5	1.43	0.29	5	1.81	0.71	-2.93	ast1	5	1.68	0.22	5	2.12	1.00	-3.21
ald	3	-0.93	1.00	2	0.29	1.00	-3.15	ald	3	-0.87	1.00	2	0.09	1.00	-3.32
P-value	**0.292**							**P-value**	**0.223**						
	Peru 1%							**Peru 2.5%**							
snorm	4	-0.60	1.00	4	1.19	0.67	-2.46	snorm	4	1.64	0.17	4	2.53	0.04	-2.80
std	2	-3.69	1.00	3	1.17	0.69	-2.55	std	3	-0.20	1.00	3	0.92	0.76	-2.96
sstd	1	-5.03	1.00	2	0.56	1.00	-2.63	sstd	2	-0.92	1.00	2	0.77	1.00	-2.99
ast	6	2.68	0.01	6	3.82	0.00	-1.68	ald	1	-2.42	1.00	1	-0.77	1.00	-3.05
ast1	5	2.68	0.01	5	3.60	0.67	-1.68								
ald	3	-2.42	1.00	1	-0.56	1.00	-2.72								
P-value	**0.099**							**P-value**	**0.170**						

Table 4.8 (Cont.)

Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss	Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss
	Czech Republic 1%								**Czech Republic 2.5%**						
snorm	3	-2.47	1.00	2	0.58	0.96	-2.82	snorm	3	1.27	0.33	3	1.92	0.17	-3.04
std	2	-3.14	1.00	4	1.00	0.76	-2.79	std	2	1.21	0.35	2	1.69	0.27	-3.02
sstd	1	-4.09	1.00	3	0.90	0.96	-2.79	sstd	4	2.20	0.06	4	2.01	0.14	-3.02
ast	6	2.60	0.02	6	3.00	0.02	-2.41	ald	1	-1.89	1.00	1	-1.69	1.00	-3.13
ast1	5	2.60	0.02	5	3.00	0.76	-2.41								
ald	4	-1.47	1.00	1	-0.58	1.00	-2.90								
P-value	**0.016**							**P-value**	**0.055**						
	Egypt 1%								**Egypt 2.5%**						
snorm	1	-2.42	1.00	1	-2.10	1.00	-2.76	snorm	1	-2.04	1.00	1	-1.67	1.00	-2.94
std	3	1.37	0.24	2	2.10	0.10	-2.19	std	3	0.68	0.69	2	1.67	0.24	-2.72
sstd	4	2.64	0.01	4	2.57	0.03	-1.88	sstd	4	2.52	0.02	4	2.72	0.02	-2.52
ald	2	-1.94	1.00	3	2.26	0.06	-2.51	ald	2	-1.84	1.00	3	1.72	0.22	-2.82
P-value	**0.014**							**P-value**	**0.018**						
	Hungary 1%								**Hungary 2.5%**						
snorm	4	1.36	0.31	3	2.51	0.05	-2.55	snorm	3	2.15	0.05	3	2.45	0.03	-2.74
std	1	-2.27	1.00	1	-0.56	1.00	-2.68	std	1	-1.57	1.00	1	-0.29	1.00	-2.82
sstd	3	0.95	0.56	4	2.84	0.02	-2.58	ald	2	-0.68	1.00	2	0.29	0.96	-2.81
ald	2	-0.24	1.00	2	0.56	0.94	-2.63								
P-value	**0.313**							**P-value**	**0.046**						
	Poland 1%								**Poland 2.5%**						
snorm	4	1.26	0.37	3	2.76	0.03		snorm	3	2.16	0.06	3	2.79	0.02	-2.76
std	1	-5.26	1.00	1	-0.75	1.00		std	1	-3.79	1.00	1	-0.27	1.00	-3.02
sstd	3	0.51	0.89	4	3.39	0.01		sstd	4	2.65	0.02	4	3.69	0.00	-2.81
ast1	5	2.99	0.01	5	4.19	0.00		ald	2	-1.64	1.00	2	0.27	0.99	-3.00
ald	2	-1.81	1.00	2	0.75	0.87									
P-value	**0.011**							**P-value**	**0.017**						

Table 4.9 (Cont.)

Model	**Rank$_{R,M}$**	**t$_{ij}$**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t$_{i}$**	**p-value$_{max,M}$**	**Loss**	**Model**	**Rank$_{R,M}$**	**t$_{ij}$**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t$_{i}$**	**p-value$_{max,M}$**	**Loss**
	Russia 1%							**Russia 2.5%**							
snorm	2	-1.11	1.00	2	0.89	0.79	-2.69	snorm	2	-0.21	1.00	3	1.63	0.32	-2.88
std	3	1.08	0.44	3	1.37	0.47	-2.60	std	3	0.54	0.83	2	1.32	0.51	-2.86
sstd	4	2.06	0.06	4	1.83	0.22	-2.54	sstd	4	1.89	0.10	4	2.22	0.09	-2.82
ald	1	-1.50	1.00	1	-0.89	1.00	-2.76	ald	1	-1.78	1.00	1	-1.32	1.00	-2.93
P-value	**0.059**							**P-value**	**0.095**						
	South Africa 1%							**South Africa 2.5%**							
snorm	1	-0.96	1.00	2	0.17	1.00	-2.92	snorm	3	1.54	0.18	3	1.51	0.29	-3.03
std	3	0.56	0.86	3	0.80	0.84	-2.86	std	2	-0.16	1.00	2	0.54	0.85	-3.07
sstd	4	1.19	0.43	4	1.61	0.34	-2.85	ald	1	-1.10	1.00	1	-0.54	1.00	-3.10
ald	2	-0.66	1.00	1	-0.17	1.00	-2.93								
P-value	**0.425**							**P-value**	**0.180**						
	Turkey 1%							**Turkey 2.5%**							
snorm	4	0.65	0.76	6	4.24	0.00	-2.57	snorm	4	1.47	0.26	6	6.08	0.00	-2.80
std	1	-3.10	1.00	1	-0.79	1.00	-2.87	std	1	-4.64	1.00	1	-1.52	1.00	-3.13
sstd	2	-2.88	1.00	3	0.91	0.93	-2.82	sstd	2	-3.62	1.00	3	2.03	0.21	-3.04
ast	6	1.96	0.09	5	2.97	0.01	-2.36	ast	6	2.26	0.05	5	3.91	0.00	-2.72
ast1	5	1.96	0.09	4	2.60	0.93	-2.36	ast1	5	2.26	0.05	4	3.39	0.21	-2.72
ald	3	-1.59	1.00	2	0.79	0.96	-2.79	ald	3	-2.50	1.00	2	1.52	0.52	-3.05
P-value	**0.086**							**P-value**	**0.046**						
	China 1%							**China 2.5%**							
snorm	1	-0.52	1.00	1	-0.09	1.00	-3.06	snorm	3	1.03	0.44	3	0.96	0.60	-3.21
std	3	-0.27	1.00	3	0.14	1.00	-3.04	std	2	-0.30	1.00	2	0.13	0.99	-3.24
sstd	4	1.41	0.30	4	1.43	0.45	-2.98	ald	1	-0.57	1.00	1	-0.13	1.00	-3.25
ald	2	-0.34	1.00	2	0.09	1.00	-3.05								
P-value	**0.300**							**P-value**	**0.443**						

Table 4.10 (Cont.)

Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss	Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss
	India 1%								**India 2.5%**						
snorm	4	0.23	0.97	6	4.31	0.00	-2.90	snorm	4	0.86	0.62	6	6.23	0.00	-3.08
std	1	-5.01	1.00	1	-1.44	1.00	-3.17	std	1	-5.55	1.00	1	-1.23	1.00	-3.33
sstd	2	-3.92	1.00	3	1.59	0.39	-3.08	sstd	2	-4.11	1.00	3	2.43	0.07	-3.22
ast	6	2.17	0.06	4	3.33	0.01	-2.66	ast	6	2.62	0.02	4	4.03	0.00	-2.95
ast1	5	2.17	0.06	5	3.33	0.01	-2.66	ast1	5	2.62	0.02	5	4.03	0.00	-2.95
ald	3	-1.31	1.00	2	1.44	0.49	-3.06	ald	3	-2.66	1.00	2	1.23	0.64	-3.28
P-value	**0.061**							**P-value**	**0.016**						
	Indonesia 1%								**Indonesia 2.5%**						
snorm	6	1.95	0.12	6	2.82	0.03	-2.71	std	1	-4.06	1.00	1	-2.09	1.00	-3.35
std	1	-3.32	1.00	1	-0.98	1.00	-3.12	sstd	2	-0.62	1.00	3	2.38	0.07	-3.25
sstd	2	-1.16	1.00	3	2.08	0.18	-2.98	ast	5	1.64	0.22	5	3.05	0.01	-3.16
ast	5	0.76	0.81	5	2.33	0.11	-2.85	ast1	4	1.64	0.22	4	3.05	0.07	-3.16
ast1	4	0.76	0.81	4	2.33	0.18	-2.85	ald	3	0.11	1.00	2	2.09	0.15	-3.22
ald	3	-0.70	1.00	2	0.98	0.86	-2.99								
P-value	**0.123**							**P-value**	**0.224**						
	South Korea 1%								**South Korea 2.5%**						
snorm	4	-0.86	1.00	3	1.07	0.81	-2.87	snorm	4	-0.98	1.00	3	1.28	0.66	-3.05
std	1	-2.95	1.00	1	-0.46	1.00	-2.99	std	1	-3.53	1.00	1	-0.92	1.00	-3.14
sstd	2	-1.73	1.00	4	1.54	0.48	-2.88	sstd	3	-1.53	1.00	4	2.37	0.10	-3.04
ast	6	1.98	0.09	6	2.52	0.07	-2.52	ast	6	2.43	0.03	6	3.13	0.02	-2.81
ast1	5	1.98	0.09	5	2.52	0.48	-2.52	ast1	5	2.43	0.03	5	3.13	0.10	-2.81
ald	3	-1.26	1.00	2	0.46	1.00	-2.95	ald	2	-1.58	1.00	2	0.92	0.88	-3.09
P-value	**0.087**							**P-value**	**0.031**						
	Malaysia 1%								**Malaysia 2.5%**						
snorm	4	-1.22	1.00	2	0.06	1.00	-3.49	snorm	4	-0.51	1.00	3	1.69	0.33	-3.61
std	1	-3.80	1.00	1	-0.06	1.00	-3.50	std	1	-5.27	1.00	1	-1.07	1.00	-3.78
sstd	2	-2.82	1.00	4	0.96	0.83	-3.45	sstd	2	-3.15	1.00	4	2.87	0.02	-3.70
ast	6	2.16	0.04	6	4.08	0.00	-2.57	ast	6	2.24	0.03	6	3.71	0.00	-3.21

Table 4.11 (Cont.)

Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss	Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss
ast1	5	2.16	0.04	5	2.66	0.83	-2.57	ast1	5	2.24	0.03	5	3.09	0.02	-3.21
ald	3	-1.85	1.00	3	0.17	1.00	-3.48	ald	3	-2.29	1.00	2	1.07	0.77	-3.72
P-value	**0.041**							**P-value**	**0.032**						
	Pakistan 1%							**Pakistan 2.5%**							
snorm	4	-0.10	1.00	6	8.16	0.00	-3.16	snorm	4	1.34	0.31	6	7.18	0.00	-3.30
std	1	-4.81	1.00	1	-0.13	1.00	-3.37	std	1	-6.92	1.00	1	-0.68	1.00	-3.57
sstd	2	-4.42	1.00	3	1.53	0.46	-3.34	sstd	2	-6.53	1.00	3	1.43	0.50	-3.55
ast	6	2.00	0.06	5	3.20	0.01	-2.82	ast	6	1.68	0.17	5	2.95	0.01	-3.28
ast1	5	2.00	0.06	4	2.76	0.46	-2.82	ast1	5	1.68	0.17	4	2.95	0.50	-3.28
ald	3	-1.67	1.00	2	0.13	1.00	-3.35	ald	3	-1.85	1.00	2	0.68	0.95	-3.53
P-value	**0.061**							**P-value**	**0.172**						
	Philippines 1%							**Philippines 2.5%**							
snorm	4	0.32	0.84	4	8.39	0.00	-3.11	snorm	6	1.96	0.07	6	7.75	0.00	-3.24
std	1	-3.50	1.00	1	-2.14	1.00	-3.48	std	1	-4.31	1.00	1	-2.32	1.00	-3.63
sstd	2	-2.27	1.00	5	9.80	0.00	-3.36	sstd	2	-2.56	1.00	4	5.77	0.00	-3.53
ast	6	1.45	0.17	3	2.14	0.13	-2.86	ast	5	1.30	0.28	3	3.14	0.01	-3.23
ast1	5	1.45	0.17	2	2.14	1.00	-2.86	ast1	4	1.30	0.28	2	2.32	1.00	-3.23
ald	3	-0.44	1.00	6	10.78	0.00	-3.19	ald	3	-0.77	1.00	5	6.80	0.00	-3.43
P-value	**0.171**							**P-value**	**0.070**						
	Taiwan 1%							**Taiwan 2.5%**							
snorm	3	-1.36	1.00	1	-0.21	1.00	-3.12	snorm	3	-1.26	1.00	3	0.50	0.99	-3.28
std	1	-3.52	1.00	3	0.23	1.00	-3.08	std	1	-4.68	1.00	2	0.16	1.00	-3.31
sstd	4	-1.31	1.00	5	2.59	0.05	-2.89	sstd	4	-1.21	1.00	6	3.19	0.01	-3.16
ast	6	2.03	0.06	6	2.64	0.04	-2.25	ast	6	2.50	0.02	5	3.13	0.02	-2.78
ast1	5	2.03	0.06	4	2.44	1.00	-2.25	ast1	5	2.50	0.02	4	3.13	0.99	-2.78
ald	2	-2.02	1.00	2	0.21	1.00	-3.09	ald	2	-3.08	1.00	1	-0.16	1.00	-3.32
P-value	**0.064**							**P-value**	**0.022**						

Table 4.12 (Cont.)

Model	**Rank$_{R,M}$**	**t_{ij}**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t_i**	**p-value$_{max,M}$**	**Loss**	**Model**	**Rank$_{R,M}$**	**t_{ij}**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t_i**	**p-value$_{max,M}$**	**Loss**
	Thailand 1%							**Thailand 2.5%**							
snorm	4	0.74	0.80	4	2.17	0.13	-2.96	snorm	6	1.32	0.37	4	2.83	0.03	-3.17
std	1	-4.27	1.00	1	-1.40	1.00	-3.20	std	1	-5.55	1.00	1	-2.02	1.00	-3.41
sstd	2	-2.49	1.00	2	1.40	0.58	-3.13	sstd	2	-2.87	1.00	2	2.02	0.22	-3.34
ast	6	1.08	0.58	6	2.29	0.10	-2.93	ast	5	1.02	0.55	6	2.87	0.03	-3.20
ast1	5	1.08	0.58	5	2.29	0.13	-2.93	ast1	4	1.02	0.55	5	2.87	0.03	-3.20
ald	3	-0.36	1.00	3	1.47	0.53	-3.07	ald	3	-0.28	1.00	3	2.67	0.05	-3.28
P-value	**0.584**							**P-value**	**0.367**						
Post-crisis period: 22/7/2017 to 19/2/2019															
	Brazil 1%							**Brazil 2.5%**							
snorm	2	-1.62	1.00	6	5.20	0.00	-2.59	snorm	4	-0.85	1.00	4	1.53	0.41	-2.95
std	4	-0.91	1.00	2	0.29	0.99	-2.57	std	1	-3.30	1.00	1	-0.33	1.00	-3.02
sstd	1	-1.81	1.00	3	0.37	0.98	-2.60	sstd	3	-1.09	1.00	3	0.74	0.92	-2.96
ast	6	2.17	0.06	5	4.97	0.00	-2.32	ast	6	2.05	0.06	6	4.30	0.00	-2.75
ast1	5	2.17	0.06	4	3.48	0.98	-2.32	ast1	5	2.05	0.06	5	4.30	0.41	-2.75
ald	3	-0.93	1.00	1	-0.29	1.00	-2.64	ald	2	-1.14	1.00	2	0.33	1.00	-2.98
P-value	**0.058**							**P-value**	**0.062**						
	Chile 1%							**Chile 2.5%**							
snorm	2	-0.71	1.00	3	0.16	1.00	-3.71	snorm	2	-0.54	1.00	1	-0.01	1.00	-3.89
std	3	-0.58	1.00	1	-0.12	1.00	-3.72	std	3	-0.31	1.00	2	0.01	1.00	-3.89
sstd	1	-0.84	1.00	2	0.12	1.00	-3.71	sstd	1	-0.54	1.00	3	0.06	1.00	-3.89
ald	4	1.33	0.30	4	1.33	0.50	-3.63	ald	4	0.95	0.51	4	0.89	0.78	-3.84
P-value	**0.29**							**P-value**	**0.510**						
	Colombia 1%							**Colombia 2.5%**							
snorm	3	-1.41	1.00	1	-0.50	1.00	-3.27	snorm	4	-0.47	1.00	3	0.88	0.90	-3.41
std	1	-2.27	1.00	2	0.50	0.99	-3.21	std	1	-3.74	1.00	1	-0.76	1.00	-3.48
sstd	2	-2.19	1.00	4	0.57	0.98	-3.21	sstd	2	-2.45	1.00	4	1.42	0.54	-3.44
ast	6	2.10	0.07	6	2.67	0.05	-2.89	ast	6	1.92	0.10	6	2.93	0.03	-3.25
ast1	5	2.10	0.07	5	2.67	0.98	-2.89	ast1	5	1.92	0.10	5	2.93	0.54	-3.25
ald	4	-1.27	1.00	3	0.51	0.99	-3.25	ald	3	-1.20	1.00	2	0.76	0.94	-3.44

Table 4.13 (Cont.)

Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss	Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss
P-value	**0.066**							**P-value**	**0.101**						
	Mexico 1%								**Mexico 2.5%**						
snorm	4	0.84	0.72	6	2.29	0.12	-2.91	snorm	4	0.84	0.74	6	2.60	0.07	-3.26
std	1	-3.26	1.00	1	-0.10	1.00	-3.18	std	1	-3.74	1.00	1	-0.15	1.00	-3.41
sstd	3	0.01	1.00	3	1.63	0.44	-3.02	sstd	3	-0.71	1.00	3	1.35	0.68	-3.34
ast	6	1.11	0.54	5	1.97	0.23	-2.92	ast	6	1.45	0.35	5	2.42	0.10	-3.23
ast1	5	1.11	0.54	4	1.97	0.44	-2.92	ast1	5	1.45	0.35	4	2.42	0.68	-3.23
ald	2	-1.09	1.00	2	0.10	1.00	-3.17	ald	2	-1.62	1.00	2	0.15	1.00	-3.40
P-value	**0.536**							**P-value**	**0.349**						
	Peru 1%							**Peru 2.5%**							
snorm	1	-1.68	1.00	1	-0.25	1.00	-3.27	snorm	1	-1.54	1.00	1	-0.39	1.00	-3.42
std	4	-0.62	1.00	3	0.82	0.91	-3.17	std	3	-1.41	1.00	2	0.39	1.00	-3.40
sstd	2	-1.50	1.00	2	0.25	1.00	-3.26	sstd	4	-1.24	1.00	4	1.84	0.27	-3.41
ast	6	1.98	0.08	6	2.97	0.02	-2.95	ast	6	2.18	0.05	6	3.21	0.01	-3.24
ast1	5	1.98	0.08	5	2.68	0.65	-2.95	ast1	5	2.18	0.05	5	3.13	0.27	-3.24
ald	3	-1.18	1.00	4	1.26	0.65	-3.21	ald	2	-1.51	1.00	3	0.97	0.84	-3.39
P-value	**0.076**							**P-value**	**0.053**						
	Czech Republic 1%							**Czech Republic 2.5%**							
snorm	2	-1.32	1.00	2	1.82	0.22	-3.47	snorm	2	-0.59	1.00	4	2.82	0.03	-3.65
std	1	-3.76	1.00	1	-1.82	1.00	-3.59	std	1	-5.39	1.00	1	-2.04	1.00	-3.78
sstd	3	-1.09	1.00	5	3.08	0.02	-3.45	sstd	3	-0.51	1.00	5	4.16	0.00	-3.64
ast	6	1.11	0.40	4	2.12	0.15	-3.22	ast	5	0.61	0.71	3	2.49	0.05	-3.57
ast1	5	1.11	0.40	3	2.12	0.22	-3.22	ast1	4	0.61	0.71	2	2.04	1.00	-3.57
ald	4	1.06	0.42	6	4.42	0.00	-3.26	ald	6	1.95	0.07	6	8.98	0.00	-3.50
P-value	**0.396**							**P-value**	**0.067**						
	Egypt 1%							**Egypt 2.5%**							
snorm	4	-0.66	1.00	3	1.32	0.55	-2.94	snorm	4	0.23	0.97	4	1.97	0.18	-3.14
std	2	-2.54	1.00	2	1.10	0.71	-3.00	std	2	-4.57	1.00	1	-0.10	1.00	-3.30
sstd	1	-3.94	1.00	1	-1.10	1.00	-3.09	sstd	1	-5.43	1.00	2	0.10	1.00	-3.29

Table 4.14 (Cont.)

Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss	Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss
ast	6	1.89	0.10	6	4.46	0.00	-2.52	ast	6	1.66	0.18	6	3.23	0.01	-3.02
ast1	5	1.89	0.10	5	2.65	0.52	-2.52	ast1	5	1.66	0.18	5	3.23	0.18	-3.02
ald	3	-0.83	1.00	4	1.36	0.52	-2.95	ald	3	-0.61	1.00	3	1.54	0.39	-3.20
P-value	**0.098**							**P-value**	**0.181**						
	Greece 1%							**Greece 2.5%**							
snorm	4	0.80	0.58	6	6.10	0.00	-2.67	snorm	6	2.15	0.05	6	6.32	0.00	-2.83
std	1	-4.72	1.00	1	-2.44	1.00	-3.02	std	1	-7.25	1.00	1	-3.07	1.00	-3.20
sstd	2	-3.64	1.00	5	2.91	0.03	-2.94	sstd	2	-5.36	1.00	5	5.78	0.00	-3.12
ast	5	1.35	0.26	2	2.44	0.08	-2.57	ast	5	1.16	0.39	4	4.10	0.00	-2.90
ast1	6	1.35	0.26	3	2.44	0.08	-2.57	ast1	4	1.16	0.39	2	3.07	1.00	-2.90
ald	3	-0.19	1.00	4	2.71	0.05	-2.78	ald	3	-0.15	1.00	3	3.77	0.00	-3.00
P-value	**0.263**							**P-value**	**0.051**						
	Hungary 1%							**Hungary 2.5%**							
snorm	3	-1.63	1.00	3	0.26	1.00	-3.17	snorm	3	-1.30	1.00	2	0.98	0.79	-3.35
std	1	-2.55	1.00	1	-0.25	1.00	-3.20	std	1	-3.75	1.00	1	-0.98	1.00	-3.40
sstd	2	-1.68	1.00	2	0.25	1.00	-3.18	sstd	2	-1.31	1.00	3	0.98	0.78	-3.35
ast	6	1.80	0.12	6	2.33	0.09	-2.72	ast	6	1.52	0.20	6	2.34	0.09	-3.11
ast1	5	1.80	0.12	5	2.33	0.42	-2.72	ast1	5	1.52	0.20	5	2.34	0.19	-3.11
ald	4	-0.44	1.00	4	1.58	0.42	-3.06	ald	4	-0.07	1.00	4	1.97	0.19	-3.27
P-value	**0.123**							**P-value**	**0.204**						
	Poland 1%							**Poland 2.5%**							
snorm	1	-5.95	1.00	1	-0.37	1.00	-3.23	snorm	2	-1.76	1.00	3	2.30	0.05	-3.44
std	3	0.28	0.88	3	0.79	0.60	-3.17	std	3	-0.18	1.00	2	0.22	0.99	-3.43
sstd	2	-3.98	1.00	2	0.37	1.00	-3.22	sstd	1	-2.08	1.00	1	-0.22	1.00	-3.44
ald	4	0.96	0.46	4	1.82	0.08	-3.13	ald	4	1.60	0.15	4	2.92	0.01	-3.38
P-value	**0.464**							**P-value**	**0.145**						

Table 4.15 (Cont.)

Model	$Rank_{R,M}$	t_{ij}	p-$value_{R,M}$	$Rank_{max,M}$	t_i	p-$value_{max,M}$	Loss	Model	$Rank_{R,M}$	t_{ij}	p-$value_{R,M}$	$Rank_{max,M}$	t_i	p-$value_{max,M}$	Loss
	Qatar 1%							**Qatar 2.5%**							
snorm	1	-2.47	1.00	1	-2.28	1.00	-3.13	snorm	1	-2.23	1.00	1	-2.04	1.00	-3.43
std	3	0.89	0.61	2	2.28	0.06	-2.75	std	3	0.96	0.57	3	2.18	0.09	-3.21
sstd	4	2.29	0.04	3	2.41	0.04	-2.49	sstd	4	2.25	0.05	4	2.27	0.07	-3.09
ald	2	0.25	0.97	4	2.60	0.02	-2.78	ald	2	0.39	0.92	2	2.04	0.12	-3.23
P-value	**0.037**							**P-value**	**0.052**						
	Russia 1%							**Russia 2.5%**							
snorm	4	-0.32	1.00	4	1.43	0.41	-2.75	snorm	4	0.26	0.97	5	2.07	0.12	-3.08
std	2	-2.06	1.00	1	-0.05	1.00	-2.82	std	1	-3.94	1.00	1	-0.62	1.00	-3.22
sstd	1	-2.99	1.00	2	0.05	1.00	-2.82	sstd	2	-3.24	1.00	3	0.69	0.93	-3.20
ast	6	1.20	0.40	6	2.22	0.08	-2.48	ast	6	1.03	0.54	6	2.12	0.10	-3.01
ast1	5	1.20	0.40	5	2.05	0.41	-2.48	ast1	5	1.03	0.54	4	2.06	0.93	-3.01
ald	3	-0.56	1.00	3	0.19	1.00	-2.79	ald	3	-0.61	1.00	2	0.62	0.95	-3.16
P-value	**0.402**							**P-value**	**0.536**						
	South Africa 1%							**South Africa 2.5%**							
snorm	3	-0.77	1.00	3	0.83	0.92	-2.72	snorm	3	0.01	1.00	2	1.12	0.65	-2.97
std	1	-3.82	1.00	1	-0.44	1.00	-2.81	std	1	-3.48	1.00	1	-1.12	1.00	-3.06
sstd	4	-0.31	1.00	4	2.71	0.04	-2.63	sstd	4	2.19	0.06	4	3.42	0.01	-2.87
ast	6	2.16	0.06	6	2.81	0.03	-2.37	ald	2	-0.46	1.00	3	1.44	0.44	-2.99
ast1	5	2.16	0.06	5	2.81	0.04	-2.37								
ald	2	-1.49	1.00	2	0.44	1.00	-2.78								
P-value	**0.063**							**P-value**	**0.059**						
	Turkey 1%							**Turkey 2.5%**							
snorm	5	0.63	0.80	4	1.10	0.70	-1.93	snorm	5	0.34	0.94	4	1.21	0.62	-2.54
std	2	-1.17	1.00	3	0.33	0.99	-2.22	std	1	-2.36	1.00	1	-0.85	1.00	-2.69
sstd	6	0.83	0.68	5	1.49	0.41	-1.83	sstd	6	0.54	0.83	5	1.23	0.61	-2.50
ast	4	-0.26	1.00	6	4.21	0.00	-2.18	ast	4	0.13	0.99	6	2.86	0.03	-2.56
ast1	3	-0.26	1.00	2	0.28	1.00	-2.18	ast1	3	0.13	0.99	2	0.85	1.00	-2.56

Table 4.16 (Cont.)

Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss	Model	$Rank_{R,M}$	t_{ij}	p-value$_{R,M}$	$Rank_{max,M}$	t_i	p-value$_{max,M}$	Loss
ald	1	-1.28	1.00	1	-0.28	1.00	-2.28	ald	2	-0.66	1.00	3	0.86	0.85	-2.62
P-value	**0.679**							**P-value**	**0.832**						
	UAE 1%							**UAE 2.5%**							
snorm	3	-2.05	1.00	1	-1.21	1.00	-3.55	snorm	2	-1.76	1.00	1	-1.11	1.00	-3.72
std	4	-0.73	1.00	4	2.13	0.09	-2.95	std	4	2.05	0.05	4	2.14	0.07	-3.43
sstd	1	-2.72	1.00	3	1.46	0.72	-3.23	sstd	3	1.14	0.40	3	1.74	0.59	-3.55
ast	6	2.25	0.03	6	2.41	0.03	-2.08	ald	1	-2.07	1.00	2	1.11	0.59	-3.66
ast1	5	2.25	0.03	5	2.41	0.09	-2.08								
ald	2	-2.11	1.00	2	1.21	0.72	-3.45								
P-value	**0.026**							**P-value**	**0.050**						
	China 1%							**China 2.5%**							
snorm	2	-0.91	1.00	3	0.81	0.81	-3.40	snorm	4	-1.58	1.00	3	1.00	0.87	-3.50
std	3	-0.15	1.00	2	0.32	0.97	-3.38	std	1	-4.80	1.00	1	-1.00	1.00	-3.55
sstd	1	-1.12	1.00	1	-0.32	1.00	-3.41	sstd	3	-1.58	1.00	2	1.00	0.87	-3.50
ald	4	1.38	0.26	4	1.48	0.38	-3.31	ast	6	2.78	0.01	6	3.96	0.00	-3.25
								ast1	5	2.78	0.01	5	3.96	0.42	-3.25
								ald	2	-1.69	1.00	4	1.66	0.42	-3.48
P-value	**0.264**							**P-value**	**0.010**						
	India 1%							**India 2.5%**							
snorm	2	-1.24	1.00	2	0.63	0.97	-3.53	snorm	4	-0.72	1.00	4	1.26	0.68	-3.67
std	1	-3.21	1.00	1	-0.63	1.00	-3.59	std	1	-3.11	1.00	1	-0.72	1.00	-3.75
sstd	3	-1.21	1.00	4	1.17	0.72	-3.52	sstd	3	-0.80	1.00	3	1.12	0.78	-3.67
ast	5	1.92	0.09	5	2.93	0.03	-3.18	ast	6	1.95	0.09	6	2.92	0.02	-3.47
ast1	6	1.92	0.09	6	2.93	0.03	-3.18	ast1	5	1.95	0.09	5	2.92	0.68	-3.47
ald	4	-1.10	1.00	3	0.81	0.92	-3.51	ald	2	-1.95	1.00	2	0.72	0.96	-3.71
P-value	**0.08**							**P-value**	**0.094**						
	Indonesia 1%							**Indonesia 2.5%**							
snorm	3	-1.34	1.00	1	-0.29	1.00	-3.15	snorm	3	0.26	0.98	2	0.98	0.69	-3.32
std	1	-2.63	1.00	2	0.29	1.00	-3.11	std	1	-1.96	1.00	1	-0.98	1.00	-3.40
sstd	4	0.06	1.00	4	1.36	0.57	-3.00	sstd	4	1.27	0.34	4	2.87	0.02	-3.27

Table 4.17 (Cont.)

