POLICY UNCERTAINTY, ECONOMIC DISTANCE, AND MACROECONOMIC VARIABLES IN DEVELOPING ECONOMIES

By

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ABSTRACT

Although economic policy uncertainty (EPU) is a less explored source of uncertainty that is related to economic policy, economic policy uncertainty in describing the state of an economy has assumed dominance in decision-making in countries and has remained relevant to investors, governments, and policy makers across the globe. This has become the standard because studies have proved that policy uncertainty has a significant effect on the overall economy and heightened EPU (especially during recessions) has the potential to harm economic activities. The literature review revealed evidence that EPU comoves with business cycles, that uncertainty influences the distance between economies, and that EPU spillover shocks from one economy to another have a significant impact on the recipient economy's economic activities. As yet, there has been scant systematic investigation of these possible interactions. The study of EPU is of major importance to emerging market economies (EMEs) because, although literature has proved the harmful effects of EPU on EMEs, the studies done is meager since majority of study on EPU have focused on developed countries. These implications of uncertainty on EMEs have made it very relevant to focus on the role uncertainty plays in EMEs.

In order to make significant contribution to the role EPU plays in EMEs, this thesis focuses on addressing three main problems. To begin, the study examines whether EPU correlates with business cycles and, if so, whether EPU is the cause or effect of recessions across business cycles. The study makes an important contribution by finding answers to why business cycles fluctuate. This study deviates from traditional sources of fluctuations and focus on uncertainty as a potential cause or effect of business cycle fluctuations. We also propose new variables as measures of

business cycles (GDP, CPI, SPX, import, export and broad money). The wavelet multiple correlation and wavelet multiple cross-correlation proposed by Fernandez-Macho (2012) is used to investigate the comovement between EPU ad business cycles. The analysis shows that business cycles commove with strong records of interdependence. The scale by scale analysis, on the other hand, has shown that the level of integration is strongest in the long-term. We further investigated the role EPU plays in the comovement of variables (gross domestic product (GDP), consumer price index (CPI), SPX (SPX), import, export and broad money) within each EME and discovered that positive correlation was generally recorded between EPU and CPI within each EME. Likewise, evidence of negative correlation for EPU was recorded between EPU and SPX across all EMEs. We also note that, although there is strong evidence of comovement between EPU and the macroeconomic variables, EPU has no lead/lag potential across all the time scales within the selected EMEs. To also clear all the inconsistencies of whether uncertainty is the cause or effect of fluctuations in the business cycle, the study adopts Diks and Panchenko (2005, 2006) non-parametric test. It was discovered that causality with respect to the economic indicators of business cycles is specific to each EMEs. We conclude that EPU is both a cause and effect of business cycles fluctuations in the selected EMEs except for India where business cycles cause EPU fluctuations.

The second objective is to ascertain the relationship between EPU and distance in EMEs. The study focuses on the investigation of economic distance and geographical distance. This section makes two contributions to the study. First, we conduct a novel investigation on the relationship between economic distance and EPU. Second, we adopt a non-parametric geospatial analysis to investigate the spatial dependence between EMEs (with respect to their EPU measures). We first find an answer to the question, “can EPU influence economic distance in EMEs?”. The extent of similarities (or dissimilarities) of economic characteristics between units (or countries) is termed as economic. Despite evidence that uncertainty increases when the economic characteristics between countries are different, no study has investigated the relationship between economic distance and EPU although EPU has a greater significant impact on an economy than uncertainty in general. The dynamic linear regression method is adopted to investigate the relationship between EPU and economic distance. We discover that macroeconomic variables were largely statistically significant and have explanatory power to explain the economic distance between the EMEs as compared to the role EPU plays in explaining the economic distance between EMEs. We therefore find limited evidence of EPU’s effects on the economic distance between EMEs. We also discover that changes in the values of import, CPI and broad money in most EMEs are statistically relevant and significantly drive the changes in the values of economic distance between the selected EMEs.

The second aspect of distance investigates the spatial autocorrelation between EMEs with respect to EPU. Tobler’s first law of geography that highlights that the nearer things are to each other, the more related they are than to distant things forms the foundation of this theoretical framework (Tobler, 1970). The Moran’s I (Moran, 1984) is used to investigate the presence of spatial autocorrelation. The results showed evidence of spatial autocorrelation across all the EMEs which support Tobler’s first law of geography. This implies that, the similarities and dissimilarities between the selected EMEs are significantly influenced by the distance between them. It was also observed that, country and geographical specific features (or characteristics) of each EME affect the outcome of the results. Thirdly, heterogeneity was recorded when the six EMEs were divided into sub regions. Finally, the study discovered that international policies (for example trade policies), terms of trade, spillover effects, monetary and fiscal policies are some of the factors that influence EPU spatial autocorrelation in EMEs.

The study further investigates the spillover effects of EPU and macroeconomic variables in EMEs and measures the amount and direction of spillover from a country to other countries. This information is essential beacause previous studies have focused on developed (advanced) economies leaving little evidence of the effects of EPU spillover in EMEs. The study investigates the amount and direction of EPU spillovers between EMEs as well as the effect of EPU shocks on macroeconomic indicators (and vice versa). To investigate the network spillover effect and directional connectedness between EPU and related macroeconomic variables in EMEs and explore their time-frequency dynamics, this investigation will use Baruník and Křehlík's (2018) methodology. The findings from this study shows evidence of spillover and causal spillover between EPU and macroeconomic variables within each EME. We discover that EPU does not dominate in the transition or receiving of spillover shocks in all the selected EMEs but rather, GDP and SPX were identified as the main transmitters of spillover shocks across all the selected EMEs. The time-varying total spillover index confirms arguments of volatilities of uncertainty in EMEs during the Great Recession that occurred during 2007-2009. Inter-country spillover analysis shows that Korea- EPU is the main transmitter of spillover shocks to the selected EMEs across all frequency bands.