Model	**Rank$_{R,M}$**	**t_{ij}**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t_i**	**p-value$_{max,M}$**	**Loss**	**Model**	**Rank$_{R,M}$**	**t_{ij}**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t_i**	**p-value$_{max,M}$**	**Loss**
ast	6	2.89	0.02	5	6.23	0.00	-2.82	ald	2	-0.09	1.00	3	1.28	0.49	-3.33
ast1	5	2.89	0.02	6	6.23	0.00	-2.82								
ald	2	-1.41	1.00	3	0.50	0.99	-3.12								
P-value	**0.016** **South Korea 1%**							**P-value** **South Korea 2.5%**	**0.343**						
snorm	3	-0.40	1.00	3	1.75	0.73	-3.18	snorm	3	-0.78	1.00	3	1.87	0.31	-3.42
std	4	1.92	0.09	4	2.05	0.09	-3.02	std	4	2.08	0.06	4	2.16	0.08	-3.30
sstd	1	-1.77	1.00	2	0.59	1.00	-3.21	sstd	2	-1.22	1.00	2	1.41	1.00	-3.42
ald	2	-1.18	1.00	1	-0.59	1.00	-3.26	ald	1	-1.97	1.00	1	-1.41	1.00	-3.48
P-value	**0.093** **Malaysia 1%**							**P-value** **Malaysia 2.5%**	**0.063**						
snorm	4	-0.45	1.00	3	0.57	0.95	-3.61	snorm	4	0.21	0.98	4	1.58	0.35	-3.84
std	2	-1.57	1.00	4	1.10	0.72	-3.62	std	2	-3.55	1.00	1	-0.33	1.00	-4.00
sstd	1	-3.32	1.00	1	-0.19	1.00	-3.70	sstd	1	-4.24	1.00	2	0.33	1.00	-3.98
ast	6	1.30	0.34	6	1.79	0.23	-3.21	ast	6	1.50	0.26	6	2.29	0.09	-3.70
ast1	5	1.30	0.34	5	1.79	0.72	-3.21	ast1	5	1.50	0.26	5	2.29	0.35	-3.70
ald	3	-1.13	1.00	2	0.19	1.00	-3.68	ald	3	-1.52	1.00	3	0.69	0.94	-3.96
P-value	**0.341** **Pakistan 1%**							**P-value** **Pakistan 2.5%**	**0.255**						
snorm	6	2.02	0.06	6	3.55	0.00	-1.36	snorm	5	2.01	0.07	4	2.81	0.03	-2.32
std	2	-2.48	1.00	4	2.40	0.07	-2.57	std	2	-3.09	1.00	6	3.01	0.02	-2.96
sstd	5	1.88	0.09	5	2.47	0.06	-1.47	sstd	6	2.02	0.07	5	2.82	0.03	-2.32
ast	4	-0.99	1.00	2	1.94	0.19	-2.56	ast	3	-0.75	1.00	2	2.58	0.06	-2.87
ast1	3	-0.99	1.00	3	1.94	0.19	-2.56	ast1	4	-0.75	1.00	3	2.58	0.06	-2.87
ald	1	-3.18	1.00	1	-1.94	1.00	-3.02	ald	1	-4.11	1.00	1	-2.58	1.00	-3.18
P-value	**0.063**							**P-value**	**0.065**						

Table 4.18 (Cont.)

Model	**Rank$_{R,M}$**	**t_{ij}**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t_i**	**p-value$_{max,M}$**	**Loss**	**Model**	**Rank$_{R,M}$**	**t_{ij}**	**p-value$_{R,M}$**	**Rank$_{max,M}$**	**t_i**	**p-value$_{max,M}$**	**Loss**
	Philippines 1%								**Philippines 2.5%**						
snorm	3	-2.03	1.00	2	0.53	0.99	-3.54	snorm	3	-1.67	1.00	2	0.83	0.92	-3.66
std	1	-4.86	1.00	1	-0.53	1.00	-3.58	std	1	-4.76	1.00	1	-0.83	1.00	-3.70
sstd	2	-2.74	1.00	3	2.83	0.03	-3.49	sstd	2	-2.31	1.00	4	3.17	0.01	-3.62
ast	6	2.48	0.02	5	3.25	0.01	-3.10	ast	6	2.51	0.02	6	3.38	0.01	-3.40
ast1	5	2.48	0.02	4	3.25	0.03	-3.10	ast1	5	2.51	0.02	5	3.38	0.01	-3.40
ald	4	-0.34	1.00	6	5.19	0.00	-3.39	ald	4	-0.94	1.00	3	2.26	0.13	-3.61
P-value	**0.015**							**P-value**	**0.020**						
	Taiwan 1%								**Taiwan 2.5%**						
snorm	4	-0.94	1.00	4	1.62	0.35	-3.04	snorm	4	-1.42	1.00	4	1.12	0.76	-3.44
std	1	-2.10	1.00	2	0.20	1.00	-3.13	std	1	-2.61	1.00	1	-0.03	1.00	-3.48
sstd	3	-1.21	1.00	3	0.95	0.85	-3.06	sstd	3	-1.49	1.00	3	0.65	0.97	-3.45
ast	5	1.73	0.14	5	1.96	0.19	-2.56	ast	6	2.07	0.06	6	3.78	0.00	-3.08
ast1	6	1.73	0.14	6	1.96	0.19	-2.56	ast1	5	2.07	0.06	5	2.40	0.76	-3.08
ald	2	-2.06	1.00	1	-0.20	1.00	-3.15	ald	2	-1.97	1.00	2	0.03	1.00	-3.48
P-value	**0.140**							**P-value**	**0.065**						
	Thailand 1%								**Thailand 2.5%**						
snorm	4	-0.24	1.00	2	1.51	0.44	-3.55	snorm	4	1.05	0.47	5	3.92	0.00	-3.67
std	1	-4.42	1.00	1	-1.51	1.00	-3.75	std	1	-5.34	1.00	1	-2.79	1.00	-3.95
sstd	2	-2.80	1.00	4	2.12	0.15	-3.64	sstd	2	-2.61	1.00	6	4.53	0.00	-3.83
ast	6	1.52	0.19	6	2.54	0.06	-3.26	ast	6	1.44	0.24	4	3.71	0.00	-3.63
ast1	5	1.52	0.19	5	2.36	0.15	-3.26	ast1	5	1.44	0.24	2	2.79	1.00	-3.63
ald	3	-0.86	1.00	3	1.70	0.33	-3.60	ald	3	-1.06	1.00	3	3.11	0.02	-3.81
P-value	**0.188**							**P-value**	**0.245**						

Note: (VaR, ES) models are of the GAS(1,1) specification. snorm, std, sstd, ald, ast, and ast1 denote Skewed Gaussian, Student t, Skewed Student t, asymmetric Laplace, asymmetric student-t with two tail decay parameters, and asymmetric student-t with one tail decay parameter innovations in the models, respectively. Eliminated models are not listed since they can easily be inferred from the SSM listed. We write the models in lower cases to simplify the tables. t_{ij} represents test statistic for comparing two forecasts as in Diebold and Mariano (1995) and West (1996). t_i denotes the test statistic derived from sample loss of the i^{th} model relative to the average across models in M^*, see Hansen et al. (2011) for more details. Values in bold print are overall p-value for the respective SSM (selected at 95% confidence level).

4.5 Conclusions and recommendations

In this chapter, we constructed different sets of models for (VaR, ES) to forecast and examine the performance of all selected emerging markets equity returns. Emerging markets are chosen according to the MSCI classification. Our study period span between 3/6/1997 and 19/2/2019 and further split into EMC, EZC-GFC, and Post-crisis periods. The sub-samples are so chosen to reflect the tail risk modelling dynamics between tranquil and turbulent market conditions. We construct the SSM for each equity using the MCS procedure of Hansen et al. (2011). Before using the MCS procedure to choose SSMs, we employ different asymmetric distributional innovations through the GAS technique to fit (VaR, ES) models and score them by the FZL function. This approach addresses the heavy tail stylised fact in emerging markets equities and financial time series in general.

Not only does this work contribute to the growing need to correctly forecast and select the best tail risk for internal risk management purposes, it also fits well with the Basel III framework for comparative back testing to reduce regulatory arbitrage. This is a new study for emerging markets equities as far as risk analysis is concerned. This improves regulatory oversight on emerging markets equities and hence may engender investor confidence.

Our empirical results show that, about one-third of the equities contain all six (6) initial models in the SSM between the two percentiles and across the three sub-sample periods. Hence, we can say they exhibit homogeneous risk models, their tail risk models are time-invariant, and percentile-independent. This in turn can reduce the burden on risk managers in their quest for a single best model. Empirically, the homogeneity in the SSM is suggestive of well diversified portfolios for the respective equity, given that different distributional assumptions are applied to the returns. Bernardi and Catania (2016) opine that, the fact that diversified portfolios are characterised by inversely related risks and returns properties, so does diversification mitigate against negative and positive tail events that affect conditional distribution and kurtosis of equity returns.

The remaining equities show less homogeneity in the models with SSM of size ranging between five (5) and three (3). Their SSMs are also time-varying across the different market episodes as well as percentile-dependent. However, we find the Chinese equity stands out as the most heterogeneous as per the SSM sizes, is time-varying, and percentile-dependent. These suggest that modelling the tail risk of the Chinese equity may be more difficult than the rest and thus makes diversification involving this equity beneficial. In general, the least number of members in the SSM recorded is three, which is one-half of the initial number of models and hence does not suggest a bad level of model heterogeneity. Finally, we also find that model ranks differ for many markets in the different sub-periods. These suggests the need to be mindful of market dynamics when modelling tail risk when the specific order of model superiority is of importance.

Lastly, the implications of these results, in the context of this thesis is that they portray another angle to understand the differences and/similarities in EMEs. Here we find the contrast among the tail risks in emerging markets equities, specifically in the face matching the Basel III standards. While some of the equities show similar tail risk model features (in terms of their SSMs), there is no definite factor (either size of the market, geographical proximity, and financial market maturity, among others) that can be attributed to this pattern. More importantly, the general parameters indexing institutions used in classifying markets (i.e. economic development measured by a gross national income (GNI) per capita threshold, size and liquidity of markets, market accessibility, and stability of institutional framework) are not accountable for these phenomena. We are only left with the peculiar differences in EMEs to account for the dissimilarities in the tail risk models of about two-thirds of the 24 equities used in this study. In a nutshell, this study throws a further challenge to the mechanism of "bucketing" different markets into one class, as a practice of indexing institutions.

Appendix 4.1: List EMEs, summary statistics, price and log-returns plots

Table 4.19: List of EMEs

Emerging market economies		
Americas	***EMEA***[45]	***Asia***
Brazil, Chile, Colombia, Mexico, & Peru.	Czech Republic, Egypt, Greece, Hungary, Poland, Qatar, Russia, South Africa, Turkey, & United Arab Emirates.	China, India, Indonesia, South Korea, Malaysia, Pakistan, Philippines, Taiwan, & Thailand.

Source: MSCI (2018).

[45] Europe, Middle East, & Africa.

Table 4.3: Summary statistics of emerging markets equities

Panel 1

					EMC period					
EME	**Brazil**	**Chile**	**Colombia**	**Mexico**	**Peru**	**Czech R.**	**Hungary**	**Poland**	**Russia**	**S. Africa**
In-sample										
Mean	-0.0013	0.0007	-0.0017	-0.0004	-0.0015	-0.0002	0.0004	-0.0008	-0.0036	-0.0011
Variance	0.001	0.0002	0.0003	0.0007	0.0003	0.0003	0.0009	0.0007	0.0031	0.0005
Skewness	-0.2028	-0.0915	0.9975	-0.8926	-0.5219	-0.2573	-1.2901	-0.4108	-0.4361	-0.9289
Kurtosis	4.0959	0.9952	13.8062	15.6128	4.0608	1.4845	8.0828	2.2371	5.1469	5.5044
Normtest.W*	0.9373	0.9897	0.8503	0.8438	0.9338	0.9811	0.8707	0.9632	0.9188	0.91
Observations	386	386	386	386	386	386	386	386	386	386
Out-of-sample										
Mean	0.0001	-0.0004	-0.0008	0.0016	-0.0002	0.0005	0.0001	-0.0001	0.0021	0.0006
Variance	0.0009	0.0001	0.0004	0.0004	0.0002	0.0003	0.0004	0.0005	0.0015	0.0002
Skewness	0.5863	-0.1458	0.0316	0.5047	0.5437	-0.0303	0.2896	0.1832	-0.3391	0.1151
Kurtosis	6.8546	0.3979	1.6269	4.1154	8.3319	1.8335	5.9219	1.5601	3.106	2.9068
Normtest.W*	0.9092	0.9934	0.969	0.9549	0.8681	0.9737	0.9101	0.9825	0.9649	0.9676
Observations	251	251	251	251	251	251	251	251	251	251
	Turkey	**China**	**India**	**Indonesia**	**S. Korea**	**Malaysia**	**Pakistan**	**Philippines**	**Taiwan**	**Thailand**
In-sample										
Mean	-0.001	-0.0021	-0.001	-0.0043	-0.0017	-0.0043	-0.002	-0.0019	-0.0008	-0.0021
Variance	0.0013	0.001	0.0003	0.0044	0.0023	0.0022	0.0009	0.0009	0.0004	0.0018
Skewness	-0.3416	0.1264	-0.0476	-0.6714	0.5032	-0.5197	-0.682	0.2581	-0.2029	0.8907
Kurtosis	2.8197	2.791	2.1872	6.803	5.399	13.5286	6.1176	1.9256	3.6476	3.0657
Normtest.W*	0.9584	0.9555	0.9768	0.8882	0.9046	0.8485	0.8921	0.9761	0.9578	0.9426
Observations	386	386	386	386	386	386	386	386	386	386
Out-of-sample										
Mean	0.003	0.0003	0.002	0.002	0.0036	0.0033	0.0004	-0.0004	0.0005	0.0005
Variance	0.0009	0.0005	0.0003	0.0013	0.0009	0.0006	0.0005	0.0003	0.0003	0.0008
Skewness	0.1223	-0.0057	0.5294	0.2425	0.3512	2.5061	-0.3278	-0.2898	0.3362	1.6823
Kurtosis	1.4286	1.0213	2.212	2.15	0.7528	16.0403	3.6293	1.7441	1.8495	7.2103
Normtest.W*	0.9756	0.9826	0.972	0.9605	0.9817	0.8245	0.9489	0.9762	0.9726	0.8955
Observations	251	251	251	251	251	251	251	251	251	251

Panel 2

EZC-GFC periods

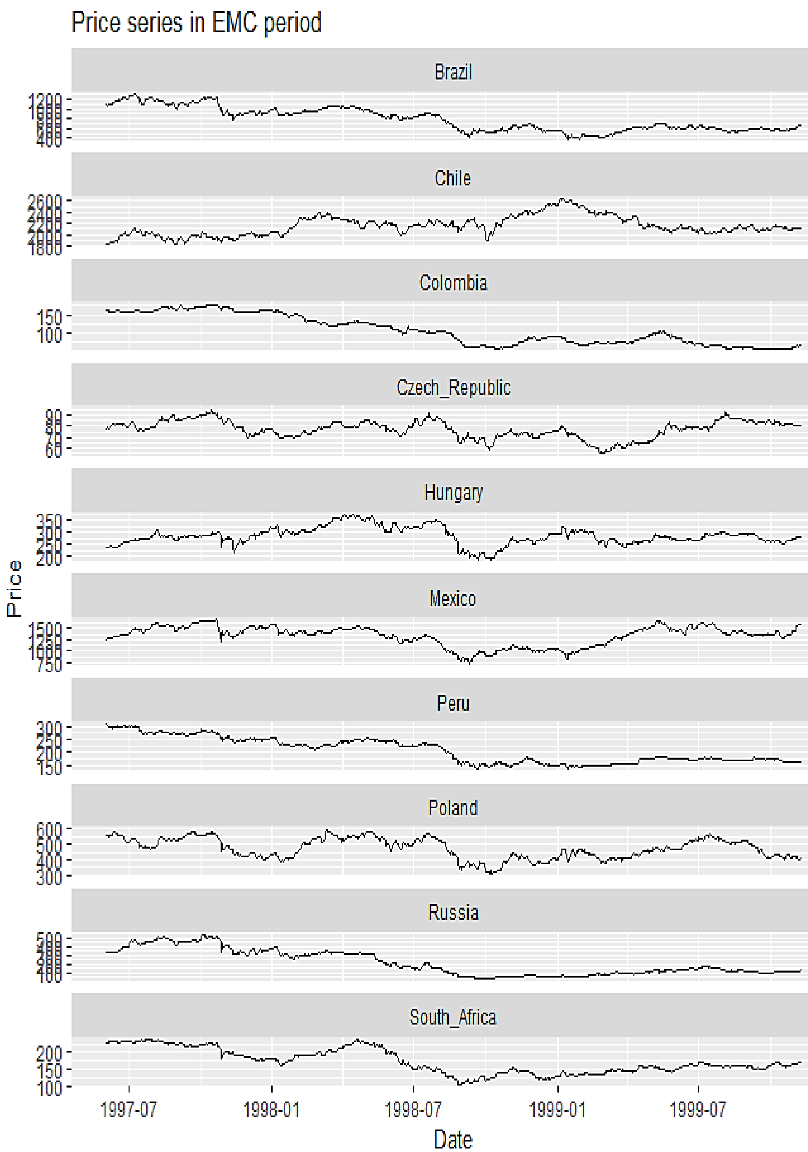
EME	**Brazil**	**Chile**	**Colombia**	**Mexico**	**Peru**	**Czech R.**	**Egypt**	**Hungary**	**Poland**	**Russia**	**S. Africa**
In-sample											
Mean	0.0005	0.0001	0.0006	0.0001	0.0007	0.0001	-0.0002	-0.0002	-0.0001	-0.0002	0.0002
Variance	0.0008	0.0002	0.0003	0.0004	0.0006	0.0005	0.0004	0.0009	0.0007	0.0009	0.0005
Skewness	-0.34	0.10	-0.57	0.02	-0.20	-0.13	-1.31	0.04	-0.15	-0.40	-0.26
Kurtosis	7.39	4.15	7.31	6.46	4.43	12.48	9.49	6.66	3.61	13.79	4.31
Normtest.W*	0.90	0.95	0.92	0.91	0.94	0.87	0.87	0.92	0.96	0.85	0.95
Observations	1117	1117	1117	1117	1117	1117	1117	1117	1117	1117	1117
Out-of-sample											
Mean	-0.0008	0.0003	0.0001	0.0001	-0.0002	-0.0008	-0.0001	-0.0007	-0.0005	-0.0007	-0.0003
Variance	0.0003	0.0002	0.0001	0.0002	0.0003	0.0003	0.0003	0.0006	0.0004	0.0003	0.0003
Skewness	-0.4012	-0.3717	-0.2977	-0.5325	-2.0863	-0.2472	0.1194	-0.0039	-0.4503	-0.4767	-0.0823
Kurtosis	2.8153	2.0132	1.3133	3.7946	18.8797	1.7321	6.0009	1.8141	3.278	2.6419	1.5615
Normtest.W*	0.9706	0.9694	0.9779	0.9611	0.8744	0.9817	0.8918	0.9771	0.9588	0.963	0.9818
Observations	559	559	559	559	559	559	559	559	559	559	559
	Turkey	**China**	**India**	**Indonesia**	**S. Korea**	**Malaysia**	**Pakistan**	**Philippines**	**Taiwan**	**Thailand**	
In-sample											
Mean	0.0003	0.0003	0.0003	0.0006	0.0003	0.0004	-0.0003	0.0002	0.0001	0.0006	
Variance	0.0007	0.0005	0.0005	0.0005	0.0006	0.0002	0.0003	0.0003	0.0003	0.0004	
Skewness	-0.12	0.03	0.19	-0.20	-0.13	-0.76	-0.60	-0.62	-0.20	-0.59	
Kurtosis	3.86	5.02	6.89	5.96	17.11	7.54	4.00	5.52	2.40	6.17	
Normtest.W*	0.96	0.94	0.94	0.93	0.86	0.94	0.94	0.95	0.96	0.94	
Observations	1117	1117	1117	1117	1117	1117	1117	1117	1117	1117	
Out-of-sample											
Mean	0.0001	-0.0003	-0.0004	0.0001	-0.0002	0.0002	0.0005	0.0008	-0.0001	0.0003	
Variance	0.0003	0.0002	0.0002	0.0002	0.0003	0.0001	0.0001	0.0001	0.0002	0.0002	
Skewness	-0.7096	-0.0774	0.0299	-0.8424	-0.2481	0.1149	-0.0468	-0.2729	-0.1666	0.0337	
Kurtosis	4.1957	2.8964	1.334	6.533	2.4566	4.8323	1.9312	2.2967	1.9308	2.9585	
Normtest.W*	0.9542	0.959	0.9847	0.9254	0.9653	0.9431	0.9682	0.9684	0.9699	0.9671	
Observations	559	559	559	559	559	559	559	559	559	559	

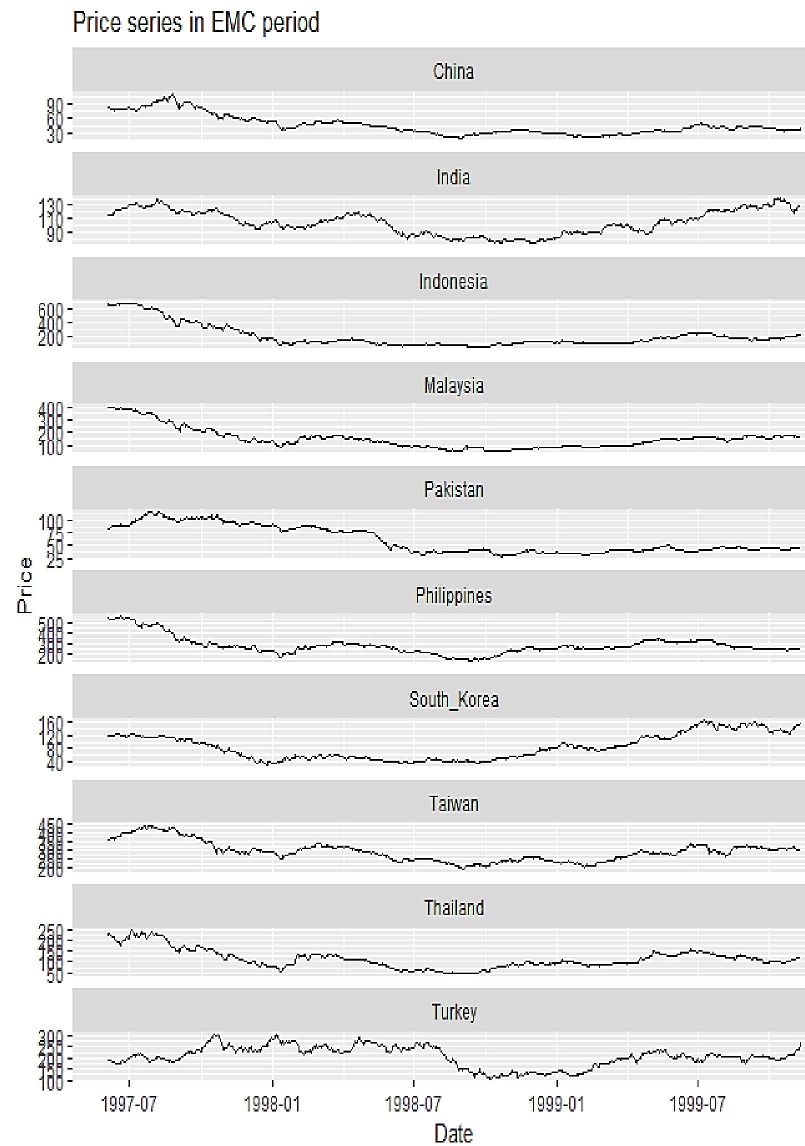
Panel 3

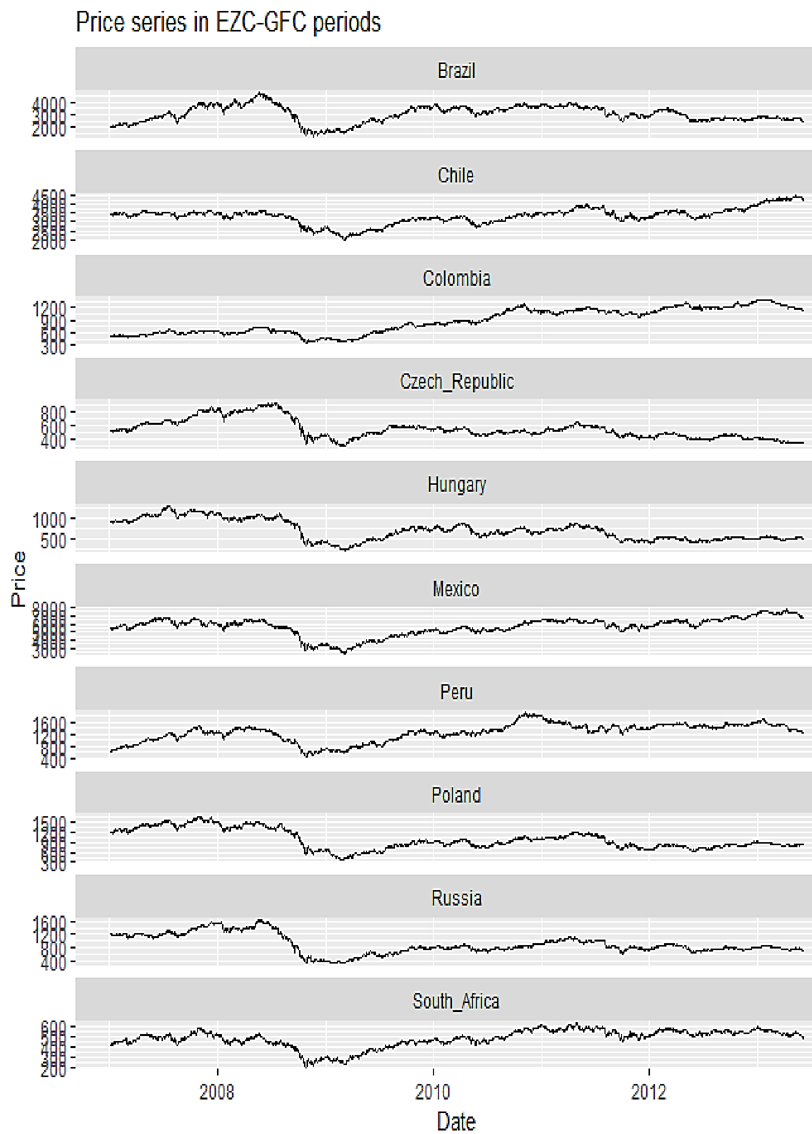
						Post-crisis period						
EME	**Brazil**	**Chile**	**Colombia**	**Mexico**	**Peru**	**Czech R.**	**Egypt**	**Greece**	**Hungary**	**Poland**	**Qatar**	**Russia**
In-sample												
Mean	-0.0003	0.0001	-0.0007	-0.0002	0.0001	-0.0004	0.0001	-0.0011	0.0001	-0.0003	-0.0004	-0.0002

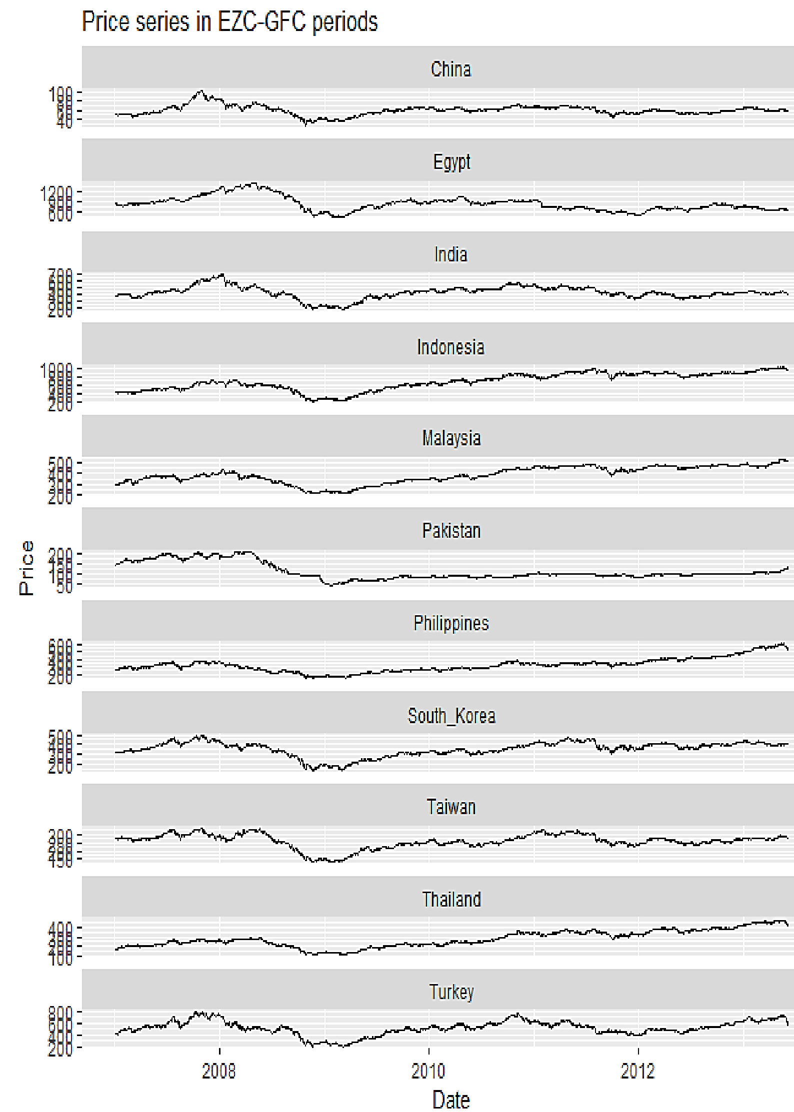
Variance	0.0004	0.0001	0.0002	0.0002	0.0002	0.0002	0.0004	0.0009	0.0002	0.0002	0.00071	0.0004
Skewness	0.18	-0.24	-0.13	-0.60	0.40	-0.21	-6.69	-0.96	-0.21	-0.49	-0.05	-0.03
Kurtosis	1.82	1.55	2.28	4.97	1.80	1.35	117.18	9.50	2.13	3.58	9.14	7.26
Normtest.W*	0.98	0.98	0.97	0.96	0.98	0.99	0.68	0.90	0.98	0.96	0.87	0.93
Observations	990	990	990	990	990	990	990	990	990	990	611	990
Out-of-sample												
Mean	0.0004	0.0001	0.0002	-0.0003	0.0006	0.0003	0.0001	0.0001	0.0005	0.0001	0.0001	0.0001
Variance	0.0003	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	0.0002	0.0002	0.0002	0.0001	0.0001
Skewness	-1.26	-0.05	-0.13	-0.57	-0.28	-0.39	-0.54	-0.18	-0.19	-0.11	0.10	-1.82
Kurtosis	12.68	1.48	1.12	3.08	1.46	1.23	3.33	0.95	1.01	0.60	5.96	17.03
Normtest.W*	0.92	0.98	0.99	0.97	0.98	0.99	0.95	0.99	0.99	0.99	0.89	0.91
Observations	497	497	497	497	497	497	497	497	497	497	497	497
	S. Africa	**Turkey**	**UAE**	**China**	**India**	**Indonesia**	**S. Korea**	**Malaysia**	**Pakistan**	**Philippines**	**Taiwan**	**Thailand**
In-sample												
Mean	0.0001	-0.0005	-0.0004	0.0002	0.0002	-0.0001	0.0001	-0.0004	0.0001	-0.0001	0.0002	-0.0001
Variance	0.0003	0.0004	0.0002	0.0002	0.0001	0.0002	0.0001	0.0001	0.0001	0.0002	0.0001	0.0002
Skewness	-0.25	-0.09	-0.21	-0.17	-0.51	-0.13	-0.16	0.20	-0.22	-0.73	-0.15	-0.07
Kurtosis	2.94	2.46	9.87	3.07	4.22	3.78	1.45	3.86	3.60	6.23	2.31	3.87
Normtest.W*	0.97	0.97	0.86	0.96	0.95	0.94	0.98	0.96	0.96	0.93	0.97	0.95
Observations	990	990	611	990	990	990	990	990	990	990	990	990
Out-of-sample												
Mean	-0.0002	-0.0006	-0.0001	0.0003	0.0001	0.0001	0.0001	0.0001	-0.0014	0.0001	0.0001	0.0004
Variance	0.0003	0.0004	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001
Skewness	-0.22	-1.44	-0.32	-0.12	-0.37	-0.29	-0.36	-0.84	-0.09	0.04	-0.96	-0.09
Kurtosis	1.21	9.48	2.16	0.57	0.87	1.85	1.71	3.89	1.84	0.27	6.98	2.23
Normtest.W*	0.99	0.91	0.95	0.99	0.99	0.97	0.98	0.95	0.98	1.00	0.93	0.96
Observations	497	497	497	497	497	497	497	497	497	497	497	497

Note: Normtest.W indicate that normality is rejected at all levels of significance. S. Korea, S. Africa, Czech R., and UAE denote South Korea, South Africa, Czech Republic, and United Arab Emirates, respectively.*


Price series in EMC period
Brazil
Chile
Colombia
Czech_Republic
Hungary
Mexico
Peru
Poland
Russia
South_Africa
Price
1997-07
1998-01
1998-07
1999-01
1999-07
Date


Price series in EMC period
China
India
Indonesia
Malaysia
Pakistan
Philippines
South_Korea
Taiwan
Thailand
Turkey
Price
1997-07
1998-01
1998-07
1999-01
1999-07
Date


Price series in EZC-GFC periods
Brazil
Chile
Colombia
Czech_Republic
Hungary
Mexico
Peru
Poland
Russia
South_Africa
Price
2008
2010
2012
Date


Price series in EZC-GFC periods
China
Egypt
India
Indonesia
Malaysia
Pakistan
Philippines
South_Korea
Taiwan
Thailand
Turkey
Price
2008
2010
2012
Date

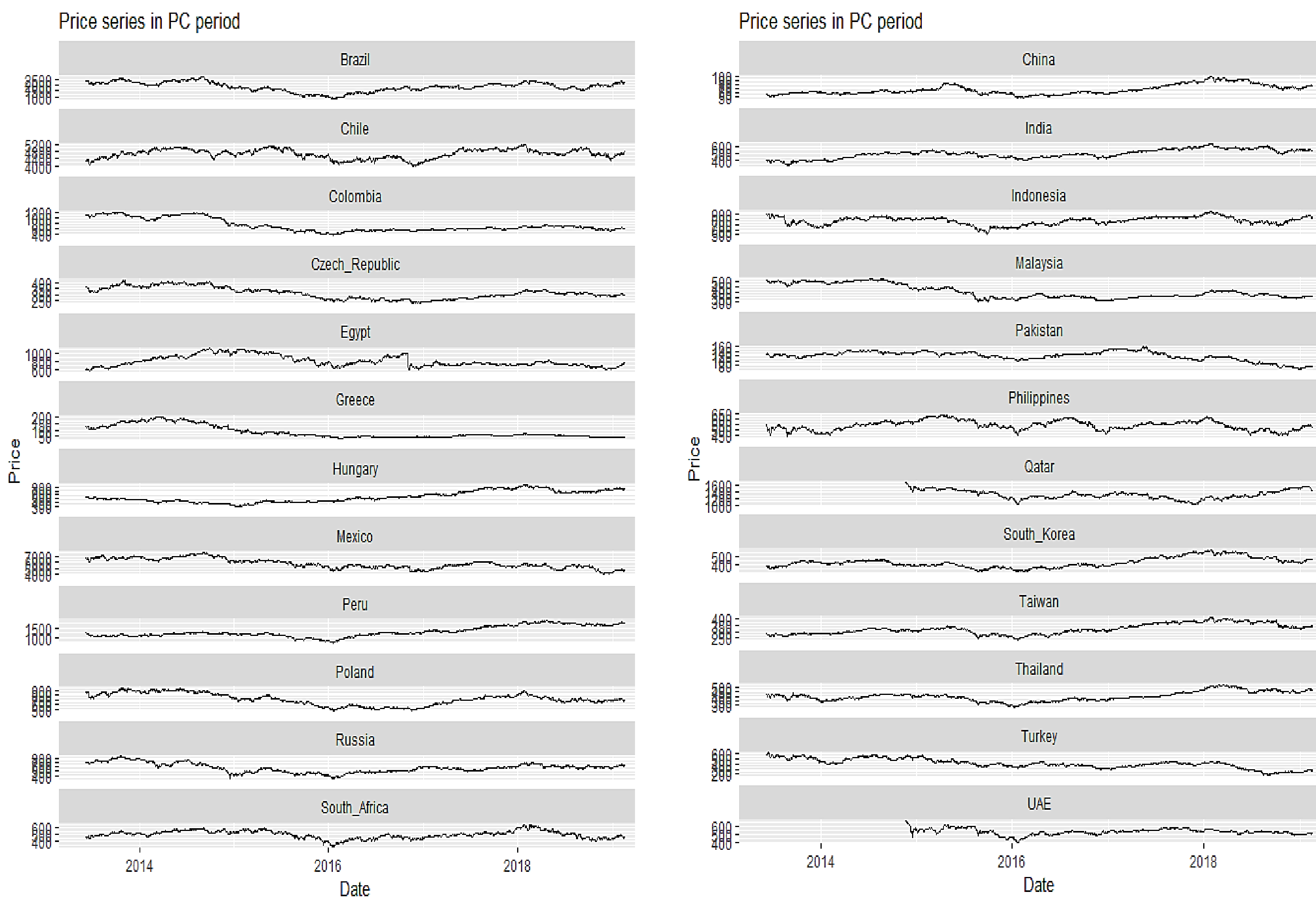
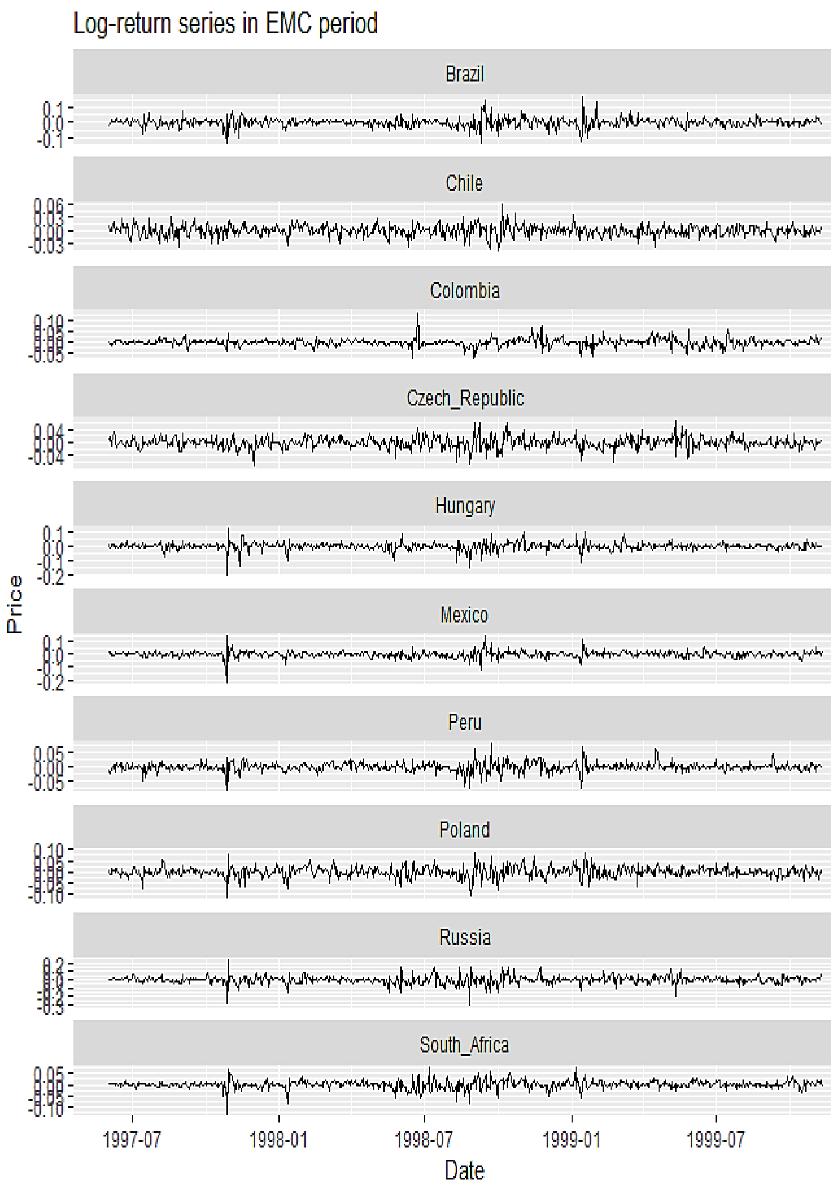
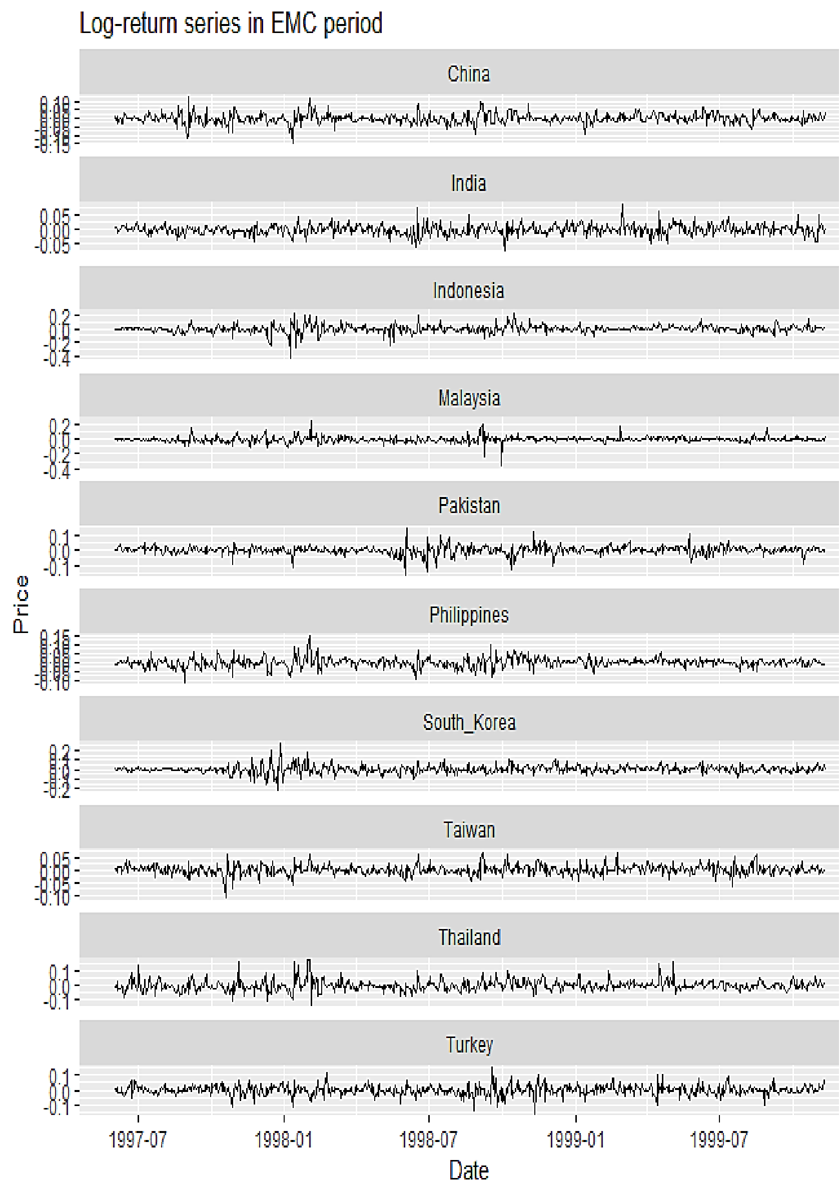


Figure 4.1: Price plots of emerging markets equities


Log-return series in EMC period
Brazil
Chile
Colombia
Czech_Republic
Hungary
Mexico
Peru
Poland
Russia
South_Africa
Price
1997-07
1998-01
1998-07
1999-01
1999-07
Date


Log-return series in EMC period
China
India
Indonesia
Malaysia
Pakistan
Philippines
South_Korea
Taiwan
Thailand
Turkey
Price
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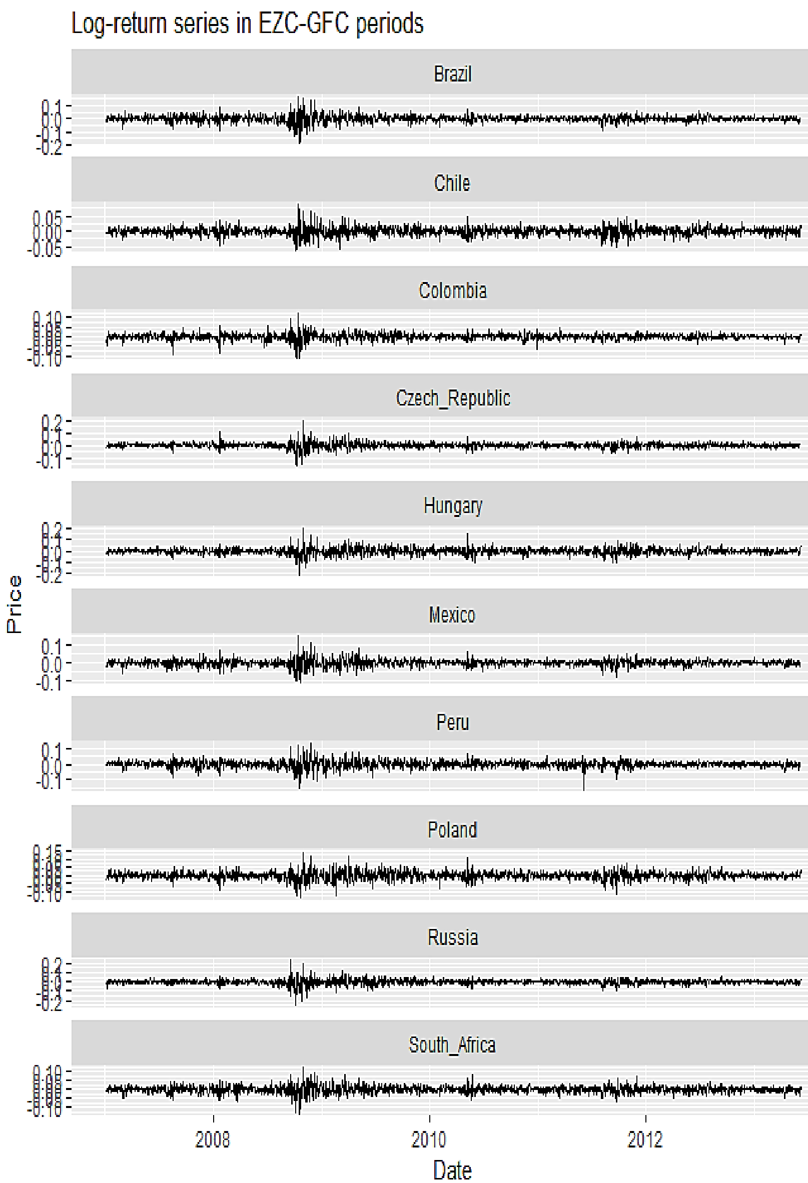
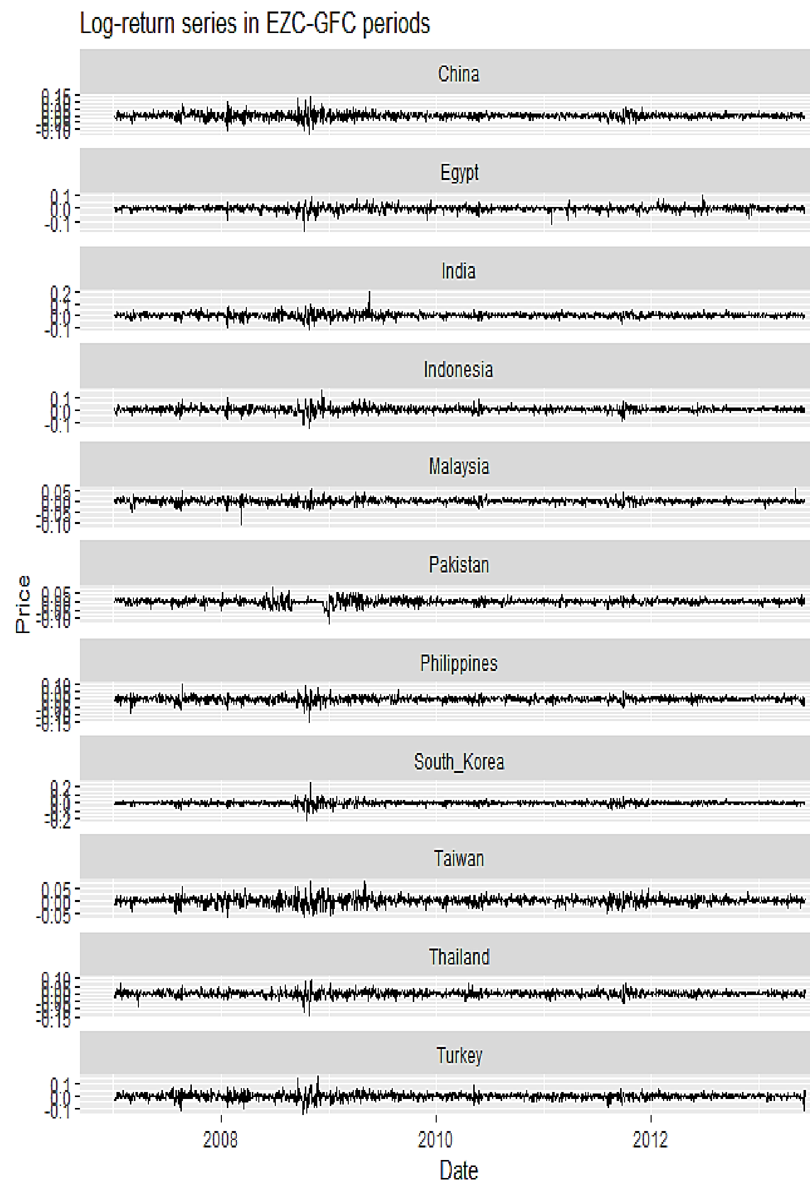
1998-01
1998-07
1999-01
1999-07
Date


Log-return series in EZC-GFC periods
Brazil
Chile
Colombia
Czech_Republic
Hungary
Mexico
Peru
Poland
Russia
South_Africa
Price
2008
2010
2012
Date


Log-return series in EZC-GFC periods
China
Egypt
India
Indonesia
Malaysia
Pakistan
Philippines
South_Korea
Taiwan
Thailand
Turkey
Price
2008
2010
2012
Date

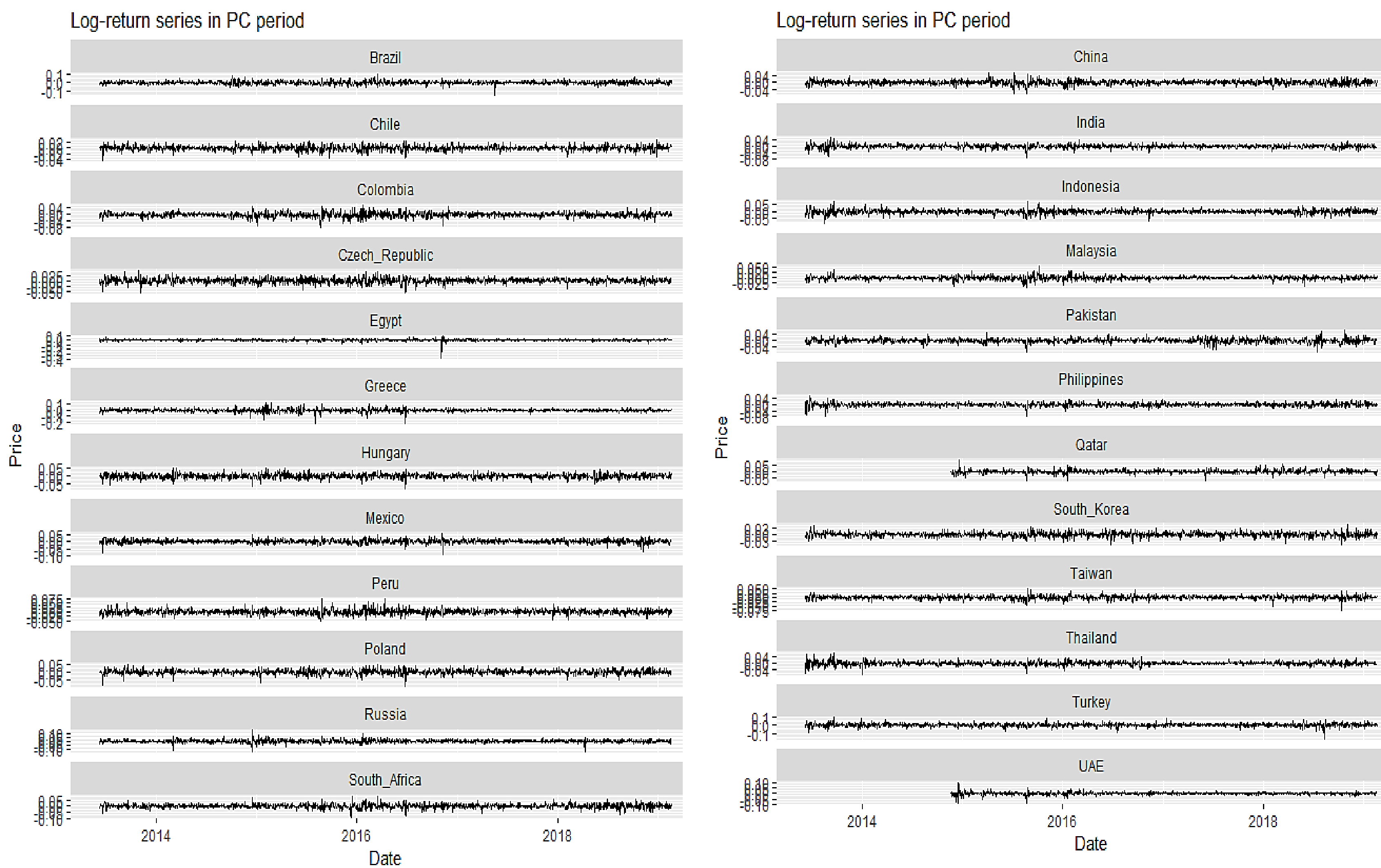


Figure 4.2: Log-returns plots of emerging markets equities

CHAPTER FIVE

SHAPE SHIFT-CONTAGION IN EMERGING MARKETS EQUITIES

5.1 Introduction

The concepts of interdependence and contagion have been explored for many years, with the number of studies on the rise particularly since the Asian, Russian, Mexican, and Brazilian crises in the late 1980s and early 1990s (Diebold & Yilmaz, 2009; Forbes & Rigobón, 2002; Rigobón & Forbes, 2001). Perhaps, these should not come as a surprise since categorisation of countries into blocs, regions, markets, and economies among others, is premised on distinguishing features of either geography, trade, economics, or finance, among others. They also point to the integration of otherwise segmented markets (Bekaert et al., 1998; Kearney, 2012).

There are wider and deeper cross-border market relations beyond only EMEs, especially with the United States (Arouri et al., 2013; Baele et al., 2004; Yao et al., 2018). For instance, at the speed of stock market liberalisation in the 1990s, private investment booms were attended by sporadic capital inflows and high instabilities (Santiso, 2003). These were coupled with severe currency crises spreading among EMEs such as Mexico, Thailand, South Korea, Russia, Brazil, and Argentina. In recent times, the flow of funds into and out of EMEs, to a large extent, is at the impulses of developed markets' dynamics. For example, many investors pulled out funds from emerging market ETFs in the middle of 2018 due to rising interest rates in the United States. The $35 billion iShares MSCI Emerging Markets ETF had $2.2 billion wiped off in a week; the most since January 2014. In the same week, the biggest emerging markets ETF, the $65 billion

Vanguard FTSE Emerging Markets ETF also lost about $270 million; its second-worst performance in over two years (Bloomberg, 2018).

These shock transmissions and financial markets interdependence have unavoidable implications for both domestic and global market participants. Among others, (Alagidede et al., 2011; Bekaert et al., 2014; Bekaert & Harvey, 2017; Boako & Alagidede, 2017; Ftiti et al., 2015) underline the implications for return behaviour, risk reduction, international portfolio diversification, hedging and trading strategies, and policies. Further, the emphasis on whether returns, volatilities, or higher moments (especially, skewness and kurtosis) are used in investigating interdependence and contagion is of critical importance. This is because the distributional properties emanating from stylised facts of returns engender specific considerations in risk analysis and portfolio diversification (Amaya et al., 2015; Bali et al., 2011; Barinov, 2011; Bessembinder, 2018; Chang et al., 2013; Hadar & Seo, 1990; Müller & Wagner, 2018).

Several studies have employed returns and return volatilities in the spillover literature. Volatility contagion is rather scarce, save studies such as Edwards and Susmel (2001), Baur (2003), Baruník et al. (2016), Diebold and Yilmaz (2009), Diebold and Yilmaz (2014), Tiwari et al. (2018), among others. The literature on the examination of interdependence and contagion with higher moments' origins is rather fledgling and scanty. Notable studies include Ang and Timmermann (2011), Fry-McKibbin et al. (2017), Fry-McKibbin et al. (2018), Chan et al. (2019), Harvey and Siddique (2000), among others, albeit with limited analysis of connectedness in the moments. Hong et al. (2009), for instance, introduced a bivariate VaR Granger causal skewness and kurtosis spillovers amongst the United States dollar, Euro, and Japanese Yen. Hashmi & Tay (2012) also present a bivariate skewness spillovers between Hong Kong, Singapore, and world[46] equities using a skewed-t distribution.

However, when it comes to EMEs the literature on higher moments as the origins of interdependence and contagion transmissions is almost non-existent. The only available study is Del Brio et al. (2017), who perform only a static analysis of the skewness and kurtosis spillovers between block emerging and developed markets indices. This study lacks a deeper analysis of individual markets because the authors use block indices. Hence, we deviate from the large body which focuses on first and second order moments and add to the relatively small literature on higher order comoments. Furthermore, a lively debate in the literature borders on whether a spillover constitutes interdependence or contagion (Forbes & Rigobón, 2002). This study contributes to the discussion by using higher moments of emerging markets equities returns to disentangle connectedness from contagion.