The study therefore makes significant contributions to the study. First, we find answers to why business cycles fluctuate. Second, we also propose new variables as measures of business cycles

(GDP, CPI, SPX, import, export and broad money). Third, we conduct a novel investigation on the relationship between economic distance and EPU. Forth, we adopt a non-parametric geospatial analysis to investigate the spatial dependence between EMEs (with respect to their EPU measures). Fifth, we investigate the severity of the amount and direction of EPU spillover received and contributed by one economy to another economy. The study offers a number of significant investment and policy recommendations arising from the findings in this thesis.

The study offers a number of significant investment and policy recommendations arising from the findings in this thesis. Policymakers should establish a robust and precise implementation framework that ensures transparency and credibility to help minimise the wait-and-see (delay) approach of investors and agents as a result of the uncertainty of future happenings. Decisions made by policymakers should be communicated openly and promptly. Due to extensive understanding of the key transmitters and recipients of shocks at various frequencies, investors can intelligently plan their portfolio diversification methods. In the event of weak interactions, investors should diversify their portfolio to maximise their return on investment. With the detailed information about the short-, medium-, and long-term net spillover received from and contributed by the EMEs, policy makers are well equipped to efficiently forecast global and country specific uncertainty fluctuations, make well informed predictions and implement policies that can significantly reduce uncertainty in the economy. Based on the results on the causal relationship between EPU and business cycles, policy makers can now implement and amend predictable fiscal and monetary policies that will prevent or reduce the occurrence of uncertainty and business cycle fluctuations. This will make investors feel more secure to invest in the economy. Policy makers and regulators are advised not to generalise policy formulations, amendments and regulations but should rather be focused on each EME.

Keywords: Economic policy uncertainty; Emerging market economies; Business cycles; Comovement; Economic distance; Spatial distance; Spatial autocorrelation; Shock spillover; Dynamic connectedness

JEL classification: C1, C3, C5, C8, C10, C14, E6, E32, F14, F44, G1, G11, M2

DECLARATION

I, **Abigail Naa Korkor Adjei**, 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.

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Doctoral research candidate

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Signed on the 26th day of May, 2021.

DEDICATION

This work is dedicated to my parents. God richly bless you. To my Dad, thank you for the moral support and ensuring that I strictly followed my personal timetable and schedules to the latter. I am very grateful. Thank you Mum for all the inspirations and the sacrifices you made for me throughout this academic journey. Please know that they didn’t go unnoticed.

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TABLE OF ACRONYMS AND ABBREVIATIONS

ABBREVIATION	MEANING
CAGE	Cultural, Administrative/Political, Geographic, and Economic
CPI	Consumer Price Index
EME	Emerging Market Economy
EMEs	Emerging Market Economies
EPU	Economic Policy Uncertainty
GDP	Gross Domestic Product
GFEVD	Generalised Forecast Error Variance Decomposition
IMF	International Monetary Fund
LISA	Local Indicators of Spatial Association
LOWESS	Locally Weighted Scatterplot Smoothing
SPX	Share Price Index
WMC	Wavelet Multiple Correlation
WMCC	Wavelet Multiple Cross Correlation
VAR	Vector autoregression
VIX	Volatility Index

CHAPTER ONE

INTRODUCTION

1.1 Background to the study

The role of uncertainty in describing the state of an economy has remained relevant to investors, governents, and policy makers across the globe. This has become the standard since studies have proved that policy uncertainty may have first order effects on the overall economy (Nguyen, Kim & Papanastassiou, 2018; Bloom, 2009; Baker, Bloom & Davis, 2013). Second, Federal Open Market Committee (2009) and International Monetary Fund (2012, 2013), also proved that the significant role of EPU in an economy intensified during the Global Financial Crises (GFC), serial crises in the Eurozone as well as partisan policy disputes in the US. They further argued that, uncertainties about tax, spending, regulatory, and monetary policies caused a drastic drop in activities at the beginning of the recession and slowed the recovery process. Third, research has shown that heightened EPU has the potential to harm economic activities (see, Wang, Chen, & Huang, 2014; Arouri & Roubaud, 2016; Economic Survey, 2019; Chowdhury, Bayar, & Kiliç, 2013; Nguyen et al., 2018; Gulen & Ion, 2016; Sum, 2012; Baker, et al., 2013; Colombo, 2013; Ghirelli, Gil, Pérez, & Urtasun, 2019b).

According to Knight (1921), uncertainty is people's inability to predict the likelihood of events happening in the future. The measurement of uncertainty has been an overwhelming task due to its unobservable nature (Biljanovska, Grigoli, & Hengge, 2021). This has led empirical studies to employ a variety of observable macroeconomic indicators and proxies in the place of uncertainty. For example, Rossi and Sekhposyan (2015) developed an index which is based on the comparison between the realised forecast error and the unconditional distribution of forecast errors for selected macroeconomic variable. They classify a macroeconomic environment as uncertain when the realised forecast error is located at the tail of the distribution where the realisation is very difficult to predict. This uncertainty index distinguishes between uncertainty on the upside and uncertainty on the downside. Bloom (2009) also used stock market volatility as a proxy for uncertainty. Kamber, Karagedikli, Ryan and Vehbi (2016) adopted the implied volatility index of SP 500 (VIX) as their measure of uncertainty. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) also proxied uncertainty by dispersion in firm-level earnings, industry-level earnings, total factor productivity, and the predictions of forecasters. Baker, Bloom and Davis (2016) developed an EPU index based on newspaper coverage frequency. Mongey and Williams (2017) also refer to uncertainty shocks as the volatility of idiosyncratic shocks. The EPU index proposed by Baker et al. (2013) is used as a proxy for uncertainty in this thesis. This is because, recent research has debated and proven that it is the most prominent measure of uncertainty (see, Biljanovska, Grigoli, & Hengge, 2017; Ghirelli, Pérez, & Urtasun, 2019; Hassett & Sullivan, 2015). This index can be used to indicate some significant prior historical events by displaying heightened values during the time of those occurrences, and it can also be used to track the ongoing evolution of EPU since 1985. This index also includes different categories of policy such as monetary, fiscal, regulatory and health policies. When compared to other competitor uncertainty indices, this index has a wider coverage since it is available for a number of developed and emerging markets and its methodology has been validated against potential concerns regarding newspaper reliability, accuracy, bias, and consistency. The index's usefulness is demonstrated by its use by major data sources like Bloomberg, FRED, Haver, and Reuters, and the fact that it has been used as a variable in a number of studies.

This thesis contributes to the ongoing research on EPU by focusing on key aspects of EPU in emerging market economies (EMEs). The study of uncertainty is of major importance to EMEs because of the following characteristics. First, studies have shown that the Great Recession that occurred during 2007-2009 led to a significant rise and higher levels of volatilities of uncertainty in most EMEs as a result of the transmission of US shocks (Fernandez-Villaverde, Guerrón-Quintana, Rubio-Ramírez, & Uribe, 2011; Bloom, 2014). Second, EMEs suffer much more severe falls in investment and private consumption as a result of exogenous uncertainty shock (Carrière-Swallow & Céspedes (2013). Third, study has also proven that monetary and fiscal policy actions (as compared to general uncertainty) has a greater significant impact in increasing and decreasing uncertainty shocks in EMEs (Krol, 2014). Fourth, in recent time, EMEs have influenced the rise in EPU by transmitting these negative shocks to other countries (Dizioli, Guajardo, Klyuev, Mano, & Raissi, 2016; and Russel, 2016). Fifth, EMEs classifications are mostly based on their rate of development, amount of wealth, and financial and economic system similarities. The differences between EMEs have been mostly overlooked in classifications. This research elucidates the differences and similarities among the selected EMEs. Last, studies on the effect of EPU in EMEs are meagre since majority of study on EPU have focused on developed countries (Redl, 2018). These implications of uncertainty on EMEs have made it very relevant to focus on the role uncertainty plays in EMEs.

We examine the relationship between EPU and macroeconomic variables through three themes: interdependene, distance and spillover analysis. The first phase is to further examine the relationship between EPU and business cycle fluctuations. A business cycle is defined as the alternation of ups (expansions) and downs (contraction) phases in economic activities (Burns &

Mitchell, 1946). Studies on the business cycle have used variables such as output, employment, consumption, investment, industrial production, and gross output as proxies for the business cycle. Following Lucas (1997) argument that business cycles are all alike, various literature have proved that business cycles of different sectors (Long & Plosser, 1983; Christiano & Fitzgerald, 1998), different industries (Hornstein, 2000), different regions and different countries (Carlino & Sill, 1998; Kouparitsas, 2001) comove when compared to the same measure (economic variable proxy) of economic activity. This study tests Lucas's (1977) argument to ascertain if business cycles commove. However, in this analysis, specific macroeconomic variables are used as proxies for business cycles. The variables chosen represent real economic activities in various sectors of the economy, and also reflect the impact of EPU shocks and economic policy measures in an economy. The variables are CPI, broad money, trade (export of goods and import of goods), GDP, and SPX. We further investigate if EPU comove with business cycles within and across EMEs. The study on the relationship between EPU and business cycles is relevant since the aftermath of the Great Recession revealed the interdependence of EPU and business cycles. Economists have been looking into what causes the correlation between EPU and business cycles since this discovery, but they have yet to come to a consensus (Christiano and Fitzgerald, 1998; Ludvigson et al., 2015). This is due to a lack of theoretical agreement on whether uncertainty is a cause or an effect of economic swings (see, for example, Leduc & Liu, 2016; Fajgelbaum, Schaal, & Taschereau-Dumouchel, 2017; Kraft, Schwartz, & Weiss, 2018). Second, the empirical findings conducted have some limitations. For example, studies focused on identifying aggregate shocks which according to researchers are not necessarily the cause of the comovement. To the best of the author's knowledge, no time-frequency analysis of EMEs has been performed. Time-frequency analysis is important because investors make investment decisions at different times and frequencies (Bandi and Tamoni, 2017). As a result, more robust measurements are needed to study the relationship between EPU and business cycles fluctuations. This study also aims to investigate whether uncertainty is what causes business cycles to be alike. The findings provides more infomation on the relationship between EPU and macroeconomic variables. Thus, does uncertainty influence the periodic ups and downs in the business cycle (also referred to as economic activities)?