This study examines interdependence and contagion through the higher moments of emerging markets equity returns. In the process, we contribute to both theory and empirics in terms of the definition, measurement, and sources of interdependence and contagion. First, the study proffers fresh insights into how interdependence and contagion are propagated within EMEs and between DMEs alike. A deeper understanding is essential for both traders and policy makers in EMEs. Financial markets' interdependence, for instance, seems to have benignant effects (Argy, 1996;

[46] A market-capitalisation weighted average of weekly returns from the United States, United Kingdom, and Japanese markets are used as the world factor (Hashmi & Tay, 2012).

Bekaert et al., 2014; Bekaert & Harvey, 2003; Kearney, 2012). Contagion, on the other hand, has mostly malignant impacts, especially for weak EMEs (Kristin & Kristin, 2012). Thus, regardless of how either interdependence or contagion is measured (Claessens & Forbes, 2013; Forbes & Rigobón, 2002; Sewraj et al., 2018; Wang et al., 2017) and the controversy over how contagion is defined (Bodart & Candelon, 2009; Kim & Lee, 2018; Kristin & Kristin, 2012; Yang et al., 2016), their implications merit not only academic interest but also policy significance. This study offers new dimensions to both the general and specific definitions of interdependence, the origins of connectedness and contagion, and how these are measured.

Second, in this study we extend the definition of *shift-contagion* by hypothesising *"shape shift-contagion"*. As it may be clear to the reader now, the name derives from the use of shape parameter estimates as input series. Prior to FR-SC, most empirical studies on contagion focused on periods during financial shock/crises (see for example, Aït-Sahalia et al., 2015; Feinstein, 2017; Kenourgios, 2014; Kenourgios et al., 2011). However, the narrative has largely changed to include periods after a shock has occurred. Boako and Alagidede (2016) argue that transmission mechanisms of shocks are mostly indirect and hence targeted markets may be affected Post-crisis periods. The authors then proposed the *delayed shift-contagion* by studying longer periods. However, traditionally, the *shift-contagion* tracks significant increases (or changes) in cross-market linkages *"after"* a shock to one country (or group of countries). That is to say, a simple extension of the study periods makes only so much difference since the *shift-contagion* hypothesis originally encapsulates periods after a shock. There has been a growing number of studies in this regard (for instance, BenSaïda, 2018; Caporin et al., 2018; Claessens & Forbes, 2013; Dimitriou et al., 2013; Kenourgios et al., 2016; Xu et al., 2017).

Nonetheless, a deeper critique of the FR-SC may not be with respect to time distance from crises periods but in its methodological assumptions. It is worth noting that, the main premise of the FR-SC is heteroscedasticity bias adjustment which speaks to the scale (variance) parameter of the return distribution. It argues that cross-market correlations are conditional on market volatility (i.e. different markets experience varied levels of idiosyncratic volatilities) and hence unless this is corrected, conclusions are almost erroneous. The FR-SC further employs a t-test on cross-market correlation coefficients across stable, chaotic, and full (comprising both stable and chaotic) periods to test for contagion. However, the *"shape shift-contagion"* traces the contagion (incidence of contagion) through the shape parameters of return distributions. We circumvent the heteroscedasticity bias of FR-SC by employing a rolling window estimation of the shape parameters as input data. At the same time, the rolling window approach captures the time evolution in the higher moments. Further, the Baruník and Křehlík (2018) (BK18) spillover technique uses in this study avoids the heteroscedasticity bias with its in-built rolling window mechanism. It adjusts the correlation matrix of vector autoregression (VAR) residuals by the cross-sectional correlations (see also Diebold & Yilmaz, 2014).

Third, this study contributes to the definition of *comoment*. In the narrow sense of using skewness and kurtosis of the selected emerging markets equities to examine interdependence and contagion, we augment the definitions *coskewness* and *cokurtosis*[47], respectively. We define comoment as the connectedness in the higher moment series among the ten (10) selected markets in this study using wavelet multiple correlations (WMC), wavelet multiple cross correlations (WMCC), and BK18

[47] Comoment, coskewness, and cokurtosis are not defined in strong mathematical and statistical terms as in, for instance, Fry-McKibbin et al. (2018), Boudt et al. (2016), Ranaldo & Favre (2005), among others.

methodologies. It is evident that *comoment* is a convenient tool for evaluating diversification potential of assets in terms of risk (i.e. volatility), risk of asymmetry (skewness), and extreme events (kurtosis) (see Fry-McKibbin et al., 2010; Fry-McKibbin et al., 2014; Martellini & Ziemann, 2010). Moreover, *comoments* help to quantify the marginal contribution of each asset to a portfolio's risk (Ranaldo & Favre, 2005). Thus, the resulting spillovers from our analysis can be regarded as marginal connectedness and/or contagion. Therefore, this study encapsulates a very rich information on emerging markets equity dynamics, which would otherwise go unnoticed. Specifically, this study shows higher moments of emerging markets equities as important sources of interdependence and contagion.

Fourth, the study contributes to how interdependence and contagion are measured by undertaking a systematic approach in arriving at spillover and estimates. We carefully select the (Freimer et al., 1988) generalised lambda distribution (FKML-GLD) from family of Stable distributions to estimate rolling window higher moments. The FKML-GLD is elected for its mathematical simplicity and ability to adequately fit extreme tails of data easily (Karian & Dudewicz, 2016; Su, 2007, 2010). To sidestep the bottleneck of distributional assumptions, we measure interdependence and contagion through non-parametric frequency-domain WMC, WMCC (Fernández-Macho, 2012), and time- and frequency-time domain connectedness of BK18 methods. The BK18 is able to capture time-varying instability, non-linearity, and non-stationarity in the returns. Dealing with non-linearities, non-stationaries, and asymmetries have become increasingly important in spillover studies. For instance, Bampinas and Panagiotidis (2017) employ the local Gaussian correlation to capture non-linearities between United States stock markets and 1-4 months maturities of West Texas Intermediate daily spot and futures crude oil prices (see also Bae et al., 2003; Baur, 2013; Bodart & Candelon, 2009). The WMC and WMCC are also able to deal with non-stationarities and non-linearities (see Polanco-Martínez, 2019). While the WMC and WMCC are able to determine frequency-domain lead/lag relations within a set of variables, the BK18 further accounts for both composite and pairwise (bi-directional) spillover at the various frequencies and at varying times. Furthermore, the BK18 measures net spillovers as the difference between spillovers "from" and "to" in the system. The BK18 also helps us to measure contagion in similar fashions as Saiti et al. (2016), Adam (2013), and Diebold and Yilmaz (2009). In effect, this measurement is in consonance with Forbes and Rigobón (2002) (i.e. a sharp increase in cross-market spillovers at some frequency band(s) as opposed to continuous high levels of connectedness). The techniques employed in this study also appeal to the heterogeneous market hypothesis (HMH) (Müller et al., 1993). The HMH prompts the need to delineate spillovers into short-, medium, and long-run horizons to suit different investment and policy preferences.

While many studies on spillovers have used the Diebold and Yilmaz (2009, 2012) technique, we choose the BK18 for valid reasons. First, the Diebold and Yilmaz (2009, 2012) does not imply causality in the spillovers. But the BK18 implies causality using the "within" connectedness as shown in equations 5.12 and 5.13 in Section 4.2.2. Second, the BK18 relies on local stationarity of the VAR system as against a strict requirement of global stationarity for all the variables in the Diebold and Yilmaz (2009, 2012) framework. Last, rolling window has the potential to introduce serial correlation into the series using the Diebold and Yilmaz (2009, 2012) approach, but this has not been documented for BK18.

We use the top nine (9) emerging markets equities according to the constituents of the MSCI emerging markets index and the MSCI United States index. The MSCI United States index is added as a proxy for the rest of the world. Also, it does not interface with any emerging market which helps to avoid double counting. Further, the United States is deemed the originator of the 2007-2009 global financial crisis (GFC) (see Cheung et al., 2019; Crotty, 2009; Martin, 2011; Mollah et al., 2016; Nguyen & Pontell, 2010). It is only appropriate that the connectedness of asymmetric and extreme returns of emerging markets equities are examined by including the United States equity.

Our empirical results indicate that spillovers are time-varying and frequency-dependent across the system for both asymmetric and extreme returns shock propagation. Contagious episodes are short-lived and "*delayed*" after the GFC but also during the EZC. Further, we find that the United States does not dominate in spillovers, however, it is mostly a **net transmitter.** In addition, large markets do take centre stage in connectedness but Brazil and Mexico which place 5th and 8th, respectively, have strong impact in the system. Portfolio diversification potentials are strong in the short-term while policy efforts may be directed at all frequencies across both large and small markets.

5.2 Theoretical models and empirical methodology

This section deals with the theoretical and empirical models for estimating shape paramters and connectedness indices in this chapter.

5.2.1 GLD and shape parameters

Besides the normal distribution, there is essentially no end to the number of asymmetric distributions. Popular among them in the empirical literature that have been proven to adequately capture shape behaviour of financial times-series include, but not limited to Cauchy, Normal Inverse-Gaussian (NIG) (Mudholkar & Tian, 2002; Shushi, 2018), GLD (Ramberg & Schmeiser, 1974; Freimer et al., 1988; King & MacGillivray, 1999; Su, 2010), skewed t (Zhu & Galbraith, 2010, 2011), Johnson's family (Shenton & Bowman, 1975), GEV (Coles et al., 2001; Gilli & Këllezi, 2006), Generalised Pareto (Hussain & Li, 2015; Zhao et al., 2020), among others. In all of these the GLDs have been chosen for this study. They have proven to describe better the shape distributions of returns (Chalabi et al., 2012; Corlu & Corlu, 2015; Corlu & Meterelliyoz, 2016; Corlu et al., 2016; King & MacGillivray, 1999). In addition, one will appreciate the mathematical simplicity of the GLD in the family of Stable distributions.

The GLD (Ramberg & Schmeiser, 1974) was introduced as the inverse distribution function of Tukey's lambda (TL) distribution (Hastings Jr et al., 1947). It is given as

$$Q(U) = \begin{cases} \dfrac{[U^{\lambda} - (1-U)^{\lambda}]}{\lambda}, \lambda \neq 0 \\ \dfrac{logU}{1-U}, \lambda = 0 \end{cases} \tag{5.1}$$

where U a uniform $(0, 1)$ random variable and the transformation $Q(*)$, referred to as the quantile function, yields $Q(\alpha)$ as the α^{th} quantile $(0 < \alpha < 1)$ or $100\alpha^{th}$ percentile of the distribution of X (Fisher, 1922).

The Freimer et al. (1988) (FKML-GLD) is even better as it places the only restriction of $\lambda_4 > 0$ in

$$F^{-1}(\rho|\lambda) = \lambda_1 + \left[\frac{\rho^{\lambda_3 - 1}}{\lambda_3} - \frac{(1-\rho)^{\lambda_4 - 1}}{\lambda_4}\right] / \lambda_2 \tag{5.2}$$

defined over all λ_3 and λ_4 (Su, 2007), where ρ are the probabilities $\rho \in [0, 1]$, λ_1, λ_2 are location and λ_3, λ_4 represent scale parameters, respectively. The probability density function (pdf) of the GLD at $x = F^{-1}(\rho \mid \lambda)$ is given as

$$f(x) = f\big(F^{-1}(\rho|\lambda)\big) = \frac{\lambda_2}{\lambda_3 \rho^{\lambda_3 - 1} - \lambda_4 (1-\rho)^{\lambda_4 - 1}} \tag{5.3}$$

wherefore parameter combinations of λ must yield $f(x) \geq 0$ and $\int f(x)dx = 1$ (Pfaff, 2016) which can exhibit either a finite support (bounded both on left and right) or an infinite support (unbounded)[48]. Distributions with infinite support provide a better fit to data compared to those with finite supports (Karian & Dudewicz, 2016; Van Staden, 2014).

In estimating the parameters, we have employed rolling window technique. For daily moments, the partition the data into $k = N - m + 1$ subsamples where $m^{49} = 20$ denotes the window length,

[48] See (Chalabi et al., 2012; Van Staden, 2014) for detailed tabulation of regions, classes, and supports for FKML-GLD.

[49] This is representative of one month of trading days.

and N denotes sample size. Rolling window estimation of moments has recently been applied to capture time-variation and non-stationarity in the time series (Fernández-Macho, 2018; Polanco-Martínez, 2019; Tiwari et al., 2016). Further, the MLE technique is used to ascertain the FKML-GLD parameters. The MLE is usually preferred in non-linear modelling with non-normal data and has proven to perform better than different approaches to fitting GLD to data (Myung, 2003; Su, 2007).

5.2.2 Frequency- and time-domain spillover

5.2.2.1 Wavelet multiple correlation (WMC) and wavelet multiple cross correlation (WMCC)

In order to fully capture frequency dynamics of connectedness it is natural to decompose the connectedness into bands that correspond to short-, medium-, and long-terms (as frequencies) suiting different preferences of economic agents. The extant literature supports the notion that economic agents work at different investment horizons pursuant to their risk and return preferences (Jiang et al., 2017; Lahmiri, 2016; Wang et al., 2015; Xu et al., 2016). One of the main advantages of the time-frequency techniques over popular methods to study comovement[50] is the ability to enable multi-scale analysis of time series (Masih & Majid, 2013). We employ the WMC, WMCC and BK18 techniques in this study.

The wavelet multiple and cross correlation start with the Maximal Overlap Discrete Wavelet Transform (MODWT) (Gençay et al., 2001; Percival & Walden, 2000). Let $X_t = x_{1t,}\, x_{2t,}, \dots, x_{nt}$ be a real-valued multivariate random process and let

[50] The Vector Error Correction Model (VECM) is one widely employed techniques to assess co-movement.

$W_{jt} = w_{1jt,} w_{2jt,}, \dots, w_{njt}$ denote the corresponding scale λ_j wavelet coefficients obtained by applying the MODWT. Fernández-Macho (2012) defines the wavelet multiple correlation (WMC) denoted by $\Phi X(\lambda_j)$ as a single set of multiscale correlations from

$$\Phi X(\lambda_j) = \sqrt{1 - \frac{1}{max\, diag P_j^{-1}}}. \tag{5.4}$$

For each λ_j the square roots of the coefficient of determination of the regression formed by the linear combination of $w_{ijt}, i = 1, 2, \dots, n$ variables for which such coefficient of determination is maximum. From extant literature it is known that for a regression of a regressand z_i on a set of predictors $\{z_k, k \neq i\}$, a coefficient of determination can be obtained as $R_i^2 = 1 - {}^{1}/_{\rho^{ii}}$, i^{th} diagonal element of the inverse of the complete correlation matrix P, where P_j is the $(n \times n)$ correlation matrix of $W_{jt} = w_{1jt,} w_{2jt,}, \dots, w_{njt}$ and $max\, diag(*)$ elects the maximum element in the diagonal argument.

From regression theory, we denote the fitted values of z_i by $\hat{z}_i$. The WMC can also be expressed as

$$\Phi X(\lambda_j) = \frac{Corr(w_{i\,jt}, \widehat{w}_{i\,jt}) Cov(w_{i\,jt}, \widehat{w}_{i\,jt})}{\sqrt{Var(w_{i\,jt}) Var(\widehat{w}_{i\,jt})}}, \tag{5.5}$$

where w_{ij} is chosen to maximise $\Phi X(\lambda_j)$ and $\widehat{w}_{i\,jt}$ are the fitted values in the regression of w_{ij} on the rest of the wavelet coefficients at scale λ_j. The wavelet multiple cross-correlation (WMCC)

$$\Phi X, \tau\left(\lambda_j\right) = Corr(w_{i\,jt}, \widehat{w}_{i\,jt+\tau}) = \frac{Cov(w_{i\,jt}, \widehat{w}_{i\,jt+\tau})}{\sqrt{Var(w_{i\,jt})Var(\widehat{w}_{i\,jt+\tau})}} \tag{5.6}$$

is generated by allowing a lag τ between observed and fitted values of the variable at each scale λ_j. Confidence intervals from WMC are calculated using the Fisher (1915) transformation defined as $arctanh(r)$, where $arctanh(*)$ is the inverse hyperbolic tangent function.

In order to calculate WMC and WMCC the MODWT has to be applied to each of the daily and weekly stock index returns as indicated by Percival and Walden (2000). In the spirit of Fernández-Macho (2012) we have chosen to use $J = 7$ for daily shape parameters. A scale $J > 7$ is not advisable since the number of feasible wavelet coefficients gets critically small for high levels. Each J produces J number of wavelet coefficients and $J - (J - 1)$ scaling coefficient (Daubechies, 1992; Fernández-Macho, 2012; Percival & Walden, 2000; Ranta, 2010). The corresponding daily ranges are presented in Table 5.1.

5.2.2.2 Baruník & Křehlík (2018) spillover index

Inspired by Diebold and Yilmaz (2012), Baruník and Křehlík (2018) measure connectedness using generalised forecast error variance decompositions (GFEVDs). The decomposition is based on the matrix of a vector autoregressive (VAR) (5.7) model of local covariance stationarity. Let K-variate process $Y_t = (y_{1,t}, \dots, y_{K,t})'$ at $t = 1, \dots, T$ and a VAR(ρ) may be represented as

$$Y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \epsilon_{t,} \tag{5.7}$$

where ϕ_i and ϵ_i are coefficient matrices and white noise with (likely non-diagonal) covariance matrix Π. Each variable in the system (5.7) is regressed on its own ρ lags and the ρ lags of all the other variables. Thus, ϕ contains a complete information of the connections between all variables. Note the usefulness of working with a $(K \times K)$ matrix $\left(\boldsymbol{I}_K - \emptyset_1 L - \cdots - \emptyset_p L^p\right)$ with identity $\boldsymbol{I}_K$. If the roots of the characteristic equation $|\theta(z)|$ lie outside of the unit circle, the VAR system has a moving average $MA(\infty)$

$$Y_t = \psi(L)\epsilon_t, \tag{5.8}$$

with $\psi(L)$ being an infinitely lagged polynomial. The GFEVD which is the contribution of the kth variable to the variance of forecast error of the element j can be written as

$$(\Theta_H)_{j,k} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H} ((\psi_h \Pi)_{j,k})^2}{\sum_{h=0}^{H} (\psi_h \Pi_{h'})_{j,k}}, \tag{5.9}$$

where $h = 1, \ldots, H$ and $\sigma_{kk} = (\Pi_{kk})$. This is possible because the connectedness measure depends on variance decompositions, being the transformations of ψ_h and serve as contribution of the shocks to the system. Since contributions in the row do not sum to unity, for the sake completeness, the matrix Θ_H is standardised as

$$(\widetilde{\Theta}_H)_{j,k} = \frac{(\Theta_H)_{j,k}}{\sum_{k=1}^{N} (\Theta_H)_{j,k}}. \tag{5.10}$$

For total connectedness in system, the pairwise connectedness (5.10) can be aggregated. According to Diebold and Yilmaz (2012) this can be defined as the share of variance in the forecasts contributed by errors other than own error (or the ratio of the sum of the off-diagonal elements to the sum of the entire matrix) as presented in

$$C_H = 100 * \frac{\sum_{j \neq k} (\widetilde{\Theta}_H)_{j,k}}{\sum \widetilde{\Theta}_H} = 100 * \left(1 - \frac{Tr\{\widetilde{\Theta}_H\}}{\sum \widetilde{\Theta}_H}\right), \tag{5.11}$$

where $Tr\{.\}$ is the trace operator, denominator is the arithmetic sum of all elements in the matrix. It is, thus, apparent that the connectedness signifies the relative contribution of the forecast variance from the other variables in the system. It follows that bi-directional ("*to*" market i from all other markets k, and vice versa ("*from*")) connectedness can be measured. From these "*net*" connectedness is also measured as the difference between "*to*" spillovers and "*from*" spillovers. Hence a market with a positive net spillover is a **net transmitter** while the one with a negative spillover is a **net recipient** of shocks.

At this stage the spectral representation of connectedness is presented. Given a frequency response function of $\psi(e)^{-i\omega} = \sum_h e^{-i\omega h}\psi_h$ of Fourier transformable coefficients ψ_h with $i = \sqrt{-1}$, a spectral density of Y_t at frequency ω can be defined as $MA(\infty)$ filtered series

$$S_{y(\omega)} = \sum_{h=-\infty}^{\infty} E\,(Y'Y_{t-h})e^{-i\omega h} = \psi(e^{-i\omega})\Pi\psi'(e^{+i\omega}). \tag{5.12}$$

The power spectrum $S_{y(\omega)}$ describes the distribution of the variance of Y_t over the frequency components ω. The causation spectrum over $\omega \in (-\pi, \pi)$ is defined in (3.13); noting that it represents the portion of the ith variable due to shocks in the kth variable at a given frequency ω. It follows that

$$(\mathcal{F}(\omega))_{j,k} = \frac{\sigma_{kk}^{-1}|\psi(e^{-i\omega})\Pi_{j,k}|^2}{(\psi(e^{-i\omega})\Pi\psi'(e^{+i\omega}))_{j,j}} \tag{5.13}$$

can be interpreted as *within-frequency* causation on account of the denominator. It is only regular to weight $(\mathcal{F}(\omega))_{j,k}$ by the frequency share of the variance of the jth variable in order to obtain a natural decomposition of GFEVD to frequencies. The weighting function can be defined as

$$\Gamma_j = \frac{(\psi(e^{-i\omega})\Pi\psi'(e^{+i\omega}))_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\psi(e^{-i\lambda})\Pi\psi'(e^{+i\lambda}))_{j,j}\,d\lambda} \tag{5.14}$$

summing up real-valued[51] numbers up to 2π and denotes the power of the jth variable at a given frequency. Practical financial applications require measuring connectedness over time horizons. Hence, it is appropriate to quantify connectedness over frequency bands[52] rather than at single frequencies. In formal terms, for a frequency band $d = (a, b): a, b \in (-\pi, \pi), a < b$, the GFEVDs can be defined as

$$(\Theta_d)_{j,k} = \frac{1}{2\pi}\int_a^b \Gamma_j(\omega)\big(\mathcal{F}(\omega)\big)_{j,k}\,d\omega. \tag{5.15}$$

Over the same frequency band d, a scaled[53] generalised variance decomposition can be defined in

$$(\widetilde{\Theta}_d)_{j,k} = (\Theta_d)_{j,k} / \sum\nolimits_k (\Theta_\infty)_{j,k}. \tag{5.16}$$

Subsequently, the *within-frequency* and frequency connectedness over d are defined in (5.17) and (5.18), respectively.

$$C_d^W = 100.\left(1 - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum \widetilde{\Theta}_d}\right) \tag{5.17}$$

$$C_d^F = 100.\left(\frac{\sum \widetilde{\Theta}_d}{\sum \widetilde{\Theta}_\infty} - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum \widetilde{\Theta}_\infty}\right) = C_d^W.\left(\frac{\sum \widetilde{\Theta}_d}{\sum \widetilde{\Theta}_\infty}\right) \tag{5.18}$$

[51]Though the Fourier transform of the impulse response is generally a complex-valued quantity, the generalised causation spectrum is the squared modulus of the weighted complex numbers, thus producing a real-valued quantity (Baruník & Křehlík, 2018).
[52] In the wavelets framework connectedness is also frequency bands as well. For consistency, the same frequency bands have been chosen for both WMCC and BK18.
[53] Scaling factor is 100 as seen in equations 5.11, 5.17, and 5.18. It is also the minimum forecast horizon H in the empirical implementation of the connectedness in the BK18 framework.

It is worth noting that C_d^W gives the connectedness occurring within a frequency band and it is weighted exclusively by the power of the series on the given frequency band. However, C_d^F, decomposes the overall connectedness into distinct parts which sum up to the original connectedness measure (Baruník & Křehlík, 2018). We use the frequency bands $(\pi + 0.00001, \pi/4, \pi/16, \pi/32, \pi/64, 0)$ (see Baruník & Křehlík, 2018; Tiwari et al., 2018; Tiwari et al., 2019). The corresponding daily ranges are presented in Table 3.1.

5.3 Data, samples and preliminary analysis

The series used as inputs in the WMC, WMCC and VAR are the daily one-month rolling estimates of lambda 3 (L3) and lambda 4 (L4) representing skewness and kurtosis, respectively, from the GLD. The series are the daily log-returns ($r_t = lnP_t - lnP_{t-1}$) from January 1, 2001 to February 18, 2019. These were gleaned from the Bloomberg Terminal. They comprise the top nine (9) MSCI emerging markets index and the MSCI United States index. The top nine (9) emerging markets index country constituents are China (33%), South Korea (13.02%), Taiwan (11.35%), India (9.16%), Brazil (7.23%), South Africa (5.89%), Russia (3.77%), Mexico (2.65%), and Thailand (2.34%). All[54] others take up the remaining 11.59%. The MSCI United States index is added as a proxy for the rest of the world. It does not also interface with any emerging market which helps to avoid double counting. Further, the United States is deemed the originator of the 2007-2009 global financial crisis (GFC) (Cheung et al., 2019; Crotty, 2009; Martin, 2011; Mollah et al., 2016; Nguyen & Pontell, 2010).

[54] https://www.msci.com/emerging-markets, as at March 29, 2019.

Stationarity tests are presented in Table 5.2. We use a VAR model with two lags chosen by Akaike, Hannan-Quinn, and Schwarz Information Criteria; AIC, BIC, and HQIC, respectively. A 100-day ahead forecast horizon (H) and a rolling window size of 100 are used. The rolling window mechanism avoids the need to exogenously specify crisis start and end periods. We are able to account for major changes in the shape spillovers (by plotting the resulting spillover indices) as we roll the data across the full sample period (Yilmaz, 2010). This is one of the strengths of the Diebold-Yilmaz and Baruník-Křehlík spillover frameworks.

To account for both time and frequency domain spillovers, frequency bands are selected to capture short-, medium-, and long-term dynamics. These are selected to coincide with WMC, WMCC, and BK18 techniques as shown in Table 5.1.

Table 5.1: Interpretation of time-scales & frequencies

	WMCC			BK18		
Scale	**Days**	**Interpretation**	**Frequency**	**Band**	**Days**	**Interpretation**
w_{i1}	2 ~ 4	Intraweek	d_1	3.14 ~ 0.79	1 ~ 4	Intraweek
w_{i2}	4 ~ 8	Week	d_2	0.79 ~ 0.20	4 ~ 16	Week to fortnight
w_{i3}	8 ~ 16	Fortnight	d_3	0.20 ~ 0.10	16 ~ 32	Fortnight to month
w_{i4}	16 ~ 32	Month	d_4	0.10 ~ 0.05	32 ~ 64	Month to quarter
w_{i5}	32 ~ 64	Month to quarter	d_5	0.05 ~ 0.00	64 ~ ∞	Quarter and beyond
w_{i6}	64 ~ 128	Quarter to bi-annual				
w_{i7}	128 ~ 256	Bi-annual to annual				

5.3.1 Descriptive statistics

In the Appendix 5.1 (Figures 5.5, 5.6, and 5.7) we present the price and log-returns plots of the emerging markets (and United States) equities together as well as the L3 and L4 estimates, respectively. The daily fluctuation in the prices across is hard to miss for all the series (Figure 5.5). From Figure 5.6 the log-returns also exhibit volatility clustered as expected. In Figure 5.7 we also see the time-variations in the skewness and kurtosis estimates over the whole sample period.

In Table 5.2 (Panel A) we find skewness and kurtosis values indicates non-normality and leptokurtic behaviour in the equity returns across the board. We also find that rolling L3 and L4 estimates are non-Gaussian for all the markets (Panel B). We observe an extremely large negative of L3 (-9.2E+18) and that results in equally large mean (-2E+15) and variance (1.85E+34) values. These were not captured by the summary statistics in Panel A (Min = -0.13, Max = 0.14) which are estimated benchmarked on the normal distribution. Similar deductions can be made for L4. A closer look at the return and price plots of South Korea does not reveal any abnormality that could yield such high L3 and L4 values. Hence, chances are they are the correct estimates from the GLD. The Shapiro-Wilk test confirm these by rejecting the normality assumption at all conventional levels of significance.

We also present stationarity tests with Augmented Dickey-Fuller (ADF)-Generalised Least Squares (GLS) Kwiatkowski-Phillips-Schmidt-Shin (KPSS). We can see clearly that all the series satisfy the stationarity conditions. These are (global) stationarity assumptions as required in many autoregressive models (Engle & Rangel, 2008; Stărică & Granger, 2005). However, we appeal to the BK18 framework which relies on local[55] stationarity of the series.

[55] That is stationarity within a neighbourhood of the series. In this case, in the frequency bands. his can be likened to the local Gaussian approximation and local correlation (see Bampinas & Panagiotidis, 2017; Støve, Tjøstheim, & Hufthammer, 2014).

5.4 Empirical results

While time series are typically decomposed into frequencies to denote different time horizons, their analysis can performed at these frequencies (Diebold & Yilmaz, 2011; Fernández-Macho, 2012; Huang et al., 1999; Percival & Walden, 2000) or across calendar dates (Daubechies, 1992; Fernández-Macho, 2018; Rösch & Schmidbauer, 2018; Schmidbauer et al., 2018) in the sample period. Both of these cases have been referred to as time- and frequency-varying in some quarters. But intuitively the former is only frequency-varying while the latter is both time- and frequency-varying. Nonetheless, a pattern has emerged where only frequency-dependent analysis is seen as static (Baruník & Křehlík, 2018; Diebold & Yilmaz, 2011) but when this analysis is performed across calendar dates on a rolling window basis, it is classified as time-varying (Baruník & Křehlík, 2018; Diebold & Yilmaz, 2009; Diebold & Yilmaz, 2014; Polanco-Martínez et al., 2018; Polanco-Martínez et al., 2018; Polanco-Martínez, 2019). Following from this, in context of this study, the WMC, WMCC, and the non-rolling window portion of BK18 framework is referred to as the static analyses (Section 5.4.1) whereas the rolling window version BK18 framework is termed time-varying (Section 5.4.2).