Second, the importance of distance in relation to EPU is examined. The term distance refers to the difference between country pairs. Studies that have investigated the distance (or differences) between countries have used attributes such as culture, administrative practices, geographic proximity, and economic development (Ghemawat, 2001). Studies conducted on distance show that, the differences between countries prevent or disturb the flows of information between the firm and the market (Johanson & Wiedersheim-Paul, 1975), introduces friction between countries (Shenkar et al. 2008), creates complexity (Vermeulen and Barkema 2002) to cross-border activities and increases the costs of coordination, integration and monitoring (Tan and Mahoney 2006). As a result, the existence of economic distance between economies affects the flow of economic activities between those economies (see also, Makino & Tsang, 2011; Linder 1961; Tobler, 1970; Johanson & Wiedersheim-Paul, 1975; Szulanski, 1996; and Tung & Verbeke 2010). There are still research gaps in distance-related studies because research on distance has been minimal (Tung & Verbeke 2010), and no study has investigated the relationship between distance and EPU. The study of economic distance has become particularly important because, in this era of globalisation and technological advancement, the distance between countries has become a crucial determinant of trade and capital flows between countries (Beck et al., 2006; Wilk, 2014). The study of EMEs is important in terms of trade and capital flows because research findings show that higher EPU in EMEs increases exchange rate volatility, which can have a serious impact on trade flows (Krol

2014). Despite the fact that the globalisation processes has reduced the distance between economies and resulted in the convergence and standardisation of people's values and preferences (Levitt, 1984), countries in this era differ in economic, political, social, cultural, linguistic, and geographical aspects (Ghemawat, 2001). These differences continue to influence international business decisions (Ghemawat, 2001). This study, therefore, adds to the existing literature on distance by investigating if the economic distance between EMEs can be influenced by EPU (or vice versa).

According to literature, there are certain channels through which distance influences EPU and vice versa. A large number of studies have investigated how distance affects economic activities, trade, capital, and foreign direct investment, all of which contribute to an increase in uncertainty. Geographic distance, for example, raises transportation costs, which influence patterns of international trade and industrial concentration (Krugman, 1991). Cultural distance measures the differences between economies' languages, ethnicities, religion, social norms and social networks. This distance is primarily created through the choices consumers make between substitute products based on their cultural preference. For example, these cultural preferences are based on color (Russians for example adore red), sizes of product (countries like Japanese prefer small automobile and household appliances), language (Asia refused star TV because of language barrier), and products that trigger the consumer's identity as a member of a country or association. Firms and investors face high levels of uncertainty as a result of their limited ability to control the cultural differences in values, political systems, norms, and beliefs (Håkanson & Ambos, 2010). These barriers further create contextual and behavioral uncertainty for foreign investors across countries, resulting in transactional costs that can affect an investor's performance as well as their decisions and timing of entry into foreign markets (Shenkar, 2001).

When corporations decide to internationalise their activities, institutional distance is a primary cause of foreign investors' liability of foreignness, making their legitimacy-building in a host country challenging (Eden & Miller, 2004; Kostova & Zaheer, 1999; Xu & Shenkar, 2002). The lack of knowledge about the administrative and political systems of economies, as well as their socio-cultural aspects, contributes to the "liability of foreignness" (Wu & Salomon, 2016, 2017; Hymer, 1960). Because investors are risk averse, the interference in information flow reduces investors' ability to learn about foreign countries and causes uncertainty (Makino and Tsang 2011). According to the Linder (1961) effect, the economic distance measured by the difference between the demand structures of economies is the main medium through which economies trade. When the demand structures between countries are similar, they tend to increase their bilateral trade. However, when the demand structures are dissimilar, bilateral trade declines. The significance of economic distance is also evident in studies that argue that a change in the economic characteristics (also known as economic distance) between countries leads to an increase in their uncertainty (Malhotra, Sivakumar& Zhu, 2009). The cancellation of the United States' membership in the Trans-Pacific Partnership agreement in January 2017, as well as President Trump's intentions to cancel other trade agreements (such as the North American Free Trade Agreement), resulted in an increase in the EPU of United States' trade partner countries, prompting some of them (such as Mexico) to diversify their trade partners (Baker, 2017). As a result, the economic distance between the United States and its trading partners (as measured by differences in international economic policies) influenced the EPU of US trading partners. The EMEs in this study are G20 members, which indicates they are interdependent because of their significant trade, investment, policy, and financial linkages (Schaechter, 2001; Mazurek, 2012). This implies that, there exist some economic similarities and dissimilarities between the selected EMEs.

Studies also show that EPU can influence economic distance, and the main channel is through trade. For example, one of the distance between countries that influence trade is the cost of transaction. Increased uncertainty leads to an increase in inventory costs. As a result, firms prefer to source their inputs from domestic suppliers and reduce their foreign orders to avoid higher inventory costs (Novy & Taylor, 2014). The difference in inventory costs between domestic and foreign economies causes trade to contract. Other research claims that the presence of uncertainty in an economy causes a decline in investment and consumption, lowering GDP and changing the income elasticity of trade between economies (see, Armelius, Belfrage & Stenbacka, 2014; Constantinescu, Mattoo & Ruta, 2017). This has a negative impact on the economic distance between economies as well as the terms of trade between them. Also, Malhotra, Lin and Farrell's (2016) study shows that the uncertainty between multinational enterprises leads to an increase the institutional distance between the industries. Institutional distance measures the differences in the regulatory systems, unilateral and policy measures, as well as the political and financial associations between institutions and economies (Ghemawat, 2001). In their study, the presence of cross-national uncertainty led Latin American firms to opt for full ownership over shared ownership venture. This reduced the institutional distance between multinational enterprises. Hence, uncertainty can influence the distance between economies.This study, therefore, adds to the existing literature on economic distance by investigating if the economic distance between EMEs can be influenced by EPU (or vice versa). The study on distance also introduces the concept of spatial analysis in terms of spatial weights, spatial distances, and spatial autocorrelation in order to determine if EPU similarities and dissimilarities between EMEs are caused by distance (see Owusu Junior (2020) for a recent study on spatial autocorrelation).

The third focus of this research is on directional spillover effects of EPU in EMEs. Previous studies that found evidence of uncertainty shock spillover both within and across economies were unable to determine the time-frequency version of the direction of these spillovers (see, Colombo, 2013; Zhu & Yan, 2015; Luk, Cheng, Ng, &Wong, 2020; Trung, 2019a; Diebold & Yilmaz, 2009). The time-frequency vesion of the spillover effect reveals the time varying directional spillover as well as the short-, medium-, and long-term directional spillover between economies. As a result, it reflects the degree and direction of spillover but also the evolutionary pattern across time and across frequencies. These can aid policymakers in making well-informed (short- to long-term) decisions by raising their understanding of the time-varying connection between EPU and macroeconomic variables at various time periods. Investors and policymakers can use the directional sign of spillover effects to identify the transmitter and receiver of spillover shocks in domestic and foreign economies. Furthermore, these research have primarily focused on developed (advanced) economies, leaving scant evidence of EPU spillover in emerging markets. To address this limitation, the time-frequency dynamics of the total, directional, and composite spillover effect of EPU within and across EMEs are investigated in this work.

Recent literature show that, EPU correlates with macroeconomic variables (see, Survey, 2019; Carri`ere-Swallow & C´espedes, 2013; Ghirelli, Gil, Pérez & Urtasun, 2019b). As a result, this study explicitly selects specific macroeconomic variables that represent real economic activities in various sectors of the economy, and also clearly reflect the outcome of economic policy actions as well as translate information about EPU shocks to the analysis. The variables selected are consumer price index (CPI), broad money, trade (export of goods and import of goods), gross domestic product (GDP), and share price index (SPX). The GDP represents aggregate output and is also a measure of economic development, import and export represent trade activities, broad money represents monetary policy activities, CPI is an inflation indicator as well as a measure of economic policy activities related to the purchasing power of domestic money, and SPX represents the movement of current share prices and stock market activities. Knowledge on how EPU relates with these key macroeconomic indicators in EMEs helps policy makers to better understand the impact of EPU and what influences EPU. This study also assists investors to avoid EPU shocks as a result of spillover effects and economic distance between EMEs.

1.2 Motivation of the study

Based on the review of EPU literature it is evident that business cycles, distance and spillover effects are sometimes influenced or may be affected by EPU. As yet, there has been a scanty systematic investigation of these possible interactions. Understanding these interactions may lead to reductions in the occurrences and negative impacts of EPU. Why is uncertainty relevant to economic analysis? According to Castelnuovo, Lim, and Pellegrino (2017), policy makers pay much attention to uncertainty because fluctuations in uncertainty lead to a pause in consumption and investment, which drags down economic growth in an economy. This thesis aims at specifically studying EPU because, evidence have proven that EPU has a greater significant impact on an economy than general uncertainty (Krol, 2014), EPU also has a first order effect on an economy (Bloom, 2009; Baker, Bloom & Davis 2013), EPU is statistically and economically significant in forecasting recessions (Karnizova & Li, 2014), EPU correlates strongly with the macroeconomic environment, business conditions, and other economic variables that affect investment (Survey, 2019), and lastly, EPU has vast negative impact on an economy (Gulen & Ion, 2016; Sum, 2012; Baker, et al., 2013; Colombo, 2013; and Arouri & Roubaud, 2016).

The characteristic features of EPU during the Great Recession have led researchers to investigate the potential causes of business cycle fluctuations. Previous studies have proved that EPU is found to be high during recessions across an economy, which is evident in the down turns in the business cycle. Why does high EPU comove with recession? Is it because EPU is the cause or rather effect of recessions across business cycles? As precisely argued by Leduc and Liu (2012) and more recently, Redl (2018), it is very possible that uncertainty volatilities significantly influences the movements of business cycles. Although a lot of previous literature have been able to prove the significance of uncertainty in recessions, very few have been able prove whether uncertainty is a cause or effect (or both) of the recessions (Ludvigson, Ma, & Ng, 2015). This study explicitly investigates whether EPU is a cause or effect of the business cycle using a novel approach.

Despite the vast study on the importance of distance (see, Makino & Tsang, 2011; Linder 1961; Tobler, 1970; Johanson & Wiedersheim-Paul, 1975; Szulanski, 1996; and Dellestrand & Kappen, 2012), the study of economic distance has been minimal (Tung & Verbeke, 2010) and to the best of the author’s knowledge, no study has investigated the relationship between economic distance and EPU. Also, the economic dimension of distance has become very important in recent times because economic distance have been observed to influence changes in this current era of globalisation, technological progress and other socio-economic changes (Beck, Gleditsch, &

Beardsley, 2006; Wilk, 2014). The focus on EPU in the context of economic distance has become relevant because of recent evidence in US that proved that the economic distance between US and its trade partners (measures by the difference in international economic policies) influenced the EPU of US trade partner countries (Trung, 2011). This study therefore adds a novel approach to the limited existing literature on economic distance by adopting the gravity model to investigate how the economic distance between countries influence their EPU. Evidence that EMEs are dependent and exhibit many forms of similarities (see, for example, Dell'Erba, Baldacci & Poghosyan, 2013; Ghemawat, 2011; Eun & Lee, 2010; Dunning, Kim, & Park, 2008; IMF 2011a, 2011b), logically implies that their geographical proximity plays a significant role in their dependence and similarities (Tobler, 1970). However, no such investigation has been conducted. As a result, the study on distance focuses on investigating whether nearer EMEs are more related. The study adopts the concept of spatial autocorrelation to investigate if the dependence and similarities between selected EMEs (with respect to their EPU measures) is as a result of the distance between them. The Moran's I (Moran, 1984) is used to investigate the presence of spatial autocorrelation.