5.4.1 Frequency-domain (static) analyses

5.4.1.1 WMC and WMCC

In this section, we present the results and analysis of both WMC and WMCC for L3 and L4. The numerical versions of these outputs are presented in Table 5.3. The corresponding graphics are presented in Figures 5.1 and 5.2 for WMC and WMCC, respectively. The WMC plots show upper and lower confidence bounds in blue lines sandwiching the correlations at the various scales. For

WMCC, by convention (in heatmaps) the magnitude of contemporaneous correlations is indicated by the *scale* on the right from blue to wine colour in ascending order.

Additionally, the column WMCC in Table 4.3 (exactly corresponding with Figure 5.2) shows the wavelet multiple cross correlations (with localisations, time lag, lead/lag tendencies at the various scales). Lags are up to 30 for daily returns to indicate about a month length. Markets listed are those signaling a potential to lead or lag of the others at the specific scales. This is obtained by maximising the multiple correlation against a linear combination of the rest of the markets. Further, the time lag at which the strongest or exact wavelet correlation coefficients are localised is indicated by the dashed lines (Figure 5.2). In order to determine the actual lead or lag of the market, we further analyse the localisations vis-à-vis their time lags. There are evidences of spillover effects in the shape parameter estimates since all localisations do not occur at the point of symmetry (i.e. zero time lag). Positive time lags are indicative of the lagging markets at the particular scale whereas negative time lags denote market leadership (Fernández-Macho, 2012).

We first analyse the WMC for both L3 and L4. For daily skewness (L3) correlations in the ten (10) markets, we find about at least 28% (highest correlation of 0.718) discrepancies until after the bi-annual time periods. We observe an overall increment of significant correlations from the intraday through to the bi-annual scale. This suggests a time-varying incremental interconnectedness in asymmetric returns. Since correlations are on an increasing trend we can only infer spillover but not contagion effects among the markets (Forbes & Rigobón, 2002; Saiti, et al., 2016; Fernández-Macho, 2018).

Table 5.2: Summary statistics and stationarity tests

Market	China	South Kora	Taiwan	India	Brazil	South Africa	Russia	Mexico	Thailand	United States
					Panel A					
Observations	4666	4666	4666	4666	4666	4666	4666	4666	4666	4666
Minimum	-0.13	-0.21	-0.07	-0.12	-0.18	-0.14	-0.26	-0.11	-0.18	-0.10
Maximum	0.14	0.25	0.08	0.19	0.17	0.12	0.24	0.15	0.11	0.11
Mean	0.0003	0.0004	0.0001	0.0003	0.0002	0.0002	0.0003	0.0002	0.0004	0.0002
Variance	0.0003	0.0003	0.0002	0.0003	0.0005	0.0003	0.0005	0.0003	0.0002	0.0001
Skewness	-0.11	-0.19	-0.12	-0.10	-0.26	-0.29	-0.43	-0.17	-0.49	-0.24
Kurtosis	6.35	15.08	2.81	9.55	6.85	4.02	13.55	6.88	9.38	9.34
Normtest.W*	0.93	0.91	0.96	0.92	0.94	0.96	0.89	0.93	0.93	0.90
Unit Root tests										
ADF-GLS	-31.30***	-32.44***	-27.02***	-24.07***	-31.42***	-32.38***	-31.07***	-32.94***	-30.66***	-33.01***
KPSS	0.067***	0.18***	0.02***	0.12***	0.13***	0.14***	0.28***	0.27***	0.18***	0.27***
L3					**Panel B**					
Observations	4530	4530	4530	4530	4530	4530	4530	4530	4530	4530
Minimum	-2.95	-9.2E+18	-3.36	-2.17	-1.47	-1.25	-2.80	-1.90	-1.75	-1.24
Maximum	3.73	1.84	1.75	2.49	2.96	1.96	7.30	2.38	8.79	2.33
Mean	0.45	-2E+15	0.43	0.48	0.49	0.53	0.48	0.49	0.50	0.46
Variance	0.28	1.85E+34	0.34	0.28	0.25	0.25	0.34	0.28	0.34	0.28
Normtest.W*	0.95	0.03	0.94	0.95	0.96	0.96	0.94	0.96	0.90	0.96

Table 5.3 (Cont.)

Market	China	South Kora	Taiwan	India	Brazil	South Africa	Russia	Mexico	Thailand	United States
Unit Root tests										
ADF-GLS	-14.53***	-30.07***	-5.98***	-13.48***	-11.02***	-9.85***	-8.76***	8.46***	-10.29***	-7.17***
KPSS	0.18***	0.28***	0.04***	0.76*	0.08***	0.45**	0.85*	0.37**	0.14***	1.11*
L4				**Panel C**						
Observations	4530	4530	4530	4530	4530	4530	4530	4530	4530	4530
Minimum	-4.37	-41.69	-3.04	-1.46	-1.23	-0.98	-3.92	-1.66	-1.63	-0.96
Maximum	1.87	4.58E+18	6.99	7.51	13.28	2.20	8.34	4.26	2.16	1.67
Mean	0.48	1.01E+15	0.42	0.52	0.53	0.57	0.48	0.49	0.41	0.48
Variance	0.31	4.62E+33	0.33	0.30	0.30	0.26	0.34	0.25	0.28	0.26
Normtest.W*	0.91	0.00	0.94	0.94	0.85	0.96	0.93	0.96	0.96	0.96
Unit Root tests										
ADF-GLS	-13.99***	-30.07***	-13.73***	-14.39***	-5.48***	-13.43***	-8.52***	-15.15***	-14.43***	-6.21***
KPSS	0.15***	0.28***	0.41**	0.25***	0.15***	0.11***	0.06***	0.08***	0.08***	0.20***

Note: Normtest.W indicate normality is rejected at all conventional levels of significance. [*], [**], and [***] indicate significance at 10%, 5%, and 1% levels, respectively.*

Table 5.4: Wavelet multiple correlations and cross-correlations of shape parameters

	WMC			WMCC		
Scale	**Lower**	**Correlation**	**Upper**	**Localisation**	**Time lag**	**Leader/Lagging**
L3						
w_{i1}	0.040	0.081	0.122	0.107	-28	Russia
w_{i2}	0.036	0.094	0.152	0.104	-10	India
w_{i3}	0.050	0.131	0.212	0.167	-8	Brazil
w_{i4}	0.125	0.238	0.345	0.238	0	Brazil
w_{i5}	0.153	0.310	0.453	0.345	-19	Mexico
w_{i6}	0.148	0.370	0.557	0.388	-19	South Africa
w_{i7}	0.505	**0.718**	0.848	0.750	-8	Brazil
L4						
w_{i1}	0.027	0.068	0.109	0.091	25	China
w_{i2}	0.084	0.141	0.198	0.141	0	Mexico
w_{i3}	0.106	0.187	0.265	0.187	0	Mexico
w_{i4}	0.089	0.204	0.313	0.263	26	Brazil
w_{i5}	0.195	0.349	0.487	0.354	1	Mexico
w_{i6}	0.274	**0.478**	0.641	0.516	6	Russia
w_{i7}	0.151	0.461	0.688	0.545	-27	Mexico

Note: Upper and Lower columns indicate 95% confidence interval values. Highest correlations are in boldface.

On the other hand, we find kurtosis (L4) multiple wavelet correlations increase from the intraday up to annual scale but decline afterwards. They culminate in only about 48% similarities among the markets in the long-term. While daily returns in one market can be determined by the remaining nine (9) to a degree of about 72% with respect to L3, only about 48% is true for L4 from the quarter scale and beyond. We can imply that in terms of extreme returns the EMEs and United States are less connected than with respect to asymmetric returns. In a similar fashion as L3 we find contagion tendencies to be weaker for L4 since correlation falls in the long-term. We thus rule against "*shape shift-contagion*". However, we cannot rule out spillover effects from these interactions. In terms of portfolio diversification, we surmise that it is better to be guided by comovements in kurtosis rather than skewness to mitigate against risks. In addition, we note that diversification benefits are better in the short- to medium-terms but not in the long-term.

While WMC is only able to tell us the correlation at the various scales WMCC further indicates the market leadership (or lag). In the WMCC column of Table 5.3 (and Figure 5.2) we find an interesting contrast between L3 and L4 localisations. We find market leadership at all scales except monthly (16~32) in the case of L3 but only annual scale (128~256) for L4. For L3 in WMCC with the exception of Brazil (at time lag 0), Russia (-28), India (-10), Brazil (-8), Mexico (-19), South Africa (-19), and Brazil (-8) are market leaders in ascending order of wavelet scales. On the contrary, for L4 at the intraday and week scales Mexico (0) dominates but with no lead/lag tendencies. Again Mexico (-27) leads and Mexico (1) lags but at the annual and quarter scales, respectively. China (25), Brazil (26), and Russia (6) all lag the other markets in the short-, medium-, and long-terms, respectively.

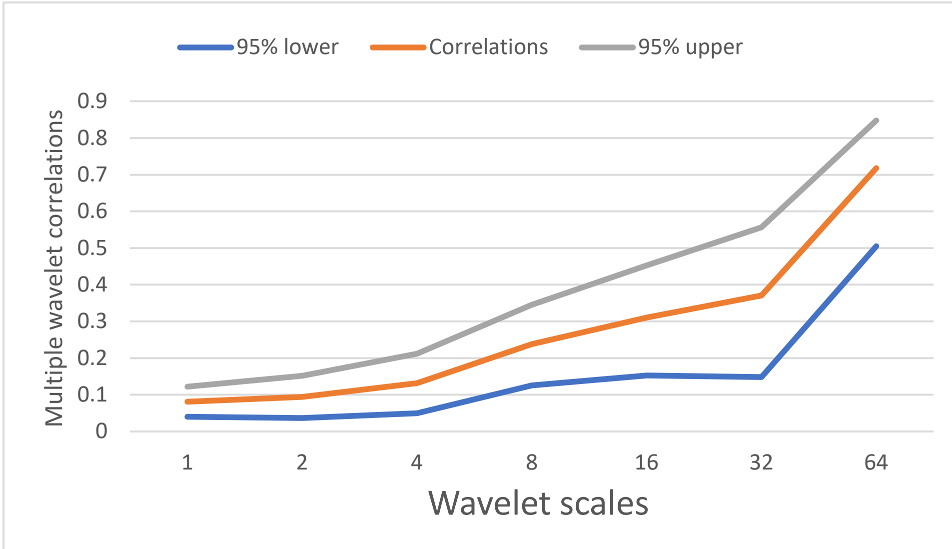
We note for L3, China, South Korea, Taiwan, Thailand, and the United States have not lead/lag potential across all time horizons. In the case of L4, we record South Korea, Taiwan, India, South Africa, Thailand, and the United States lacking lead/lag potentialities across the scales. These bring out important revelations for discussions.

First, we point out that for skewness (L3) Brazil dominates by leading the overall spillover effects while Mexico lags for kurtosis (L4). Further, the United States is missing from both WMC and

WMCC plots, hence it does not possess any leading or lagging power over the nine emerging markets. Our results contrast studies that have used return series to find the United States as the transmitter of contagion to EMEs.

Our results further contradict several literature on spillover and contagion in light of “large country effect” (Aloui & Hkiri, 2014; Calvo, 2004; Masih & Masih, 1999; Neaime, 2012; Pericoli & Sbracia, 2003; Saadi-Sedik & Williams, 2011; Suliman, 2011). On the one hand, the United States is a large country compared to the EMEs. On the other hand, though the EMEs in this study are the top 9, their sizes differ significantly. The first three, China (33%), South Korea (13.02%), and Taiwan (11.35%) alone constitute about 35% of the 88.4% of the top 9 share. But the last three; Russia (3.77%), Mexico (2.65%), and Thailand (2.34%) amount to about only 8%. That China, South Korea, Taiwan, and India do not dominate the lead/lag pattern imply that when it comes to comovement of higher returns, size of the market does not matter. Thus, shape parameters series analysis engenders a new perspective to examine interdependence and contagion in EMEs.

(a) Skewness (L3)



(b) Kurtosis (L4)

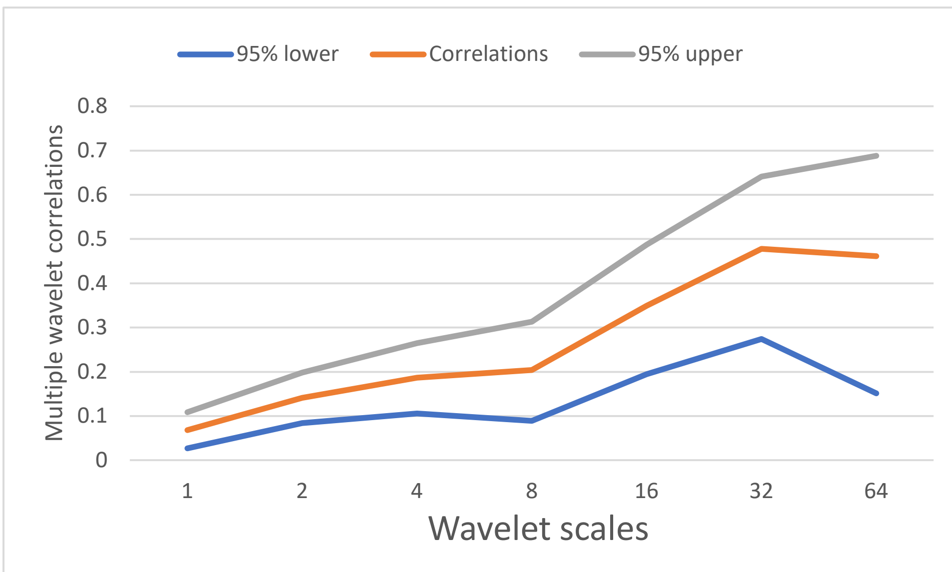
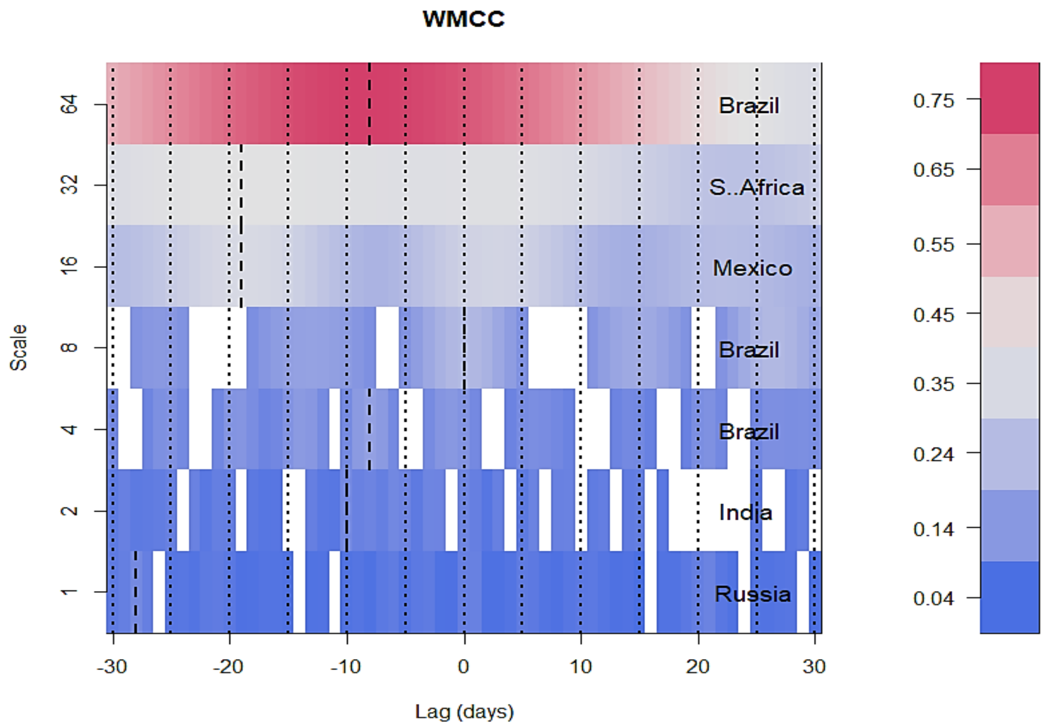


Figure 5.1: Wavelet multiple correlation of shape parameter estimates

(a) Skewness (L3)



(b) Kurtosis (L4)

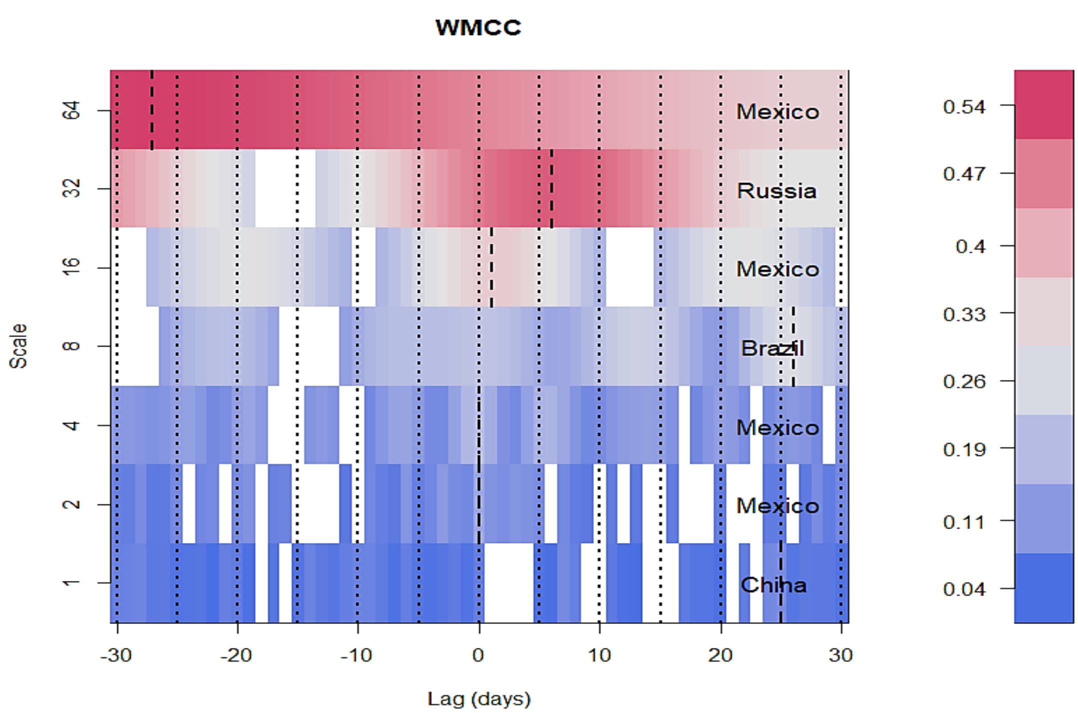


Figure 5. 2: Wavelet multiple cross correlation of shape parameter estimates
Note: Dashed-lines indicate localisations.

5.4.1.2 BK18 framework

In this section we present the total bi-directional spillovers in the frequency-domain within the markets in the BK18 framework. This is a static with the five frequency bands as shown in Table 5.4 for both skewness (Panel A) and kurtosis (Panel B). The $ijth$ entry is the estimated contribution to the forecast error variance in market i coming from innovations to market j. Diagonal entries ($i = j$) indicate the fraction of the forecast error variance of market i that is coming from its own innovations (shocks). We find that these are the largest values in the table and this is understandable. In the presentation of total connectedness in Table 5.4 we pay special attention to *within* connectedness (WTH) rather than *absolute* (ABS) connectedness. While it is interesting to find that absolute connectedness decomposed into frequency bands sum up to total connectedness, within connectedness serves an important additional purpose of indicating causality in the system. The *within* connectedness indicate spillovers weighted by the power of the series exclusively on the frequency and can be viewed as pure unweighted connectedness. Baruník & Křehlík (2018) indicate that in the use of variance decomposition, causal effects can be biased by cross-sectional dependence on the connectedness. They adjust the correlation matrix of VAR residuals by the cross-sectional correlations (see also Diebold & Yilmaz, 2014).

In Table 5.4 we find that *within* connectedness values are larger than those of *absolute* connectedness across the board. This implies that the weaker *absolute* connectedness is mainly driven by weaker contemporaneous correlations. It is, therefore, important for the reader to note that the analysis in this section can be viewed in the light of causality in the connectedness. For every *absolute* connectedness value there is a corresponding *within* connectedness value indicating causality.

In Table 5.4, in terms of skewness (Panel A) we find that the spillover among the 10 markets is dominated at the medium- and long-term frequencies as indicated by average *absolute* (*from*) spillovers of 0.74, 0.53, and 0.52 on frequency bands 4, 3, and 5, respectively. It is also observed that China and India have the highest spillovers in frequency bands 2, 3 and 4; Taiwan and South Korea have the highest in the short-term (frequency bands 1 and 2); and Mexico has the highest in the long-term. Also, Russia on frequency band 4 has the highest spillover. But in aggregate terms China and India dominate while we observe the negligible spillovers from South Africa, Thailand, Brazil, and the United States at all frequency bands.

At least two things can be implied from these dynamics. First, diversification with benefits are possible in the short-term as opposed to the long-term where spillovers are stronger. Second, there is an interplay of both large and small markets dominating causal spillovers at various frequencies. That means the large market effect is minimal when using asymmetric returns as source of spillover propagation. Last, we note that in all the time horizons the United States does not dominate in the propagation of spillovers. This also corroborates the findings from WMC and WMCC techniques in the previous section. It should be noted that these findings contradict the findings of several studies that indicate the dominance of the United States economy in the transmission of shocks and contagion (see Boubaker et al., 2016; Kim et al., 2015; Meinusch, 2017; Shahzad et al., 2017; Suardi, 2012; Wang et al., 2017; Williams, 2017). One can surmise that from the standpoint of asymmetric returns EMEs, are to be cautious of the policy implications bordering on cross-market integration and interdependence within themselves instead of with external countries like the United States. Further, we opine that impact of the GFC may not have had much of an impact on EMEs as compared to the spillover asymmetric returns within each other.

We turn our attention to the propagation of spillovers through extreme returns proxied by kurtosis comovements in Panel B. It is instructive to note that dynamics of average *absolute* and *within* connectedness are also a mirror image of those for skewness comovements. We only point out that the magnitude of spillovers engendered by extreme returns are stronger than skewness. Pertaining to spillovers per market per frequency band there are interesting revelations. First, Brazil (0.02) and Russia (0.06) have highest *from* spillover indices in the short-term (frequency bands 1 and 2, respectively). Mexico particularly dominates across short-, medium-, and long-terms in propagating spillovers. What is clear is that large market effects are completely quiet for cokurtosis. However, it is not obvious how small markets rather propagate extreme returns to relatively larger markets. At the average *absolute* and *within* connectedness levels, the policy and investment implications explained in the last paragraph pertaining spillovers also seem to be true for kurtosis.

In that last rows of frequency bands in Table 5.4 are the net spillovers for each market. As explained earlier *net* spillovers are the differences between *from* and *to* spillovers per market. The few previous paragraphs have centred on *from* spillovers but *net* spillovers bring out the **net**

transmitter and **net recipient** markets. We note that positive *net* spillover indicates that the market is a **net transmitter** while *net* negative spillover denoted **net recipient** market.

It is evident that markets are largely either **net recipients** or **net transmitters** of skewness or kurtosis shocks across the frequency bands, except in a few instances. For instance, on Panel A, China, India, Russia (except on band 2), Mexico, and Thailand are **net recipients** while South Korea, Taiwan, Brazil (except on band 2), South Africa (except on bands 3 and 4), and the United States are **net transmitters.** On Panel B **net recipients** include Russia, Mexico, and Thailand but **net transmitters** are China (except on band 2), South Korea (except on band 1), Taiwan (except on bands 4 and 5), India (except on band 2), South Africa, and the United States.

A closer inspection reveals that, China and India, for instance, are compositely **net transmitters** of extreme returns shocks but compositely **net recipients** of asymmetric return shocks. Other large markets **net transmitters** are South Korea, Taiwan, and the United States. The opposite is true for small markets in the system (Russia, Thailand, Mexico, and Brazil) apart from South Africa. We find that the United States is never a **net recipient** of any sort and this can be attributed to its strength as a global financial power house. These dynamics show a mixture of large and small markets being **net transmitters/recipients** at short-, medium-, and long-terms. In terms of magnitude, we find that the **big net transmitters** of shocks are Taiwan, South Korea, and the United States (in that order). Thus, from a regulatory standpoint, policies targeted at mitigating asymmetric and extreme return shock which can destabilise emerging markets should be directed at these three markets. In general, the spillover strengths of markets may be considered on a case by case basis as well as in respective time horizons. A one size fits all policy and investment approach to view the ***net*** spillovers may be erroneous, since they are market-specific and frequency-dependent.

The final part of our static frequency domain analysis involves net pairwise spillovers. This provides a more detailed investigation of connectedness and can help in two-country portfolio construction as well as bilateral policy decision making. The results are presented in Table 5.5. A closer view at the table indicates that pairwise net directional connectedness magnitudes vary across frequencies for both L3 and L4. Again, spillovers show alternating signs (positive/negative) in the system. There is neither a pattern for large market pairs, small market pairs, nor large-small market pairs. Therefore, it is instructive to note that pairwise net directional connectedness is also pair-specific and frequency-dependent.

5.4.2 Time-varying (time-frequency-domain) in BK18 framework

In our final analysis we consider the time evolution of total connectedness and pairwise net spillovers in the system over the sample periods. We do this by employing a rolling window technique. We use the forecast horizon of 100 days and a window size of 100. For daily series, 100 days representing about one-quarter of a year is enough a time frame to account for a time-varying phenomenon. By doing the rolling window analysis of connectedness we are able to determine the existence of contagion or otherwise as defined in this study. The rolling total and pairwise net spillovers are presented in Figures 5.3 and 5.4, respectively. For the latter, we have elected to present analysis and plots for only the pairs with the United States in the short- and long-terms. The reason is that it is unreasonable to present all 225 (45 pairs on five frequency bands). Furthermore, since the period under study does not overlap any known financial crisis episode in any of the 9 emerging markets (Buchs, 1999; Jansen, 2001; Kamin, 1999; Lauridsen, 1998; Palma, 2012; Slay, 1999). However, given the GFC the United States seems the best choice of test for not just connectedness but contagion originating from asymmetric and extreme returns.

For skewness (a) (Figure 5.3), overall connectedness increases in magnitude with frequency increases. It fluctuates around 2% to 7% in the short-term and around 1% to 65% in the long-term; having ranged between 5% and 38% in the intermediate frequencies. According to our adopted definition of contagion from the extant literature (i.e. a sharp increase in cross-market spillovers at some frequency band(s), we can detect contagion episodes for asymmetric return spillovers. In the short- to medium-terms we spot a sudden upward shift of spillover to about 15% around middle of 2017 on band 1. On band 2 we see a similar sharp increase to about 35% and 30% in 2011 and 2017, respectively. Similarly, on bands 3 and 4, spillovers shoot to about 60% and 50%, respectively.

Table 5.5: Total spillover and Net spillover indices between higher moments of the top 9 emerging markets equities and the United States

	China	S. Korea	Taiwan	India	Brazil	S. Africa	Russia	Mexico	Thailand	US	FROM_ABS[a]	FROM_WTH[b]
Panel A – Skewness (L3)												
Band 1: 3.14 to 0.79; corresponds to 1 days to 4 days												
China	15.58	0.00	0.02	0.04	0.00	0.02	0.02	0.03	0.01	0.03	0.02	0.09
S. Korea	0.01	75.01	0.19	0.03	0.00	0.00	0.01	0.03	0.01	0.01	***0.03***	**0.15**
Taiwan	0.02	0.01	11.66	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.04
India	0.05	0.02	0.01	13.03	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.06
Brazil	0.01	0.00	0.00	0.00	12.59	0.01	0.00	0.06	0.01	0.00	0.01	0.04
S. Africa	0.01	0.00	0.00	0.00	0.00	12.58	0.01	0.02	0.00	0.01	0.01	0.03
Russia	0.01	0.00	0.00	0.01	0.01	0.02	14.01	0.01	0.00	0.05	0.01	0.06
Mexico	0.00	0.00	0.00	0.00	0.03	0.01	0.01	11.11	0.00	0.00	0.01	0.03
Thailand	0.03	0.00	0.03	0.00	0.01	0.01	0.01	0.00	14.08	0.01	0.01	0.05
US	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.01	13.04	0.01	0.03
TO_ABS[a]	0.02	0.01	0.03	0.01	0.01	0.01	0.01	0.02	0.01	0.01	**0.12**	
TO_WTH[b]	0.08	0.03	0.14	0.05	0.03	0.04	0.05	0.09	0.03	0.06		**0.60**
Net	-0.002	-0.023	0.019	-0.002	-0.002	0.002	-0.002	0.010	-0.004	0.005		

Table 5.6 (Cont.)

						Panel A – Skewness (L3)						
	China	S. Korea	Taiwan	India	Brazil	S. Africa	Russia	Mexico	Thailand	US	FROM_ABS[a]	FROM_WTH[b]
						Band 2: 0.79 to 0.20; corresponds to 4 days to 16 days						
China	25.73	0.00	0.03	0.14	0.01	0.06	0.05	0.06	0.05	0.04	***0.04***	**0.19**
S. Korea	0.02	17.61	0.00	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.03
Taiwan	0.06	0.03	22.43	0.04	0.00	0.00	0.02	0.01	0.00	0.02	0.02	0.08
India	0.14	0.01	0.06	25.35	0.02	0.07	0.03	0.03	0.01	0.01	***0.04***	0.16
Brazil	0.02	0.00	0.02	0.00	24.26	0.04	0.00	0.19	0.02	0.01	0.03	0.13
S..Africa	0.01	0.02	0.05	0.03	0.00	23.22	0.05	0.01	0.01	0.03	0.02	0.09
Russia	0.06	0.03	0.02	0.01	0.01	0.02	22.92	0.04	0.00	0.01	0.02	0.09
Mexico	0.03	0.01	0.01	0.01	0.22	0.02	0.02	22.58	0.03	0.08	**0.04**	**0.18**
Thailand	0.09	0.00	0.08	0.00	0.01	0.04	0.04	0.01	25.59	0.01	0.03	0.12
US	0.01	0.02	0.01	0.03	0.02	0.01	0.01	0.02	0.04	24.99	0.02	0.07
TO_ABS[a]	0.04	0.01	0.03	0.03	0.03	0.03	0.02	0.04	0.02	0.02	0.27	
TO_WTH[b]	0.18	0.05	0.12	0.12	0.14	0.11	0.1	0.16	0.07	0.09		**1.14**
Net	-0.001	0.004	0.010	-0.010	0.002	0.006	0.003	-0.005	-0.012	0.003		
						Band 3: 0.20 to 0.10; corresponds to 16 days to 32 days						
China	24.16	0.00	0.02	0.37	0.04	0.04	0.04	0.04	0.14	0.03	*0.07*	0.31
S. Korea	0.01	3.92	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.02
Taiwan	0.04	0.04	24.77	0.03	0.01	0.00	0.04	0.01	0.00	0.05	0.02	0.10
India	0.08	0.00	0.20	24.69	0.05	0.24	0.01	0.02	0.01	0.01	0.06	0.28
Brazil	0.02	0.00	0.06	0.00	24.78	0.14	0.01	0.21	0.02	0.01	0.05	0.21

Table 5.7 (Cont.)

	Panel A – Skewness (L3)											
	China	S. Korea	Taiwan	India	Brazil	S. Africa	Russia	Mexico	Thailand	US	FROM_ABS[a]	FROM_WTH[b]
S. Africa	0.04	0.02	0.20	0.08	0.01	24.23	0.15	0.01	0.04	0.09	0.06	0.28
Russia	0.19	0.04	0.04	0.01	0.04	0.08	23.87	0.10	0.00	0.00	0.05	0.22
Mexico	0.08	0.01	0.01	0.02	0.71	0.00	0.10	23.87	0.08	0.28	**0.13**	**0.57**
Thailand	0.07	0.00	0.07	0.01	0.01	0.08	0.09	0.02	24.91	0.05	0.04	0.17
US	0.03	0.02	0.01	0.09	0.09	0.02	0.02	0.04	0.02	25.05	0.04	0.15
TO_ABS[a]	0.06	0.01	0.06	0.06	0.10	0.06	0.05	0.05	0.03	0.05	**0.53**	
TO_WTH[b]	0.25	0.05	0.27	0.27	0.42	0.27	0.21	0.20	0.14	0.23		**2.31**
Net	-0.016	0.007	0.039	-0.002	0.049	-0.001	-0.003	-0.084	-0.007	0.018		
	Band 4: 0.10 to 0.05; corresponds to 32 days to 64 days											
China	20.15	0.00	0.01	0.51	0.05	0.04	0.02	0.03	0.19	0.02	0.09	0.41
S. Korea	0.01	1.97	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.00	0.02
Taiwan	0.02	0.04	24.72	0.02	0.02	0.00	0.06	0.01	0.01	0.08	0.02	0.12
India	0.03	0.00	0.31	21.57	0.08	0.39	0.02	0.01	0.01	0.02	*0.09*	0.41
Brazil	0.02	0.00	0.09	0.00	22.75	0.22	0.03	0.20	0.01	0.01	0.06	0.28
S. Africa	0.07	0.03	0.31	0.12	0.01	23.09	0.23	0.01	0.07	0.13	0.10	0.47
Russia	0.28	0.03	0.05	0.01	0.08	0.16	22.87	0.14	0.00	0.00	0.08	0.36
Mexico	0.12	0.00	0.01	0.03	1.19	0.02	0.18	22.86	0.12	0.45	***0.21***	***1.00***
Thailand	0.04	0.00	0.03	0.02	0.01	0.12	0.12	0.03	21.42	0.09	0.05	0.21
US	0.05	0.02	0.02	0.12	0.14	0.03	0.01	0.05	0.01	22.34	0.04	0.21

Table 5.8 (Cont.)

						Panel A – Skewness (L3)						
	China	S. Korea	Taiwan	India	Brazil	S. Africa	Russia	Mexico	Thailand	US	FROM_ABS[a]	FROM_WTH[b]
TO_ABS[a]	0.06	0.01	0.08	0.08	0.16	0.10	0.07	0.05	0.04	0.08	**0.74**	
TO_WTH[b]	0.3	0.06	0.4	0.39	0.75	0.46	0.33	0.23	0.20	0.39		**3.51**
Net	-0.023	0.007	0.059	-0.004	0.100	-0.001	-0.008	-0.163	-0.004	0.037		
					Band 5: 0.05 to 0.00; corresponds to 64 infinite days							
China	11.59	0.00	0.00	0.35	0.03	0.03	0.01	0.01	0.13	0.01	0.06	0.45
S. Korea	0.01	0.99	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.02
Taiwan	0.01	0.02	15.53	0.00	0.02	0.00	0.04	0.01	0.00	0.06	0.02	0.13
India	0.01	0.00	0.22	12.72	0.07	0.29	0.02	0.01	0.00	0.02	0.06	0.49
Brazil	0.01	0.00	0.07	0.00	13.75	0.16	0.03	0.12	0.00	0.01	0.04	0.32
S. Africa	0.06	0.02	0.23	0.09	0.01	14.27	0.17	0.01	0.05	0.10	0.07	0.56
Russia	0.20	0.02	0.04	0.01	0.06	0.12	14.19	0.10	0.00	0.00	0.06	0.43
Mexico	0.08	0.00	0.00	0.02	0.89	0.02	0.14	14.1	0.08	0.32	***0.16***	***1.22***
Thailand	0.02	0.00	0.01	0.01	0.01	0.08	0.08	0.02	12.46	0.07	0.03	0.23
US	0.03	0.01	0.01	0.08	0.10	0.02	0.00	0.03	0.00	13.25	0.03	0.23
TO_ABS[a]	0.04	0.01	0.06	0.06	0.12	0.07	0.05	0.03	0.03	0.06	**0.52**	
TO_WTH[b]	0.33	0.06	0.45	0.44	0.93	0.57	0.39	0.24	0.21	0.46		**4.09**
Net	-0.015	0.004	0.041	-0.006	0.078	0.001	-0.005	-0.125	-0.002	0.030		

Table 5.9 (Cont.)

	China	S. Korea	Taiwan	India	Brazil	S. Africa	Russia	Mexico	Thailand	US	FROM_ABS[a]	FROM_WTH[b]
Panel B – Kurtosis (L4)												
Band 1: 3.14 to 0.79; corresponds to 1 days to 4 days												
China	12.6	0.00	0.01	0.05	0.00	0.01	0.01	0.02	0.01	0.00	0.01	0.05
S. Korea	0.00	75.13	0.03	0.02	0.00	0.00	0.03	0.00	0.02	0.03	0.01	0.07
Taiwan	0.01	0.00	13.25	0.01	0.01	0.00	0.00	0.00	0.02	0.00	0.01	0.03
India	0.04	0.01	0.01	14.54	0.04	0.01	0.00	0.01	0.01	0.00	0.01	0.07
Brazil	0.03	0.00	0.02	0.04	20.5	0.04	0.00	0.04	0.00	0.02	***0.02***	***0.1***
S. Africa	0.01	0.00	0.02	0.00	0.01	12.80	0.03	0.03	0.00	0.00	0.01	0.05
Russia	0.01	0.00	0.00	0.00	0.00	0.01	13.39	0.02	0.00	0.00	0.01	0.03
Mexico	0.01	0.00	0.00	0.00	0.03	0.02	0.02	13.24	0.00	0.07	***0.02***	***0.08***
Thailand	0.00	0.02	0.03	0.01	0.00	0.00	0.00	0.00	12.24	0.01	0.01	0.04
US	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.01	12.63	0.01	0.05
TO_ABS[a]	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	**0.11**	
TO_WTH[b]	0.07	0.02	0.06	0.06	0.05	0.05	0.04	0.09	0.04	0.07		**0.56**
Net	0.003	-0.010	0.007	0.003	0.003	0.001	-0.001	-0.011	0.000	0.004		
Band 2: 0.79 to 0.20; corresponds to 4 days to 16 days												
China	22.8	0.00	0.02	0.12	0.01	0.14	0.02	0.06	0.03	0.01	0.04	0.17
S. Korea	0.01	17.67	0.00	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01	0.02
Taiwan	0.01	0.02	23.04	0.01	0.04	0.03	0.01	0.01	0.06	0.02	0.02	0.09
India	0.09	0.01	0.03	28.22	0.10	0.01	0.00	0.03	0.03	0.00	0.03	0.12
Brazil	0.06	0.00	0.02	0.05	27.19	0.04	0.04	0.13	0.02	0.00	0.04	0.15

Table 5.10 (Cont.)

						Panel B – Kurtosis (L4)						
	China	S. Korea	Taiwan	India	Brazil	S. Africa	Russia	Mexico	Thailand	US	FROM_ABS[a]	FROM_WTH[b]
S. Africa	0.03	0.00	0.04	0.01	0.02	23.77	0.08	0.08	0.01	0.00	0.03	0.11
Russia	0.13	0.01	0.00	0.00	0.00	0.04	23.75	0.11	0.00	0.02	0.03	0.13
Mexico	0.05	0.01	0.00	0.01	0.19	0.07	0.05	24.08	0.01	0.25	***0.06***	***0.27***
Thailand	0.01	0.01	0.09	0.03	0.00	0.12	0.01	0.00	22.9	0.02	0.03	0.13
US	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.21	0.02	23.45	0.03	0.11
TO_ABS[a]	0.04	0.01	0.02	0.03	0.04	0.05	0.02	0.06	0.02	0.03	**0.32**	
TO_WTH[b]	0.17	0.03	0.09	0.11	0.16	0.19	0.09	0.27	0.08	0.14		**1.32**
Net	-0.001	0.001	0.001	-0.005	0.002	0.019	-0.009	0.000	-0.012	0.005		
						Band 3: 0.20 to 0.10; corresponds to 16 days to 32 days						
China	24.39	0.01	0.02	0.08	0.02	0.50	0.02	0.04	0.07	0.01	0.08	0.34
S. Korea	0.01	3.93	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.02
Taiwan	0.04	0.03	24.43	0.00	0.11	0.09	0.03	0.02	0.04	0.07	0.04	0.19
India	0.06	0.00	0.05	24.99	0.08	0.01	0.00	0.02	0.03	0.00	0.03	0.11
Brazil	0.08	0.00	0.01	0.06	22.32	0.07	0.13	0.37	0.04	0.00	0.08	0.33
S. Africa	0.03	0.00	0.05	0.02	0.05	25.09	0.06	0.08	0.01	0.00	0.03	0.13
Russia	0.44	0.01	0.00	0.01	0.01	0.10	24.22	0.20	0.01	0.07	0.08	0.37
Mexico	0.08	0.01	0.01	0.03	0.42	0.15	0.06	23.81	0.02	0.41	***0.12***	***0.52***
Thailand	0.05	0.01	0.10	0.03	0.00	0.45	0.04	0.00	24.38	0.02	0.07	0.31
US	0.01	0.00	0.01	0.03	0.04	0.04	0.01	0.38	0.03	24.54	0.05	0.23

Table 5.11 (Cont.)

	China	S. Korea	Taiwan	India	Brazil	S. Africa	Russia	Mexico	Thailand	US	FROM_ABS[a]	FROM_WTH[b]
						Panel B – Kurtosis (L4)						
TO_ABS[a]	0.08	0.01	0.03	0.03	0.07	0.14	0.04	0.11	0.03	0.06	**0.58**	
TO_WTH[b]	0.34	0.03	0.11	0.11	0.32	0.62	0.16	0.49	0.11	0.26		**2.55**
Net	0.001	0.002	-0.018	0.001	-0.002	0.111	-0.048	-0.007	-0.044	0.005		
						Band 4: 0.10 to 0.05; corresponds to 32 days to 64 days						
China	23.12	0.01	0.02	0.03	0.02	0.86	0.01	0.01	0.10	0.01	0.11	0.52
S. Korea	0.01	1.97	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.02
Taiwan	0.05	0.03	23.3	0.00	0.14	0.13	0.05	0.03	0.02	0.13	0.06	0.28
India	0.02	0.00	0.07	19.94	0.05	0.01	0.00	0.01	0.03	0.00	0.02	0.09
Brazil	0.11	0.00	0.00	0.06	17.24	0.09	0.18	0.50	0.05	0.00	0.10	0.48
S. Africa	0.02	0.00	0.05	0.04	0.07	23.31	0.03	0.05	0.00	0.00	0.03	0.12
Russia	0.71	0.01	0.00	0.01	0.01	0.21	21.97	0.28	0.02	0.12	0.14	0.66
Mexico	0.10	0.01	0.01	0.03	0.53	0.26	0.07	21.42	0.03	0.52	***0.16***	***0.75***
Thailand	0.10	0.01	0.10	0.02	0.01	0.70	0.07	0.00	23.33	0.02	0.10	0.50
US	0.01	0.00	0.01	0.04	0.07	0.07	0.01	0.51	0.03	23.11	0.07	0.36
TO_ABS[a]	0.11	0.01	0.03	0.02	0.09	0.23	0.04	0.14	0.03	0.08	**0.78**	
TO_WTH[b]	0.55	0.03	0.13	0.12	0.43	1.13	0.20	0.68	0.14	0.38		**3.79**
Net	0.007	0.002	-0.031	0.004	-0.010	0.207	-0.095	-0.015	-0.074	0.005		

Table 5.12 (Cont.)

	China	S. Korea	Taiwan	India	Brazil	S. Africa	Russia	Mexico	Thailand	US	FROM_ABS[a]	FROM_WTH[b]
						Panel B – Kurtosis (L4)						
						Band 5: 0.05 to 0.00; corresponds to 64 infinite days						
China	13.99	0.00	0.01	0.01	0.01	0.63	0.00	0.00	0.07	0.00	0.07	0.6
S. Korea	0.01	0.99	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02
Taiwan	0.04	0.02	14.31	0.00	0.09	0.09	0.04	0.02	0.00	0.10	0.04	0.31
India	0.01	0.00	0.05	11.31	0.03	0.00	0.00	0.00	0.02	0.00	0.01	0.09
Brazil	0.08	0.00	0.00	0.04	9.73	0.06	0.12	0.34	0.03	0.00	0.07	0.55
S. Africa	0.01	0.00	0.03	0.03	0.05	13.96	0.01	0.02	0.00	0.00	0.01	0.12
Russia	0.52	0.00	0.00	0.01	0.01	0.18	13.07	0.19	0.02	0.08	0.10	0.82
Mexico	0.07	0.00	0.01	0.02	0.34	0.20	0.04	12.84	0.02	0.36	***0.11***	***0.86***
Thailand	0.08	0.00	0.06	0.02	0.01	0.49	0.06	0.00	14.32	0.01	0.07	0.58
US	0.00	0.00	0.00	0.03	0.05	0.05	0.01	0.36	0.02	14.11	0.05	0.42
TO_ABS[a]	0.08	0.00	0.02	0.01	0.06	0.17	0.03	0.09	0.02	0.06	**0.54**	
TO_WTH[b]	0.65	0.03	0.14	0.12	0.47	1.38	0.22	0.76	0.15	0.45		**4.36**
Net	0.006	0.001	-0.022	0.004	-0.010	0.157	-0.074	-0.012	-0.054	0.004		

Note: [a] Absolute to measures skewness/kurtosis spillovers from country j to other countries. Absolute from measures skewness/kurtosis spillovers from other countries to country j. [b]Within to measures skewness/kurtosis spillovers from country j to other countries, including from own innovations to country k. Within from measures skewness/kurtosis spillovers from other countries to country j, including from own innovations to country k (see Tiwari et al., 2018, 2019). The largest contributions of markets per frequency band are in bold italics. S. African, S. Korea, and US represent South African, South Korea, and United States, respectively. Positive ***Net*** *denotes that the market is a* ***net transmitter*** *while negative* ***Net*** *denote* ***net recipient.***

Table 5.13: Pairwise net directional spillover between higher moments of the top 9 emerging markets equities and the United States

Panel A – Skewness (L3)

Band 1: 3.14 to 0.79; corresponds to 1 days to 4 days

China-S. Korea	China-Taiwan	China-India	China-Brazil	China-S. Africa	China-Russia	China-Mexico	China-Thailand	China-US	S. Korea-Taiwan	S. Korea-India	S. Korea-Brazil	S. Korea-S. Africa	S. Korea-Russia	S. Korea-Mexico
-0.06	-0.02	-0.13	-0.03	0.19	0.08	0.22	-0.15	0.14	1.81	0.05	0.04	-0.03	0.08	0.31
S. Korea-Thailand	S. Korea-US	Taiwan-India	Taiwan-Brazil	Taiwan-S. Africa	Taiwan-Russia	Taiwan-Mexico	Taiwan-Thailand	Taiwan-US	India-Brazil	India-S. Africa	India-Russia	India-Mexico	India-Thailand	India-US
0.04	-0.02	0.06	-0.02	0.03	0.00	0.05	-0.24	-0.02	0.10	0.00	0.02	0.07	0.00	0.04
Brazil-S. Africa	Brazil-Russia	Brazil-Mexico	Brazil-Thailand	Brazil-US	S. Africa-Russia	S. Africa-Mexico	S. Africa-Thailand	S. Africa-US	Russia-Mexico	Russia-Thailand	Russia-US	Mexico-Thailand	Mexico-US	Thailand-US
0.05	-0.05	0.24	0.02	0.01	-0.10	0.11	-0.05	0.06	-0.01	-0.07	0.35	0.00	-0.01	-0.08

Band 2: 0.79 to 0.20; corresponds to 4 days to 16 days

China-S. Korea	China-Taiwan	China-India	China-Brazil	China-S. Africa	China-Russia	China-Mexico	China-Thailand	China-US	S. Korea-Taiwan	S. Korea-India	S. Korea-Brazil	S. Korea-S. Africa	S. Korea-Russia	S. Korea-Mexico
-0.14	-0.38	0.09	-0.01	0.46	-0.13	0.33	-0.35	0.26	-0.30	0.01	0.06	-0.15	-0.22	-0.02
S. Korea-Thailand	S. Korea-US	Taiwan-India	Taiwan-Brazil	Taiwan-S. Africa	Taiwan-Russia	Taiwan-Mexico	Taiwan-Thailand	Taiwan-US	India-Brazil	India-S. Africa	India-Russia	India-Mexico	India-Thailand	India-US
0.09	-0.06	-0.23	-0.18	-0.52	0.01	-0.03	-0.79	0.08	0.24	0.45	0.16	0.16	0.03	-0.20
Brazil-S. Africa	Brazil-Russia	Brazil-Mexico	Brazil-Thailand	Brazil-US	S. Africa-Russia	S. Africa-Mexico	S. Africa-Thailand	S. Africa-US	Russia-Mexico	Russia-Thailand	Russia-US	Mexico-Thailand	Mexico-US	Thailand-US
0.43	-0.06	-0.31	0.09	-0.18	0.31	-0.09	-0.31	0.17	0.17	-0.38	-0.01	0.14	0.58	-0.31

Table 5.14 (Cont.)

Panel A – Skewness (L3)														
Band 3: 0.20 to 0.10; corresponds to 16 days to 32 days														
China-S. Korea	China-Taiwan	China-India	China-Brazil	China-S. Africa	China-Russia	China-Mexico	China-Thailand	China-US	S. Korea-Taiwan	S. Korea-India	S. Korea-Brazil	S. Korea-S. Africa	S. Korea-Russia	S. Korea-Mexico
-0.13	-0.24	2.89	0.14	0.07	-1.47	-0.39	0.74	-0.05	-0.37	0.01	0.07	-0.21	-0.26	-0.06
S. Korea-Thailand	S. Korea-US	Taiwan-India	Taiwan-Brazil	Taiwan-S. Africa	Taiwan-Russia	Taiwan-Mexico	Taiwan-Thailand	Taiwan-US	India-Brazil	India-S. Africa	India-Russia	India-Mexico	India-Thailand	India-US
0.07	-0.07	-1.73	-0.50	-1.95	0.02	-0.05	-0.63	0.35	0.50	1.61	0.05	-0.02	-0.03	-0.75
Brazil-S. Africa	Brazil-Russia	Brazil-Mexico	Brazil-Thailand	Brazil-US	S. Africa-Russia	S. Africa-Mexico	S. Africa-Thailand	S. Africa-US	Russia-Mexico	Russia-Thailand	Russia-US	Mexico-Thailand	Mexico-US	Thailand-US
1.32	-0.30	-4.96	0.13	-0.85	0.63	0.10	-0.41	0.60	-0.04	-0.91	-0.10	0.58	2.42	0.23
Band 4: 0.10 to 0.05; corresponds to 32 days to 64 days														
China-S. Korea	China-Taiwan	China-India	China-Brazil	China-S. Africa	China-Russia	China-Mexico	China-Thailand	China-US	S. Korea-Taiwan	S. Korea-India	S. Korea-Brazil	S. Korea-S. Africa	S. Korea-Russia	S. Korea-Mexico
-0.11	-0.07	4.84	0.25	-0.30	-2.62	-0.93	1.55	-0.27	-0.35	0.01	0.08	-0.24	-0.24	-0.04
S. Korea-Thailand	S. Korea-US	Taiwan-India	Taiwan-Brazil	Taiwan-S. Africa	Taiwan-Russia	Taiwan-Mexico	Taiwan-Thailand	Taiwan-US	India-Brazil	India-S. Africa	India-Russia	India-Mexico	India-Thailand	India-US
0.05	-0.06	-2.96	-0.72	-3.12	0.03	0.01	-0.23	0.66	0.85	2.68	0.06	-0.15	-0.11	-0.99
Brazil-S. Africa	Brazil-Russia	Brazil-Mexico	Brazil-Thailand	Brazil-US	S. Africa-Russia	S. Africa-Mexico	S. Africa-Thailand	S. Africa-US	Russia-Mexico	Russia-Thailand	Russia-US	Mexico-Thailand	Mexico-US	Thailand-US
2.11	-0.42	-9.89	0.02	-1.34	0.76	-0.04	-0.47	0.99	-0.39	-1.24	-0.06	0.86	3.98	0.80

Table 5.15 (Cont.)

Panel A – Skewness (L3)

Band 5: 0.05 to 0.00; corresponds to 64 infinite days

China-S. Korea	China-Taiwan	China-India	China-Brazil	China-S. Africa	China-Russia	China-Mexico	China-Thailand	China-US	S. Korea-Taiwan	S. Korea-India	S. Korea-Brazil	S. Korea-S. Africa	S. Korea-Russia	S. Korea-Mexico
-0.06	-0.01	3.41	0.18	-0.29	-1.93	-0.70	1.13	-0.20	-0.22	0.01	0.05	-0.16	-0.15	-0.02
S. Korea-Thailand	S. Korea-US	Taiwan-India	Taiwan-Brazil	Taiwan-S. Africa	Taiwan-Russia	Taiwan-Mexico	Taiwan-Thailand	Taiwan-US	India-Brazil	India-S. Africa	India-Russia	India-Mexico	India-Thailand	India-US
0.03	-0.04	-2.17	-0.50	-2.25	0.02	0.04	-0.01	0.52	0.66	2.00	0.08	-0.13	-0.10	-0.64
Brazil-S. Africa	Brazil-Russia	Brazil-Mexico	Brazil-Thailand	Brazil-US	S. Africa-Russia	S. Africa-Mexico	S. Africa-Thailand	S. Africa-US	Russia-Mexico	Russia-Thailand	Russia-US	Mexico-Thailand	Mexico-US	Thailand-US
1.55	-0.28	-7.71	-0.05	-0.95	0.47	-0.15	-0.31	0.73	-0.41	-0.84	-0.01	0.56	2.90	0.66

Panel B – Kurtosis (L4)

Band 1: 3.14 to 0.79; corresponds to 1 days to 4 days

China-S. Korea	China-Taiwan	China-India	China-Brazil	China-S. Africa	China-Russia	China-Mexico	China-Thailand	China-US	S. Korea-Taiwan	S. Korea-India	S. Korea-Brazil	S. Korea-S. Africa	S. Korea-Russia	S. Korea-Mexico
-0.01	-0.01	0.02	-0.30	-0.03	-0.02	0.07	0.05	-0.06	0.27	0.09	0.02	0.02	0.26	0.01
S. Korea-Thailand	S. Korea-US	Taiwan-India	Taiwan-Brazil	Taiwan-S. Africa	Taiwan-Russia	Taiwan-Mexico	Taiwan-Thailand	Taiwan-US	India-Brazil	India-S. Africa	India-Russia	India-Mexico	India-Thailand	India-US
0.04	0.27	-0.02	-0.13	-0.17	-0.02	0.00	-0.09	-0.01	-0.03	0.07	0.01	0.07	0.02	-0.01
Brazil-S. Africa	Brazil-Russia	Brazil-Mexico	Brazil-Thailand	Brazil-US	S. Africa-Russia	S. Africa-Mexico	S. Africa-Thailand	S. Africa-US	Russia-Mexico	Russia-Thailand	Russia-US	Mexico-Thailand	Mexico-US	Thailand-US
0.32	0.02	0.07	0.05	0.19	0.13	0.05	0.00	-0.02	0.08	0.03	-0.03	-0.01	0.09	0.0004

Table 5.16 (Cont.)

Panel B – Kurtosis (L4)

Band 2: 0.79 to 0.20; corresponds to 4 days to 16 days

China-S. Korea	China-Taiwan	China-India	China-Brazil	China-S. Africa	China-Russia	China-Mexico	China-Thailand	China-US	S. Korea-Taiwan	S. Korea-India	S. Korea-Brazil	S. Korea-S. Africa	S. Korea-Russia	S. Korea-Mexico
-0.04	0.05	0.27	-0.50	1.11	-1.03	0.10	0.14	0.04	-0.23	0.04	0.03	0.06	-0.07	0.02
S. Korea-Thailand	S. Korea-US	Taiwan-India	Taiwan-Brazil	Taiwan-S. Africa	Taiwan-Russia	Taiwan-Mexico	Taiwan-Thailand	Taiwan-US	India-Brazil	India-S. Africa	India-Russia	India-Mexico	India-Thailand	India-US
-0.05	0.05	-0.23	0.20	-0.17	0.06	0.07	-0.36	0.18	0.52	-0.02	0.00	0.13	0.00	-0.08
Brazil-S. Africa	Brazil-Russia	Brazil-Mexico	Brazil-Thailand	Brazil-US	S. Africa-Russia	S. Africa-Mexico	S. Africa-Thailand	S. Africa-US	Russia-Mexico	Russia-Thailand	Russia-US	Mexico-Thailand	Mexico-US	Thailand-US
0.16	0.42	-0.59	0.18	-0.12	0.38	0.11	-1.10	-0.12	0.57	-0.05	0.16	0.03	0.41	0.01

Band 3: 0.20 to 0.10; corresponds to 16 days to 32 days

China-S. Korea	China-Taiwan	China-India	China-Brazil	China-S. Africa	China-Russia	China-Mexico	China-Thailand	China-US	S. Korea-Taiwan	S. Korea-India	S. Korea-Brazil	S. Korea-S. Africa	S. Korea-Russia	S. Korea-Mexico
-0.04	-0.12	0.16	-0.55	4.74	-4.13	-0.42	0.17	0.03	-0.28	0.04	0.03	0.06	-0.05	0.03
S. Korea-Thailand	S. Korea-US	Taiwan-India	Taiwan-Brazil	Taiwan-S. Africa	Taiwan-Russia	Taiwan-Mexico	Taiwan-Thailand	Taiwan-US	India-Brazil	India-S. Africa	India-Russia	India-Mexico	India-Thailand	India-US
-0.06	0.005	-0.47	0.96	0.39	0.31	0.12	-0.56	0.66	0.16	-0.12	-0.05	-0.14	0.08	-0.24
Brazil-S. Africa	Brazil-Russia	Brazil-Mexico	Brazil-Thailand	Brazil-US	S. Africa-Russia	S. Africa-Mexico	S. Africa-Thailand	S. Africa-US	Russia-Mexico	Russia-Thailand	Russia-US	Mexico-Thailand	Mexico-US	Thailand-US
0.19	1.21	-0.54	0.38	-0.43	-0.37	-0.76	-4.38	-0.36	1.41	-0.28	0.64	0.17	0.28	-0.08

Table 5.17 (Cont.)