Another area that needs more investigation is the study on the size and direction of spillover of uncertainty between EMEs. Previous studies on this subject have addressed total spillovers but have not been able to address the directional spillover as well as the exact amount of spillover among economies (Colombo, 2013; Zhu & Yan, 2015; Luk, Cheng, Ng, &Wong, 2020; Trung, 2019a; Diebold & Yilmaz, 2009, 2012, 2014). However, a recent methodology developed by Baruník and Křehlík (2018) helps investigate the size and direction of EPU spillover in EMEs. This is an important investigation in EMEs because Carrière-Swallow and Céspedes' (2013) study on the impact of uncertainty shocks revealed that emerging economies suffer much more from uncertainty spillover shocks since findings showed that exogenous uncertainty shocks to EMEs reduce investment and private consumption.

This thesis provides a novel insight into the dependence of EMEs, the spillover transmitters and recipients of EMEs, how distance influences the EPU indices of EMEs, and the similarities/ dissimilarities between EMEs. An understanding of these can help reduce the occurrences and impacts of EPU.

1.3 Statement of the research problem

Various literature have enforced the significant negative role uncertainty plays in an economy (see, Baker, Bloom, & Davis, 2013; Ghirelli, Gil, Pérez, & Urtasun, 2019b; Kraft, Schwartz, & Weiss, 2018; Leduc & Liu, 2016; and Caggiano, Castelnuovo, & Pellegrino, 2017). However, the study on EPU is still in its infancy (Nguyen, Kim, & Papanastassiou, 2018). This thesis, therefore, focuses on how EPU responds to or influences EMEs by addressing three problems. These are the *interdependence, distance and spllover effects* between EPU and macroeconomic indicators in the selected EMEs. Each of these three problems are discussed in this section.

The aftermath of the Great Recession revealed the interdependence of EPU and business cycles. This finding has prompted economists to investigate the role EPU plays in the comovement and fluctuations of business cycles. Economists are yet to reach a consensus on what causes the comovement between EPU and business cycles, and as a result, business cycle research continues to struggle to find answers to this phenomenon (Christiano and Fitzgerald, 1998; Ludvigson et al., 2015). Theoretically, there is no theoretical harmony on whether uncertainty is a cause or effect of fluctuations in economic activities (see, for example, Ludvigson, Ma, & Ng, 2015; Bernanke, 1983; McDonald & Siegel 1986; Leduc & Liu, 2016; Arellano, Bai, & Kehoe, 2011; Van Nieuwerburgh & Veldkamp, 2006; Fajgelbaum, Schaal, & Taschereau-Dumouchel, 2017; Oi, 1961; Abel, 1983; Pastor & Veronesi, 2006; Segal, Shaliastovich, & Yaron, 2015; Kraft, Schwartz, & Weiss, 2018).

The majority of empirical research has also focused on identifying an aggregate shock that impacts an entire economy's activities as the cause of EPU and business cycle comovement. However, some studies have argued that an identified aggregate shock is not necessarily the cause of the comovement of EPU and business cycles. As a result, more robust measurements are needed to study the relationship between EPU and business cycles fluctuations. These studies have also been limited to indicators of real activity (the business cycle) such as production, consumption, investment, and hours worked (Hornstein, 2000). These business cycle indicators may be deemed insufficient because additional research has revealed that EPU is strongly influenced by policymakers during the implementation of fiscal, monetary, and regulatory policies (Sujan & Redek, 2008). It is thus preferable to use real activities indicators that clearly reflect the outcome of policy implementations in an economy rather than limiting the indicators to production, consumption, investment, and hours worked, which do not provide a clear picture of the cause or effect of EPU. Furthermore, studies that have used time–frequency analyses to investigate the relationship between EPU and business cycles are few and have primarily focused on developed economies. To the best of the author's knowledge, no time-frequency analysis of EMEs has been performed. Because investors make investment decisions at different times and frequencies (Bandi and Tamoni, 2017), performing time-frequency analyses provides detailed results for investors and policymakers.

This study intends to bring more clarity to this inconsistency by investigating if uncertainty is a source of the business cycle or an endogenous response to the business cycle. To begin, the study employs EPU as a measure of uncertainty. Second, the WMC and WMCC approaches, which are based on Fernandez-Macho's (2012) maximal overlap discrete transform estimator, are used to determine whether EPU and business cycles comove and, if so, the indicator (leader– follower) of the comovement relationship. Third, the study employs the Diks and Panchenko (2005, 2006) nonparametric causality test to determine whether EPU is a cause or an effect (or both) of business cycle fluctuations in a subset of EMEs.

The second problem focuses on the relationship between EPU and distance. Despite the fact that several studies have shown a link between EPU and distance, these study have concentrated on the cultural dimension of distance, ignoring the economic and spatial dimensions (see, Makino & Tsang, 2011; Linder 1961; Tobler, 1970; Johanson & Wiedersheim-Paul, 1975; Szulanski, 1996). The author, on the other hand, argues that the economic and spatial dimensions of distance are crucial characteristics of distance that might reveal a lot about the relationship between EPU and distance. Although the study of non-geographical distance has mostly focused on the cultural dimension of distance between countries (Tung & Verbeke 2010), studies conducted by Beck, Gleditsch, and Beardsley (2006), Wilk (2014), and Le (2017) have sparked the author's interest to focus on the economic dimension of distance between EMEs.