Panel B – Kurtosis (L4)

Band 4: 0.10 to 0.05; corresponds to 32 days to 64 days														
China-S. Korea	China-Taiwan	China-India	China-Brazil	China-S. Africa	China-Russia	China-Mexico	China-Thailand	China-US	S. Korea-Taiwan	S. Korea-India	S. Korea-Brazil	S. Korea-S. Africa	S. Korea-Russia	S. Korea-Mexico
-0.03	-0.29	0.07	-0.91	8.39	-7.03	-0.86	0.00	0.01	-0.28	0.03	0.03	0.06	-0.04	0.03
S. Korea-Thailand	S. Korea-US	Taiwan-India	Taiwan-Brazil	Taiwan-S. Africa	Taiwan-Russia	Taiwan-Mexico	Taiwan-Thailand	Taiwan-US	India-Brazil	India-S. Africa	India-Russia	India-Mexico	India-Thailand	India-US
-0.05	0.002	-0.69	1.34	0.87	0.51	0.14	-0.78	1.18	-0.12	-0.27	-0.10	-0.24	0.05	-0.36
Brazil-S. Africa	Brazil-Russia	Brazil-Mexico	Brazil-Thailand	Brazil-US	S. Africa-Russia	S. Africa-Mexico	S. Africa-Thailand	S. Africa-US	Russia-Mexico	Russia-Thailand	Russia-US	Mexico-Thailand	Mexico-US	Thailand-US
0.20	1.63	-0.22	0.41	-0.63	-1.81	-2.08	-6.95	-0.65	2.11	-0.52	1.07	0.28	0.08	-0.17
Band 5: 0.05 to 0.00; corresponds to 64 infinite days														
China-S. Korea	China-Taiwan	China-India	China-Brazil	China-S. Africa	China-Russia	China-Mexico	China-Thailand	China-US	S. Korea-Taiwan	S. Korea-India	S. Korea-Brazil	S. Korea-S. Africa	S. Korea-Russia	S. Korea-Mexico
-0.02	-0.23	0.03	-0.73	6.27	-5.16	-0.65	-0.10	0.00	-0.18	0.02	0.02	0.03	-0.02	0.02
S. Korea-Thailand	S. Korea-US	Taiwan-India	Taiwan-Brazil	Taiwan-S. Africa	Taiwan-Russia	Taiwan-Mexico	Taiwan-Thailand	Taiwan-US	India-Brazil	India-S. Africa	India-Russia	India-Mexico	India-Thailand	India-US
-0.02	0.00	-0.50	0.89	0.63	0.37	0.08	-0.57	0.91	-0.12	-0.22	-0.08	-0.16	0.01	-0.25
Brazil-S. Africa	Brazil-Russia	Brazil-Mexico	Brazil-Thailand	Brazil-US	S. Africa-Russia	S. Africa-Mexico	S. Africa-Thailand	S. Africa-US	Russia-Mexico	Russia-Thailand	Russia-US	Mexico-Thailand	Mexico-US	Thailand-US
0.15	1.09	-0.03	0.24	-0.43	-1.70	-1.76	-4.89	-0.51	1.51	-0.39	0.79	0.21	0.01	-0.13

Note: All values are in percentages.US – United States.

Extreme returns (b) (Figure 5.3) spillovers also follow an upward trend with frequencies. They move from average highs of about 5%, 15%, 25%, 35%, and 50% on bands 1, 2, 3, 4, and 5, respectively. We opine that the markets in the system are more connectedness by extreme returns than they are by asymmetric returns. We observe contagion episodes in extreme return spillovers at approximate times for asymmetric returns. However, the magnitudes of contagion are stronger for kurtosis than they are for skewness. For instance, around late 2016 (in the short-term) contagion can be accrued to a connectedness of about 90% (as against a 5% average) and about 25% in early 2018. Further, there are stints of contagion in late 2016 (about 35%) and mid-2017 (about 40%) on band 2. Lastly, other sudden rises in connectedness in early 2001 (about 55%) and early 2019 (about 55%).

Compositely it is clear that contagion is stronger in the medium-term than in the short-term for skewness. But for kurtosis contagion is stronger in short-term than in the medium-term. Also, contagion episodes seem to be short-lived with regards to both skewness and kurtosis. This may be explained by the resilience emerging financial markets have built since the Asian financial crisis (Batten & Szilagyi, 2011). Moreover, some of the approximate dates during which contagion occur are quite removed from the obvious 2007-2009 GFC and the Eurozone crisis. These may corroborate the "*delayed*" contagion hypothesis of Boako and Alagidede (2016). In addition, by sudden increases in spillovers in our analysis we can confirm Forbes and Rigobón's (2002) *shift-contagion*. Further, since we have used shape parameter estimates to make these confirmations, our *"shape shift-contagion"* hypothesis is adequately established. Furthermore, if we bring these three hypotheses together, we can surmise that we have established *delayed-shape shift-contagion* in this study. We can conclude from these results that while financial crises episodes pose immediate threat to many markets, it is also important that traders and policy makers focus on spillovers for longer periods in the aftermath of these crises. However, there are also contagious episodes which overlap the Eurozone crisis period. These suggest that contagion can be *“delayed”* as well as *“immediate”*.

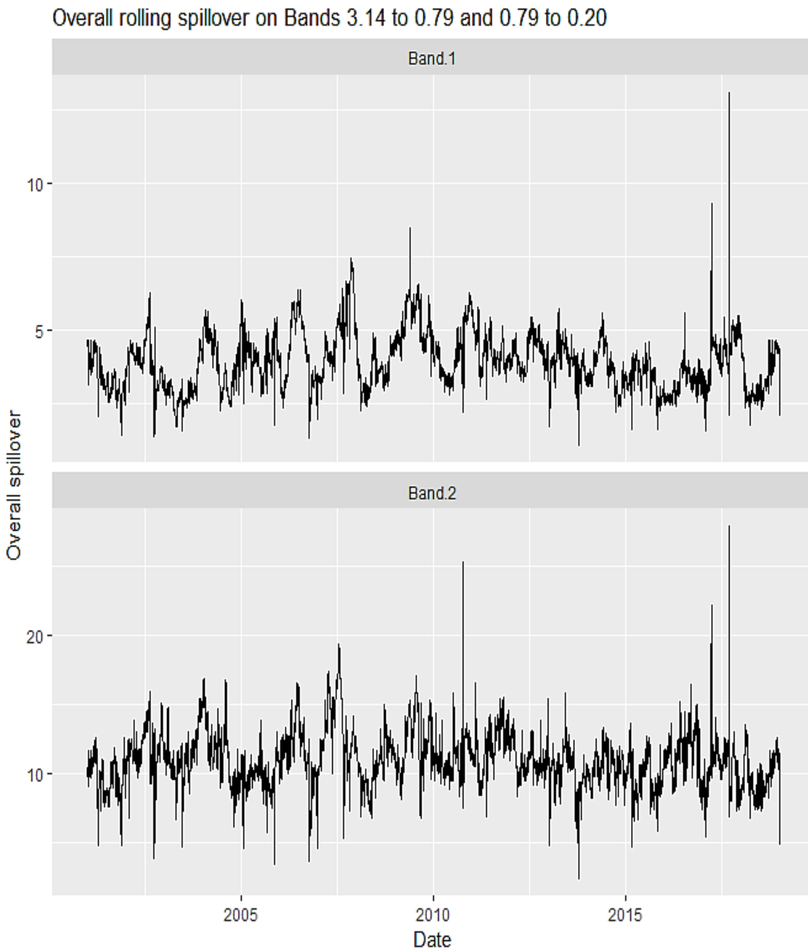
Apart from contagion, our results also suggest that the evolution of time connectedness is frequency-dependent. For that matter, we note that diversification benefits have more potential at the short-terms than in the long-terms. That is to say markets are more connected in the long-term where contagion, for instance, dissipates into interdependence. At those lower frequencies, it shows that shocks are persistent and are transmitted for longer periods for both extreme and asymmetric returns (see also Baruník & Křehlík, 2018).

In general the connectedness/spillover magnitudes are smaller as compared to other studies which have used actual returns and volatility indices (see Baruník et al., 2016; Qarni & Gulzar, 2019; Tiwari et al., 2018; Tiwari et al., 2019; Yoon et al., 2019). This can likely be explained by the difference in the data used; that comoments measure marginal contributions in the system (Ranaldo & Favre, 2005).

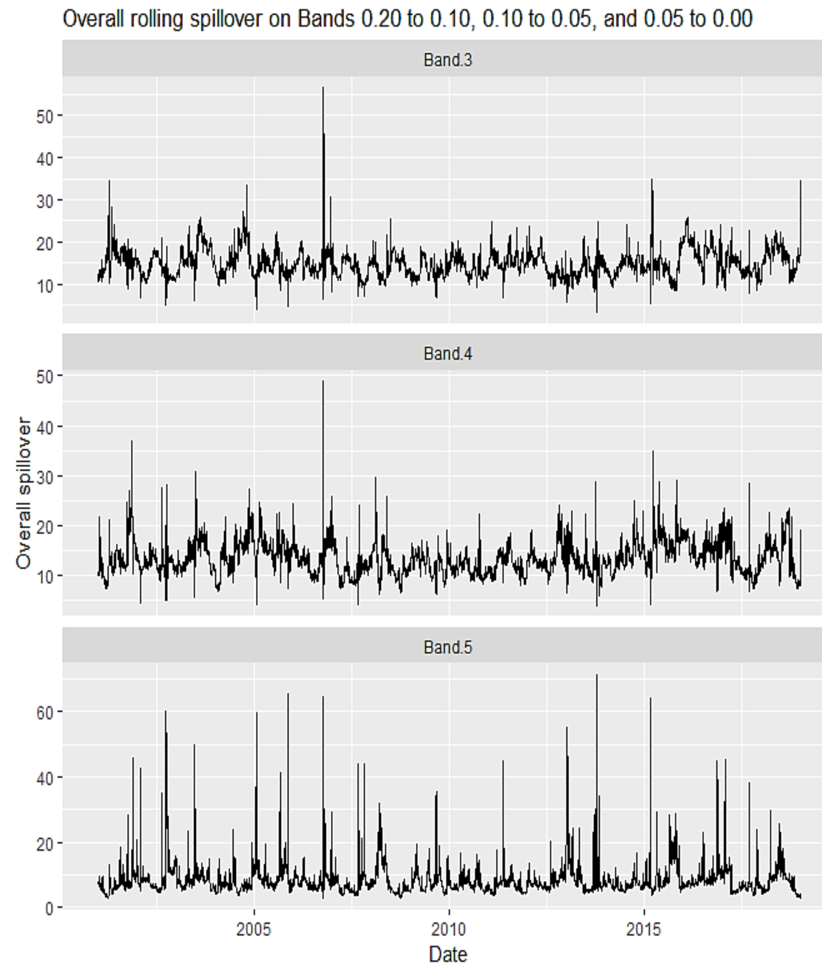
Finally, in Figure 5.4 pairwise net directional spillovers of skewness (a) we find a mixture of both negative and positive connectedness in both short- and long-terms. This is indicative of time-varying **net recipient** and **net transmitter** relationship of the EMEs with the United States with neither clearly dominating the other. We also see that connectedness is stronger in the long-term as opposed to the short-term. With sudden increases in net connectedness contagion episodes can be alluded for the United States with South Africa (in mid-2007 and mid-2014), Russia (late 2010), India (mid-2011), South Korea (mid-2016), and Brazil (late 2018). These mainly occur in the short-term and more of the high spillovers in the long-term can be seen as interdependence.

In (b) (Figure 5.4) very similar readings can be made with (a) (Figure 4.4) except for pairs involving South Korea and Taiwan. The connectedness is very weak in the short-term but momentarily contagious around 2017 and 2018, respectively. These are a bit surprising for large markets where we expected them to be strongly connected. Again, in the bivariate sense diversification is better done in the short-term and *"delayed-shape shift-contagion"* is evident for specific countries and the United States.

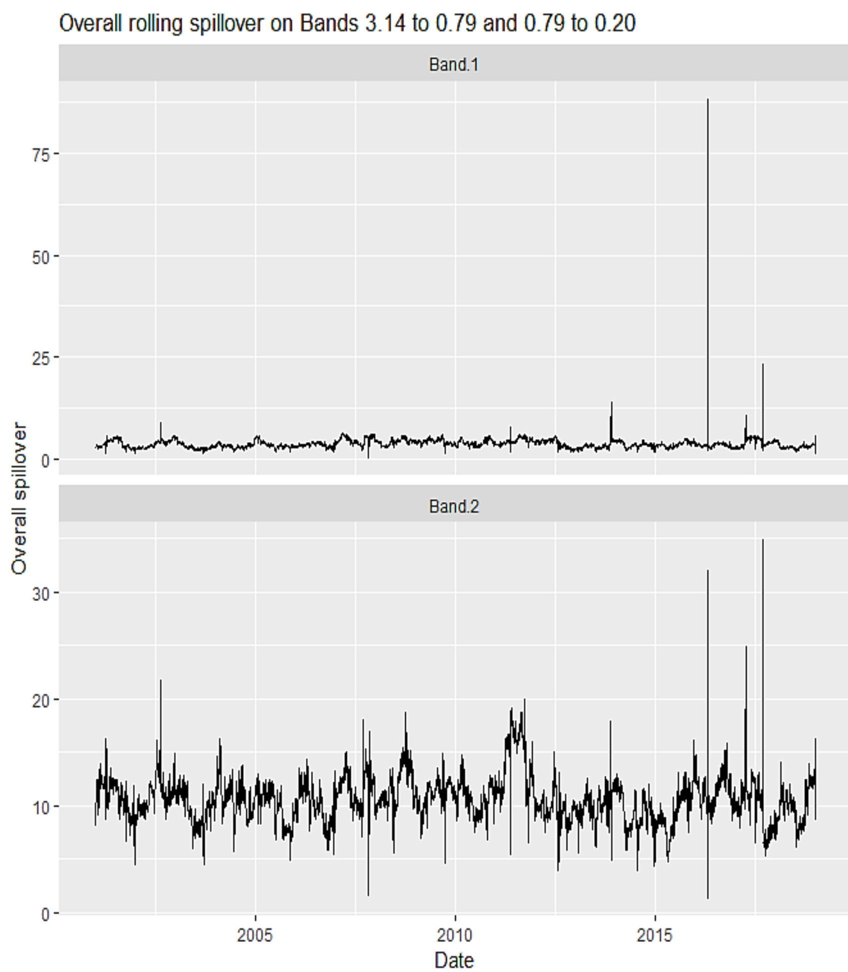
(a) Skewness (L3)



(a) Skewness (L3)



(b) Kurtosis (L4)



(b) Kurtosis (L4)

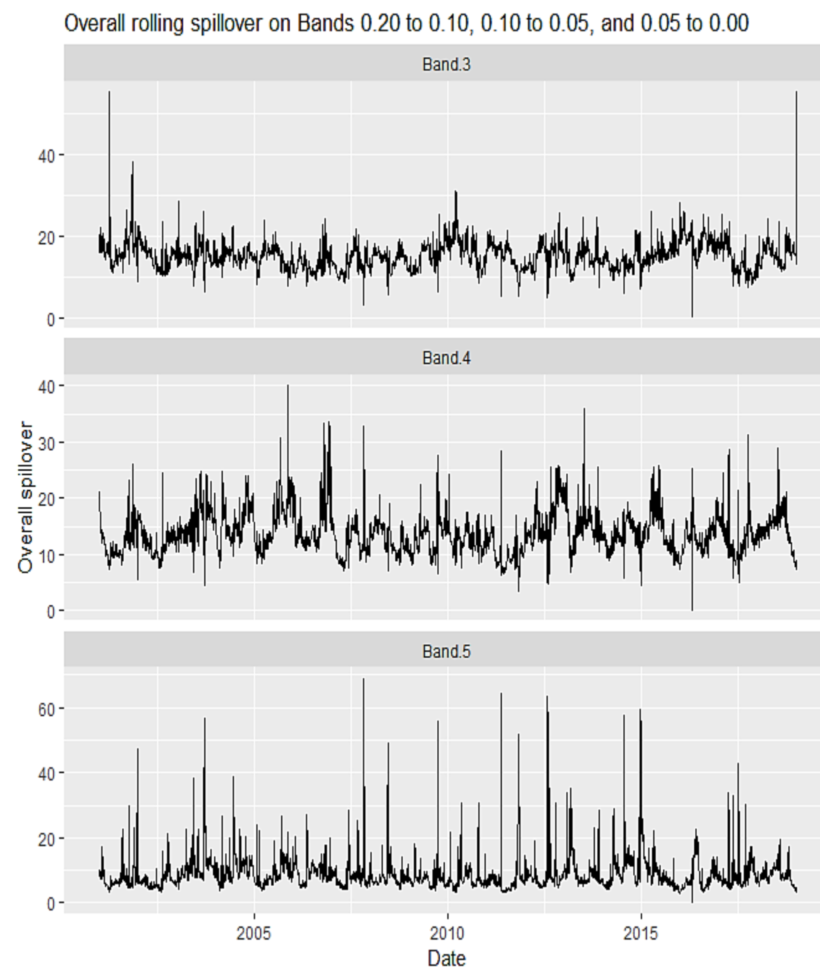
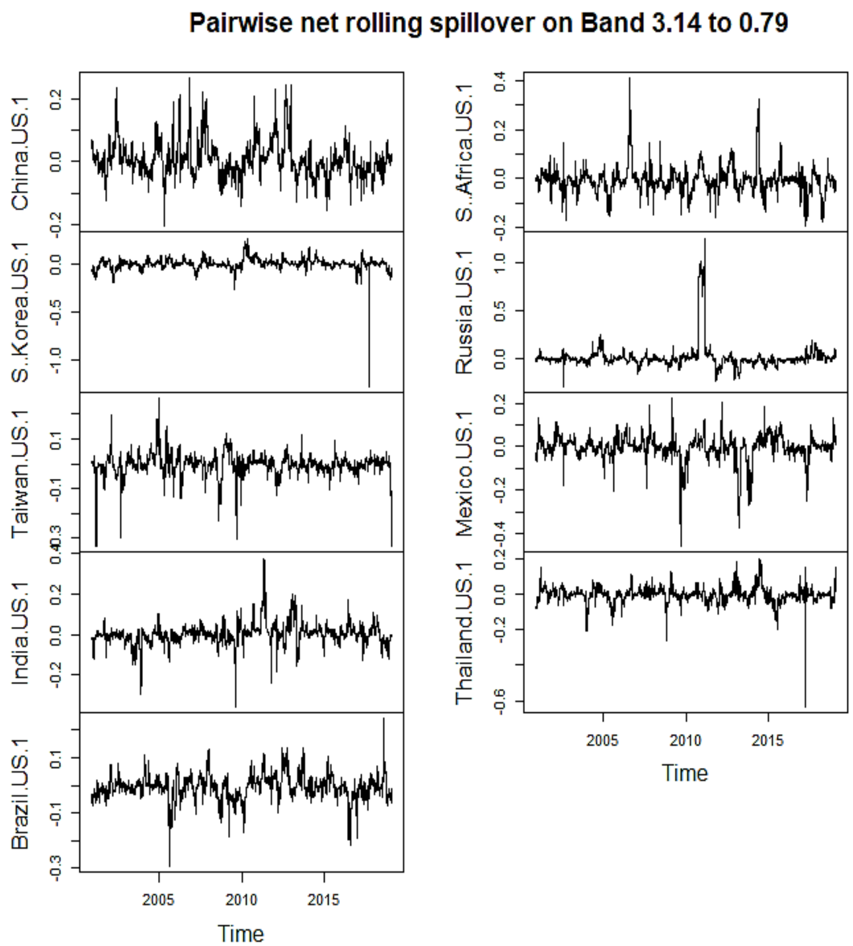
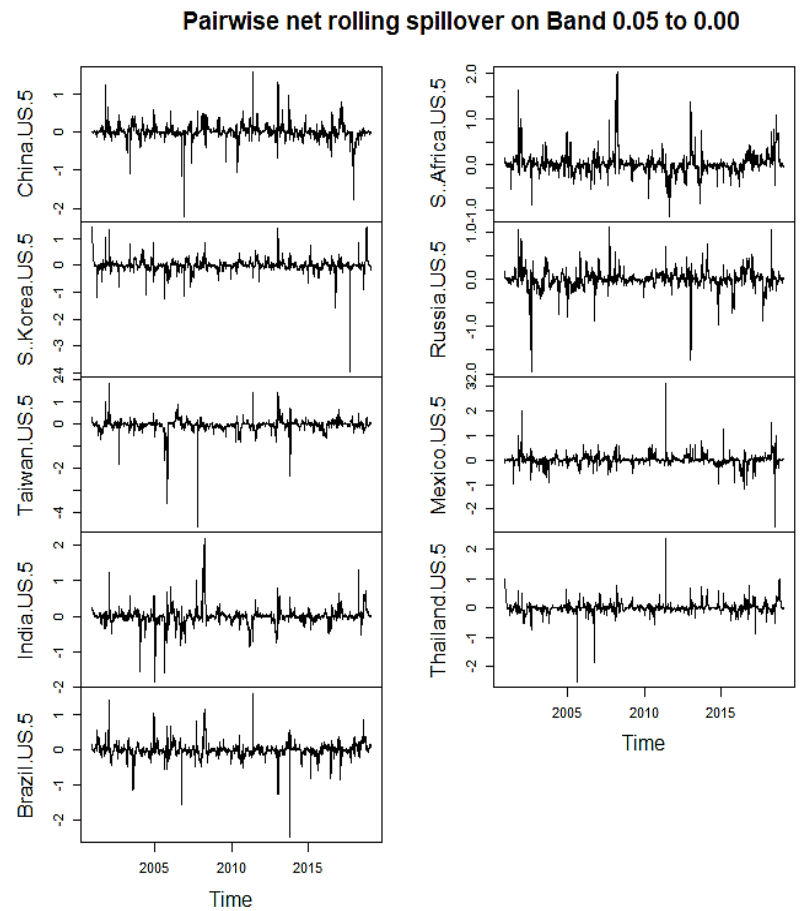


Figure 5.3: Overall rolling spillovers between higher moments of the top 9 emerging markets and United States equities

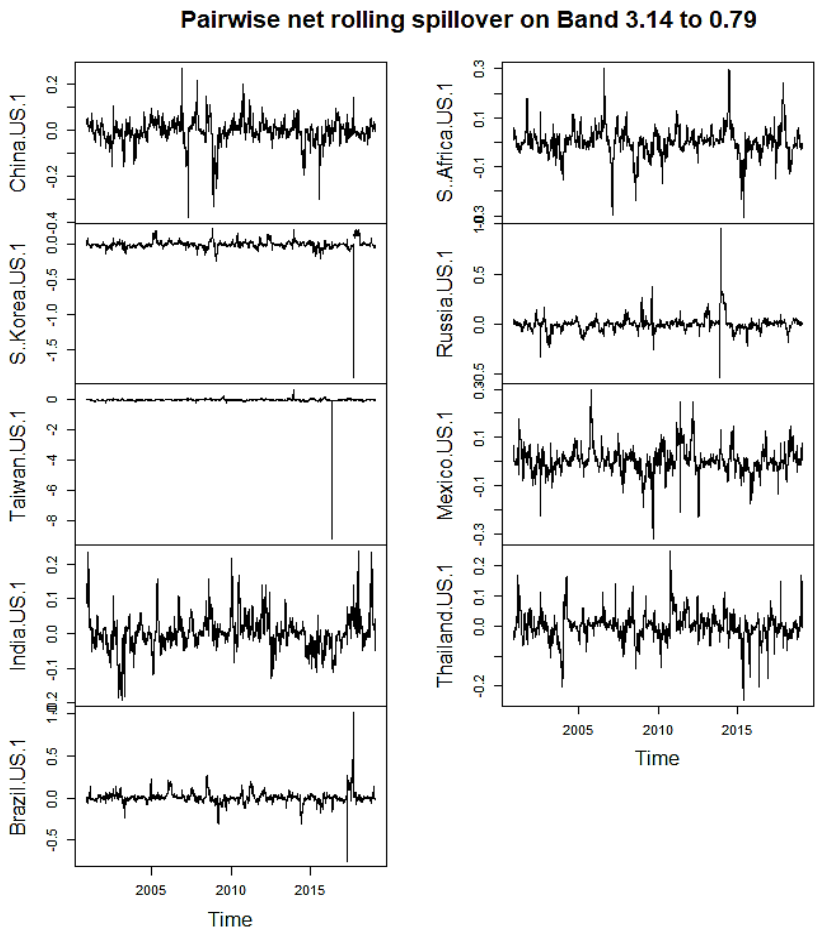
(a) Skewness (L3)



(a) Skewness (L3)



(b) Kurtosis (L4)



(b) Kurtosis (L4)

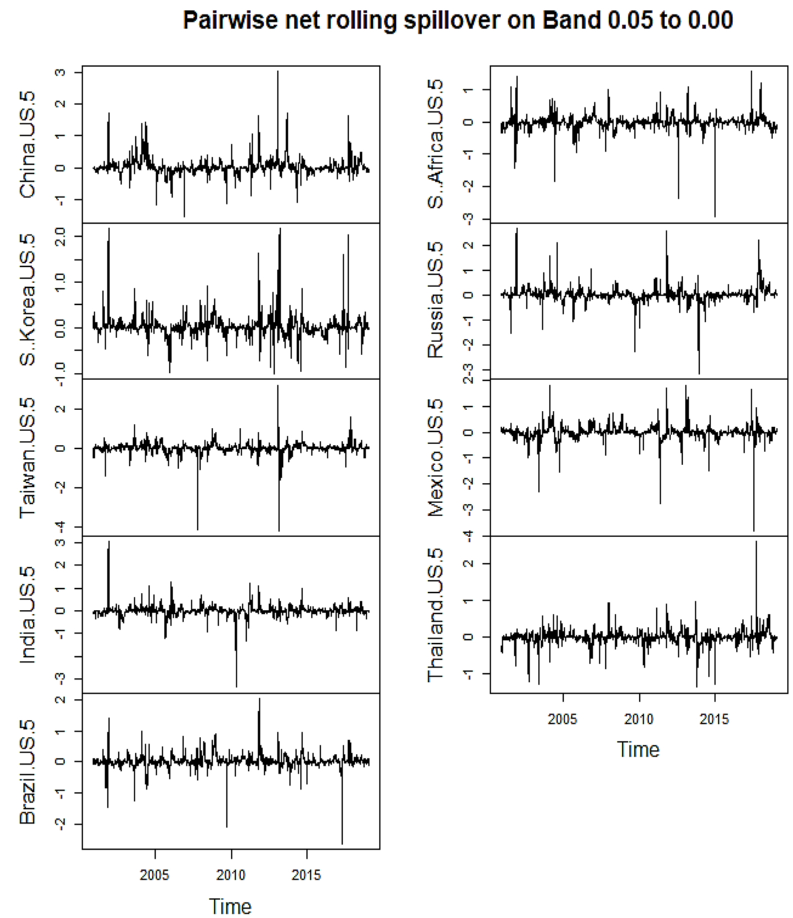


Figure 5.4: Pairwise net rolling spillovers between higher moments of the top 9 emerging markets equities and the United States

5.5 Conclusions and recommendations

This study aimed to investigate interdependence and the origins of contagion in emerging markets equities through their higher moments. We use comovements in skewness and kurtosis in this study because of the lack in the literature. The extant literatures only go beyond merely noting the importance of higher moments on risk-returns analysis and portfolio selection. We thus study interdependence and contagion through the shape parameters of emerging markets equity returns distribution.

We compute daily time series of estimates of daily skewness (represented by lambda 3; L3) and kurtosis (represented by lambda 4; L4) estimates on a 20-day rolling basis from the GLD. The study period is from 01/10/2001 to 02/18/2019. The sample period covers the 2007-2009 GFC and the 2009-2012 Eurozone crisis which are topical points in time to assess spillovers in financial markets (Ahmad et al., 2013). Further, we include the United States in the mix of the top 9 EMEs as a global market force and as known contagion propagator. To capture spillovers in the system we use both static frequency-domain (WMC, WMCC, and BK18) and time-varying frequency-domain (BK18) techniques.

The findings indicate the spillover effects and contagion dynamics differ with respect to skewness and kurtosis but not in a striking way. The markets in the system of 10 countries show more connectedness by extreme returns than they are by asymmetric returns. Connectedness also increases with increases in frequency levels and fleeting episodes of contagion dissolve into interdependence in the long-term. From both static and time-varying standpoints we reckon diversification benefits can be achieved in the short- to medium-terms, where connectedness levels are lower than in the long-term.

Our results do not provide enough evidence for the dominance of large countries in the system. Brazil and Mexico, for instance, take dominating roles in asymmetric and extreme returns spillovers under both time-varying and static analyses. Though the United States is never a **net recipient** of spillovers, it does not take centre stage as a **net transmitter.** In the pairwise net directional connectedness, countries that exhibit transient contagious relations with the United States are South Africa, South Korea, India, Brazil, Taiwan, and Russia. We surmise that policy to mitigate the downsides of market connectedness may focus mainly on EMEs rather than external markets such as the United States. Also, when it comes to asymmetric and extreme returns shock propagations both large and small countries should be equally targeted.

In general, we find contagion mostly occur away from the 2007-2009 GFC and this reinforces the idea of "*delayed*" contagion in the literature. Thus, traders and policy makers should perceive beyond crisis periods to contain consequences they bring. Based on our adopted definition of contagion and the fact that we employ shape parameter estimates of return distributions, we are able to confirm our *"shape shift-contagion"* hypothesis. In summary, our study deviates from the large body focusing on first and second order moments and add to the relatively small body of literature on higher order comoments; especially in the study of interdependence and contagion. We have shown that higher moments are equally important variables and that in the evaluation of comovements among equity markets, it is important to pay attention to short-, medium-, and long-term connectedness. These play valid roles by telling us different stories of what is happening at different times.

We finally note that changes in spillovers from the WMC, WMCC, and BK18 do not describe if they are caused by favourable or unfavourable events (Suurlaht, 2015). Therefore, an events analysis such as in Yilmaz (2010) and Baruník and Křehlík (2018) may be conducted to ascertain the specific events driving variations in connectedness. The study can also be focused on peripheral EMEs where large market domination may not be a problem. The outcomes of such study can be compared to the result here to inform policy and investment decisions.