The extent of similarities (or dissimilarities) of economic characteristics between units (or countries) is termed as economic distance (Dow & Karunaratna, 2006; Brewer, 2007; Johanson & Wiedersheim-Paul, 1975). Ghemawat (2001) also classifies economic distance as the distance that reflects differences in the economic wealth, quality and cost of natural, financial and human resources. Despite evidence that uncertainty increases when the economic distance between countries are different (Malhotra, Sivakumar & Zhu, 2009; Linder, 1961; Beck et al., 2006), to the best of the author's knowledge, no study has investigated the relationship between economic distance and EPU. Conducting an investigation on EPU rather than uncertainty in general has become necessary because evidence have proven that EPU has a greater significant impact on an economy than uncertainty in general (Krol, 2014). Can the economic distance between EMEs influence the outcome of their EPU? The authors believes that there is a possible link between EPU and economic distance because, the increase in the EPU of US trade partners as a result of changes (or anticipated changes) in US foreign economic policies, demonstrates that the economic distance (similarity or dissimilarty) between economies has an impact on their EPU (see Baker, 2017). This confirms Krol's (2018) argument that, there is a reduction (or increase) in EPU when countries have similar (or dissimilar) international economic and trade policies. Furthermore, the EMEs in this study are members of the G20. As a result, it is clear that these economies have obvious economic, financial, trade, and policy links, implying that they are not independent of one another (Mazurek, 2012). These facts back up the authors' claim that there is a link between economic distance and EPU. As a result, a novel empirical investigation of the relationship between economic distance and EPU adds empiricl facts to the body of knowledge on the relationship between economic distance and EPU. The dynamic linear method is adopted for this investigation.

The second aspect of distance intends to investigate the spatial autocorrelation between EMEs with respect to EPU. Despite the negative impact of geographical distance on investment, trade and equity flows (Ghemawat, 2001), no study has investigated if the correlation between the EPU indices of EMEs is as a result of the distance between them. This investigation has become necessary because recent literature have proved that EMEs exhibit many forms of similarities (Dell'Erba, Baldacci & Poghosyan, 2013; Eun & Lee, 2010). Second, there are evidences of spillovers of EPU to EMEs, which leads to spatial autocorrelation (Haining, 2001). Third, EMEs have global factors and economic linkages such as geographic proximity, bilateral trade and financial exposure (Jiang, Zhu, Tian & Nie, 2019; Ghemawat, 2001). This implies that, the concept of spatial (geographical) autocorrelation analysis is applicable to EPU in EMEs. Spatial autocorrelation measures the relationship variations between the values of two variables (in this study, the variable selected are EPU indices and selected macroeconomic variables) which are separated by some specific distance (in this study, we choose latitude-longitude coordinates). We, therefore, adopt this concept of spatial analysis to analyse the spatial cross-country linkages between EMEs to ascertain if the correlation between the EPU indices is as a result of the distance between EMEs.

The third issue addresses research gaps identified following a review of studies on the spillover effects of EPU in EMEs. There are empirical studies that have investigated and documented evidence that EPU shocks have significant spillover effects within and beyond an economy but, they were unable to address the amount and direction of spillover from a country to other countries (see, for example, Colombo, 2013; Zhu & Yan, 2015; Luk, Cheng, Ng, & Wong, 2020; Trung, 2019a; and Diebold & Yilmaz, 2009). Information on the amount of the EPU spillover received or contributed by one country to other countries gives policy makers and investors a more precise understanding of the nature and degree of EPU spillover in EMEs for policy implementation and decision making.

Although some progress has been made in literature to investigate EPU directional spillover (net distributors and recipients of spillover) and amount of spillover (see, Diebold & Yilmaz, 2009, 2012, 2014; Colombo, 2013; Zhu & Yan, 2015; Kang & Yoon, 2019; Yoon, Al Mamun, Uddin, & Kang, 2019; Trung, 2019a; Luk, Cheng, Ng, &Wong, 2020), these studies have mainly focused on developed (advanced) economies leaving little evidence of the effects of EPU spillover in EMEs. For example, studies conducted by Kang and Yoon (2019) selected China as the only emerging market economy (EME) in their studies; Istiak, and Alam (2020) focus on Gulf Cooperation council countries (comprising Saudi Arabia, United Aran Emirates (UAE), Qatar, Kuwait, Bahrain, and Oman); and Luk, Cheng, Ng, and Wong (2020) investigate EPU spillover from USA, Europe, Mainland China and Japan to Hong Kong (see, Trung, 2019b; and Thiem, 2018). Studies on EMEs are required because in recent time, EMEs have influenced the rise in EPU by transmitting EPU shocks to other countries (Dizioli, Guajardo, Klyuev, Mano, & Raissi, 2016; and Russel, 2016). This study extends the research on the significant effect of EPU spillover by investigating the amount and direction of EPU spillovers between EMEs as well as the effect of EPU spillover on macroeconomic indicators (CPI, broad money,GDP, SPX and trade (import and export) that proxy as real economic outcomes in countries. To address this limitation, the study adopts Baruník and Křehlík's (2018) methodology to measure pairwise, composite and net spillover. The unique feature of Baruník and Křehlík's (2018) methodology is the able to captures frequency domain as well as time-frequency dynamics. The time-frequency dynamics is measured by time domain variance decomposition while the frequency dynamics measures the decomposition into frequency bands.