Appendix 5.1: Plots of price, log-returns, L3, and L4 series

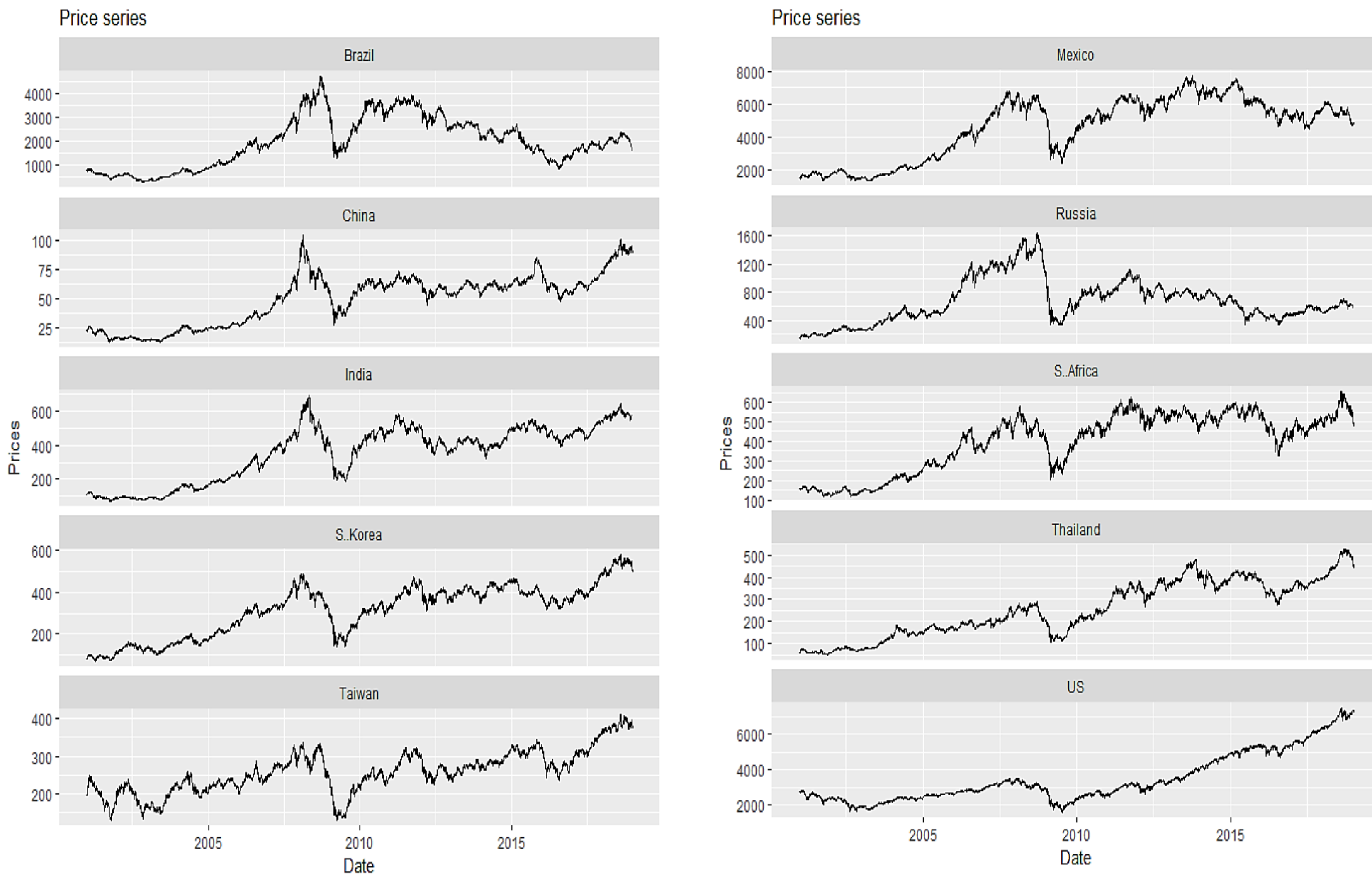


Figure 5.5: Price series of emerging markets and United States equities between 01/01/2001 and 18/02/2019

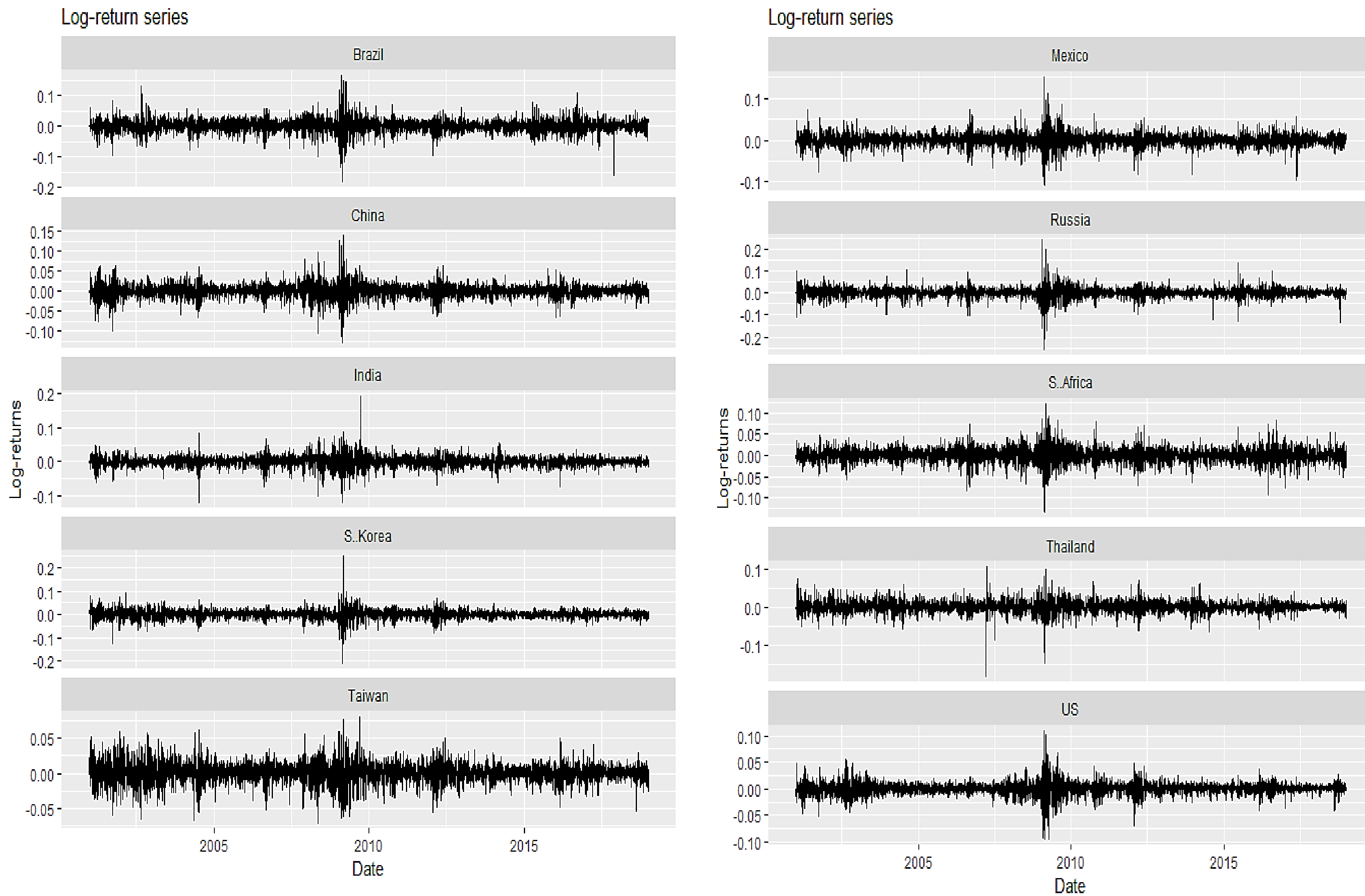
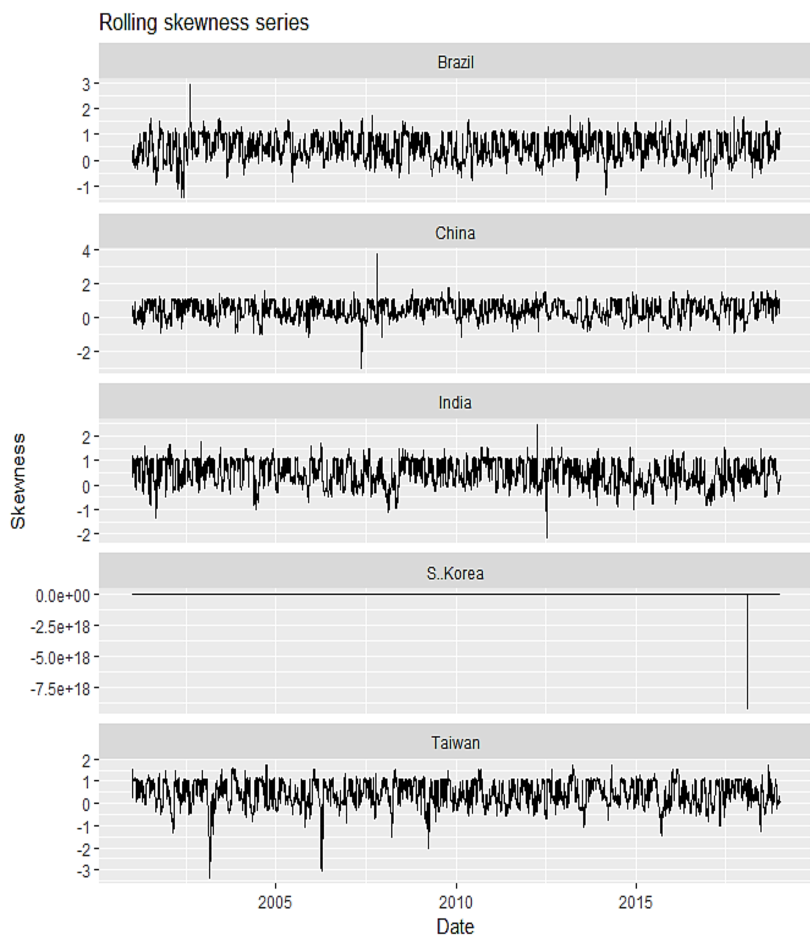
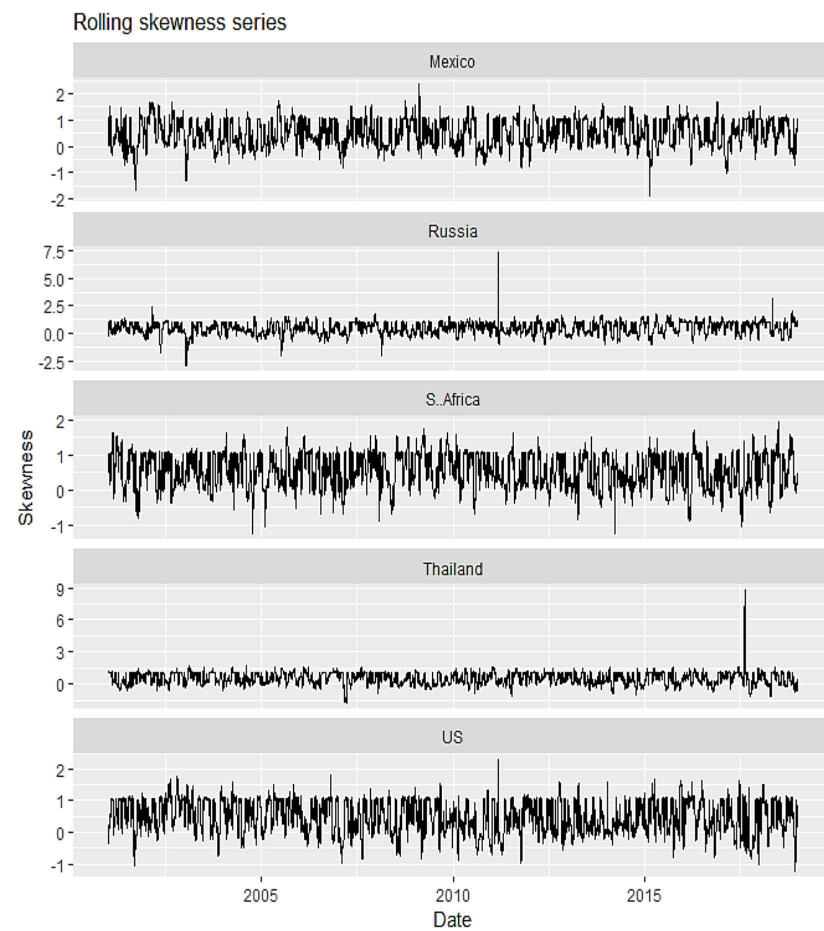


Figure 5.6: Log-returns series of emerging markets and United States equities between 01/01/2001 and 18/02/2019


Rolling skewness series
Brazil
China
India
S..Korea
Taiwan
Skewness
Date
2005
2010
2015


Rolling skewness series
Mexico
Russia
S..Africa
Thailand
US
Skewness
Date
2005
2010
2015

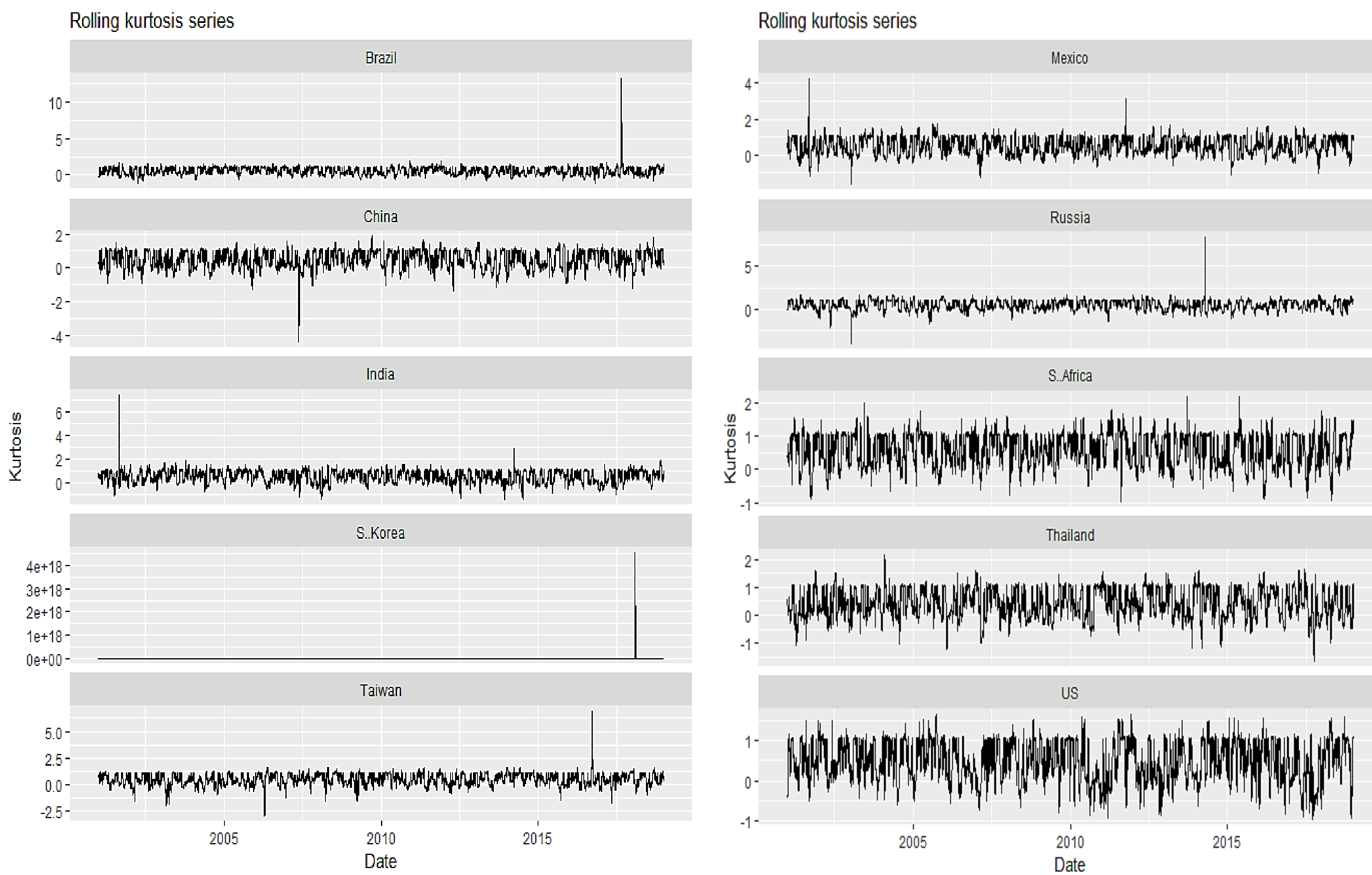


Figure 5.7: Rolling skewness and kurtosis series of emerging markets and United States equities between 01/01/2001 and 18/02/2019

CHAPTER SIX

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

6.1 Introduction

This last chapter comprises the summary, conclusions, and recommendations from the study. The chapter begins by providing summary of the main findings, followed by contributions to knowledge, and recommendations for both investment and policy which may be implied from this study. The last portion of the chapter suggests directions for future research.

6.2 Summary

This study aimed to provide some evidence for the subtle differences and/or similarities amongst EMEs. These phenomena are important for international portfolio diversification, risk management and analysis, cross-border capital flows, and macroeconomic policy, among others. There is widespread research in examining the drivers of international shock transmission channels, sources of interdependence and contagion, and origins of risks in EMEs, among others. The pattern in these studies is that they all seek to explain the differences as well as the similarities in these economies. To a large extent, the motivation for such studies have arisen from various regional crises episodes, such as the Asian financial crisis, Eurozone crisis, and the Global Financial crisis. However, the large body of literature has compared and contrasted EMEs through the lens of well-known concepts such as tail risks, financial market sophistication, macroeconomic fundamentals, returns and volatility of their equities, and even their cultural and socio-political systems, among other things. This thesis argues that there are equally important but hidden factors that can uncover deeper parallels as well as dissimilarities between EMEs.

After a careful review of the existing literature, the thesis finds pertinent questions unanswered in EMEs finance. This thesis deviates from the mainstream literature to investigate the extent to which EMEs can be compared and contrasted based on some important subtle factors. Hence, the thesis seeks to find answers to the following questions:

1. How do policy makers and investors assess emerging markets equity risks in the face of spatial time-invariant risk attributes?

2. How do emerging markets equity risk models, selection, and ranking behave?

3. What is the nature of interdependence and contagion within EMEs and between DMEs with origins from the shape parameters of equity returns?

6.3 Conclusions and findings

6.3.1 Time-varying versus spatial risk in EMEs

In the empirical investigation of time-varying tail risks and spatial risks in EMEs, the study employs the GAS models to estimate and forecast the (VaR, ES) model for emerging markets equities tail risks. In terms of spatial risks, the study applies the Tobler's first law of geography and Moran's I to EMEs GLIs to estimate spatial autocorrelations as an assessment of systemic time-invariant risks. This study is meant to ascertain the distances between EMEs via their equity tail risks vis-à-vis spatial liquidity vulnerabilities. Generally, the study finds that it is appropriate to combine tail risks in emerging markets equities and spatial risks married with liquidities build-ups. This serves the purpose to adequately examine the total risks that can distinguish one EME from another at deeper depths. By using the GLIs, we propose *"financial distance"* to extend the CAGE distance framework, in particular, but also psychic distance dimensions, in general.

We find that for the EZC-GFC periods, overall significant positive spatial autocorrelation in the EMEs suggests that the markets have stronger liquidity vulnerabilities ties which can jeopardise any portfolio constructed based on the time-varying (VaR, ES) model forecasts. For the EMEs, this also signals risk of contagion as a consequence of deeper levels of financial integration (BIS, 2011)**.** However, by regionalising the EMEs, we find zero, negative, and positive spatial autocorrelations. Nonetheless, for the Post-crisis period, overall spatial autocorrelation tends to be negative and smaller in magnitude. We surmise that policy makers in these economies may be selective in their trade and financial partnerships by being conscious of the *"financial distances"* between their potential partners. Moreover, the decision has to be taken with particular regard for the specific financial market dynamics at the time. These results corroborate the initial assumption that when the geographic footprints of an economy are linked with their liquidity profiles, the markets can be better understood and classified.

6.3.2 Tail risk modelling under Basel III

The thesis also explored the dynamics of emerging markets equity risk models under comparative back testing, pursuant to the Basel III framework. This study brings out the similar albeit deferring behaviours of emerging markets equities risk modelling under the context of moderating regulatory arbitrage. For this reason, we exploit the elicitability of the (VaR, ES) model, consistency of the FZL score function with the concurrent selection and ranking properties of the MCS algorithm. Our results show that, about one-third of the equities contain all initial models in the SSM between the two percentiles and across the three (EMC, EZC-GFC, and Post-crisis) sub-sample periods. This indicates that the risk models in these markets are homogeneous, time-invariant, and percentile-independent. This further suggests well diversified portfolios in these markets. The remaining equities show less homogeneity. At worst, they are mid-way between heterogeneity and homogeneity for the three sub-sample periods. We find that South Africa and China stand out to exhibit heterogeneity than homogeneity as well as market dynamics-dependent in risk tail risk modelling. Further, we also find that the superiority of the risk models largely differs across the EMEs and sub-periods. Lastly, we find no specific factor (such as market size, geographical proximity, soundness of financial system, and trade ties, among others) that can be attributed to this pattern. This brings to question the traditional means of using these features to classify economies. We opine that dynamics of market-specific tail risk modelling in keeping with allaying regulatory arbitrage should be an important phenomenon in grouping economies.

6.3.3 Higher moments' interdependence and contagion

In the last study, we examine the origins of interdependence and contagion in EMEs and the United States using the higher moments of their equities returns. This serves to portray how the EMEs respond to shocks from each other but most importantly from advanced markets. The outcomes of this study contribute both theoretically and empirically to the definition, origins, and measurement of interdependence and contagion. We adopt a novel GLD-based wavelets and Baruník and Křehlík (2018) spillover techniques to accomplish this. These techniques help to capture non-linearities, non-stationarities, time-variations, asymmetries, and localised interdependence and contagion in emerging markets equities, specifically emanating from the shape parameter of return distributions. The results evidence that spillover effects and contagion dynamics differ with respect to skewness (L3) and kurtosis (L4), but in a modest way. Connectedness levels also increase with longer time horizons with fleeting episodes of contagion dissolving into interdependence. From both static and time-varying standpoints, we reckon that diversification benefits can be achieved in the short- to medium-term. We also find that large markets do not dictate the direction of interdependence and contagion among countries in the system. Brazil and Mexico, for instance, take dominating roles in asymmetric and extreme returns spillovers under both time-varying and static analyses. Even though the United States is never a **net recipient** of spillovers, it does not dominate **net transmission.** In the pairwise net directional connectedness, the markets that exhibit transient contagious relations with the United States are South Africa, South Korea, India, Brazil, Taiwan, and Russia.

With regards to the *"shape shift-contagion"* hypothesis, the study finds adequate evidence to confirm it – that contagion episodes occur away from the 2007-2009 GFC. This also encapsulates the notion of *"delayed"* contagion in the literature. It is obvious to sound a call to traders and policy makers to strategise beyond crisis periods in order to contain their deferred consequences. We have shown that higher moments are equally important variables such that in the evaluation of comovements among equity markets, it is important to pay attention to short-, medium-, and long-term connectedness levels.

6.4 Recommendations

The widespread reliance on macroeconomic metrics, returns and volatilities, financial system dynamics, legal systems, and geographical proximities to cluster EMEs do not offer sufficient insights to exploit the opportunities and allay the risks in these markets. In short, the findings from this thesis are that spatial risks, the agreement of internal risk modelling with regulatory framework, and higher moments as sources of spillover are equally significant factors to consider when assembling and/or disbanding EMEs. These emphasise the need to find a wide array of reasonable features in examining EMEs so that one can broaden the possibilities for risk management, portfolio diversification, cross-border trading, and policy actions, among others. It is to be noted that these apply at the individual, firm, industry, and country levels.

In EMEs and other market classes, the use of time-varying risk models have long provided insight for equity risk management and diversification strategies. However, regardless of the accuracy and astuteness risk models or portfolio strategies, market level liquidity vulnerabilities can render them barely useful. It is even more disconcerting when the liquidity exposures are spatially correlated to some extent. Hence, investors are entreated to combine time-varying tail risk assessment of equities with spatial risk analysis in order to gain a wider perspective to operate more prudently. While doing this, risk analyst are urged to adopt models, such the (VaR, ES) model, which utilises the strengths of VaR and ES and concurrently minimises their deficiencies. Further, for policy makers in EMEs, it is imperative for them to be selective in their cross-border trade and financial partnerships. Conscious efforts may be taken to evaluate how their potential partner economies are herded in terms of dependence on both local and foreign credit. Therefore, this suggests a macroprudential scheme for Central Banks of EMEs that continues to “unherd” themselves from each other while maintaining country-specific judicious levels of liquidity, especially during periods of financial market turmoil.

Efforts continue unabated to make the global financial market place safer and sounder. The resultant effect is the current Basel III paradigm. Among others things, the framework requires internal risk models to approximate those of regulators in order to curtail regulatory arbitrage – this is achieved through comparative back testing. Given the widespread knowledge that emerging markets possess high levels of risk, subjecting internal risk models to the rubrics of comparative back testing should be taken more seriously. First, it should be seen as an effort to contribute to the safety and soundness of the global financial system. Second, the practice may engender confidence in international investor community because they will see EMEs financial systems to be more safe and sound. In addition, they will be able to transparently evaluate internal risk forecasts. Further, in appraising the Basel III-bound risk models, specialists are cautioned to be mindful of the financial market dynamics as well as the percentiles used to calibrate the equities because this affect the behaviour of models.

The techniques employed for this task allow for any arbitrary number of models to be ranked and selected for any equity. The final set of models differ according to equity, percentile level, and market period (i.e. whether tranquil or turbulent). Hence, risk analysts should painstakingly examine the set of models appropriate for a specific equity in light of these factors. This is important because in risk modelling, small oversights can result in huge losses. Additionally, the size of the final model conveys information about the homogeneity/heterogeneity of the risk models of a particular market. It is suggested that markets that exhibit heterogeneous risk models should be pursued because they show better promise for portfolio diversification. Furthermore, comparative back testing enjoin that risk managers are to aim at obtaining an optimal set of risk models rather than a single best model. Risk managers should abide by this principle not only to lessen their burden, but also to keep their investors safe and sane. Lastly, by examining the findings of this framework, policy makers are admonished to understand that markets with similar risk model characteristics are to be considered as too close. These markets can be easily contagious and hence trade and financial partnership deals should be carefully crafted to mitigate this danger.

While diverse forms of connectedness amongst EMEs tend to be advantageous in many instances, they become rather problematic when they go unchecked, leading to contagion. It is imperative that policy makers identify the sources of these dependencies which are both supported and unsupported by economic fundamentals. In so doing, they should look at the most unlikely of places in addition to monitoring mundane causes. The findings of *"shape shift-contagion"* in this thesis indicate that one of such avenues is the higher moments of equity returns. These parameters show that marginal contributions to overall connectedness paradigms can have monumental consequences when they go unchecked. Since higher moments generally signal asymmetric and extreme returns in equities, policy makers should mount efforts to arrest the factors that cause markets to swing beyond acceptable limits which cause panic in the financial markets. These actions include maintaining decent levels of other macroeconomic variables such as crude and refined oil prices, currency fluctuations, inflation, import and exports of goods and service, among others. Further, sudden stock market price hikes or drops may be due to foreign policies such as Federal Reserves' tapering actions such as experienced following the GFC, and the sheer of news of these. Governments of EMEs should embark on policies, including reducing reliance on foreign capital investments in their stock markets. They should also employ calculated public relations actions to avert panics in the wake of seemingly negative news.

As seen from the study, in the event of financial or economic crisis in one EME or other parts of the world, contagion tends to adjourn to a later date – even so marginal contagion arising from asymmetric and extreme returns, albeit at frequency-varying levels. Thus, occurrences in the financial markets that portend contagion should be monitored in the short- through to the long-term. Finally, the study suggests that policies to contain delayed higher moment contagion should be focused on EMEs, should regard both large and small markets, and should modulate the role of the United States.

6.5 Areas for future research

The thesis has duly indicated the need to compare and contrast EMEs using rather unconventional parameters. Nonetheless, this study is by no means an exhaustive exercise. The study is reasonably optimistic to spur interest in this narrow direction of empirical research. One can attribute this claim to the importance of understanding the variety of factors that set aside one market (or a group of markets) from others. Policies and strategies that could be informed by this include, but not limited to microeconomic, macroeconomic, micro-prudential, macro-prudential, market classification, and foreign direct investments.

With regards to the study of spatial risk analysis where *“financial distance”* is represented by autocorrelations GLIs, the data is limited to only 12 EMEs. While studies to expand the EMEs could not hold until the BIS expand this database, other indicators can be motivated to proxy country-dependent liquidity vulnerabilities to extend the frontiers for EMEs research. Further, given that GLIs are reported in Euro and Japanese Yen as well, a comparative study will be in order. This will engender an understanding into the role of denominating currency in the determination of EMEs liquidity challenges. In furtherance, as this study digests the economic dimensions of the CAGE distance framework to hypothesise *“financial distance”*, psychic distance dimensions remain exploitable to ascertain spatial risk aspects that can supplement time-varying risk analysis of equities. In doing this, one can expand the analysis to include more EMEs, and perhaps other market classes.

In this thesis, the scope of *“shape shift-contagion”* is limited to the top nine (9) EMEs in the MSCI classification. However, the concept can be investigated with peripheral EMEs so that comparison can be possible. In addition, connectedness dynamics in the study are blind to the precise drivers of those changes. It will be interesting to link the magnitude and direction connectedness levels to either favourable or unfortunate events in the markets. This will better inform bespoke policy actions to forestall contagion and its attendant effects. Furthermore, higher moments of return distributions have increasingly been extended beyond the conventional four parameters. Moments parameters such as coskewness, cokurtosis, and L-moments, among others, can provide for linear combination of order statistics so that both bivariate and multivariate analyses can be performed.

Connectedness studies situated in EMEs using these methods can provide robust and finer examination of higher moments interdependence and contagion.

Another vital area of research is the need to challenge the methods used to classify market economies. Given the valuable insights these unconventional factors in this study have garnered to compare and contrast EMEs, it is about time market economies are reclassified using some of these alternative approaches aside those employed by popular indexing institutions. One way to push the frontiers of finance research is to employ data-intensive reclassification of industries and markets that allow for transitory and overlapping market belongingness. Some of the techniques that can be applied to data are machine learning methods of fuzzy clustering and hierarchical agglomerative clustering. Investment and policy decisions can be informed in ways that are in consonance with the huge equity market data that is readily available.

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