1.4 Research objectives

Having reviewed the existing literature on uncertainty, its relationship with business cycle fluctuations, its correlation with distance, and its spillover effects in EMEs, this thesis investigates comovement, interdependence, economic distance, and spillover effects to compare and contrast the possible links between EPU, CPI, broad money, GDP, SPX and trade (import and export of goods and services) in EMEs. Using monthly frequency secondary data of EMEs from 01/01/1999 to 31/12/2018, the specific objectives of the study are to:

i. Explore the non-linear interdependence and causal relationships between economic policy uncertainty and macroeconomic indicators in emerging market economies.
ii. Examine the relationship between distance and economic policy uncertainty in emerging market economies.
iii. Investigate the spillover between economic policy uncertainty and macroeconomic indicators in emerging market economies.

1.5 Research questions

To fill the research gap on the relationship between major macroeconomic indicators and EPU, this thesis finds answers to the following questions:

i. Are the fluctuations of the business cycles in emerging market economies interdependent and does uncertainty dictate such interconnections?

ii. What is the relationship between distance and economic policy uncertainty in emerging market economies?

iii. What is the spillover between economic policy uncertainty and macroeconomic indicators in emerging market economies?

1.6 Justification for Selected Variables

According to Baker, Bloom, and Davis (2016), the main policies that cause the most common type of policy uncertainty in news articles are fiscal policy, monetary policy, and regulatory policy uncertainty. Second, EPU is heavily influenced by policymakers and current politics during the implementation of fiscal, monetary, and regulatory policies (Sujan & Redek, 2008). As a result, it is appropriate to include variables that reflect the outcome of fiscal, monetary, and regulatory policy uncertainty in this study. That is to say, how does EPU respond to government policy actions? The selected emerging market economies (EMEs) for this study are Brazil, China, India, Korea, Mexico and Russia. They are members of the G20 and have strong trade, investment and financial ties (Schaechter, 2001). The study's time frame was determined by the availability of time series data, which range from 1st of January 1999 to 31st of December 2018.

The variables selected are EPU index, CPI, broad money, trade (export of goods and import of goods), GDP, and SPX. To correspond our monthly EPU data, the study uses monthly macroeconomic indicators. Based on availability of monthly data, the study adopts monthly normalised GDP sourced from the Organisation for Economic Co-operation and Development (OECD) main economic indicators. Since GDP data are released quarterly, OECD developed the monthly GDP to reflect the short-term value of GDP. The monthly OECD GDP index is derived from chained volume estimates of quarterly GDP series in US dollars. The quarterly GDP series are linearly interpolated to generate monthly results, which are then aligned with the most appropriate month of the quarter. Since the study focuses on the relationship between EPU and macroeconomic variables, the objective for selecting data is to enable effective and fair comparison of variables since the effective comparison between variables produces more robust findings. Bearing in mind that GDP variables come in different magnitudes and have size disparities between countries, a simple way to ensure fair comparison is by normalising GDP (which can be sourced from OECD database). This means that the variables are set equal to each other which enable effective examination of their differences over a period of time. Normalisation also ensures that the series have the same amplitude.

Economist, financial and business analyst have used these methods to compare performance between countries over time (see, Federal Reserve Bank of Dallas, 2020). It is worth mentioning that the EPU index of Baker et al. (2013) was also normalised within each month and country to ensure stable volumes of news over time and across countries. The GDP data for each country accessed from OECD are seasonally adjusted and normalised. Broad money, export of goods and import of goods are also seasonally adjusted to eliminate the influence of seasonal factors.

Economic Policy Uncertainty: Previous literature have used various measures as proxies for EPU. For example, Leblang and Bernhard (2006) measured EPU using political events, particularly parliamentary political processes to examine the impact of policy uncertainty on exchange rate volatility. Their findings proved that political events influence exchange rate volatility. Other studies also used elections as proxy for EPU and discovered that uncertainty increases equity market volatility (Białkowski, Gottschalk, & Wisniewski, 2008; Boutchkova, Doshi, Durnev, & Molchanov, 2012), and reduces firms' investment (Julio & Yook, 2012). Choi, Furceri, Huang, and Loungani (2016) took stock market volatility as a proxy of uncertainty and discovered that uncertainty deteriorates the productivity growth rate of firms that heavily depend on external finance. Gourio, Siemer and Verdelhan (2016), also proxy uncertainty as stock market volatility. Istrefi and Mouabbi (2016) also examine the causal effects of interest rate uncertainty and proxy interest rate uncertainty by the dispersion of professional forecasts of short- and long-term interest rates while accounting for both disagreement among forecasters and the perceived variations of future aggregate shocks.

However, recent literature have stated that, the most influential proxy for uncertainty is the EPU index of Baker et al. (2013) (Biljanovska, Grigoli, & Hengge, 2021; Ghirelli, Pérez, & Urtasun, 2019; Hassett & Sullivan, 2015). This index measures economic policy-related uncertainty based on newspaper coverage frequency counts that contain keywords from these three categories: economy, policy and uncertainty, which are specified in the native language of the new papers. This index also includes different categories of policy such as monetary, fiscal, regulatory and health policies amongst others. To obtain the monthly EPU index, they scale the raw count by the total number of articles in each newspaper for each month, standardise the monthly series of scaled counts, compute their average across the newspapers, and rescale the resulting index to mean 100. This EPU index measures the continuous evolution of EPU through time going back from 1985 (for countries with large number of observations) and 2003 (for countries with short series). Unlike many other uncertainty indicators that are limited to the US, this index has a wider coverage since it is available for a number of developed and emerging markets making a total of twenty-four countries. For each of these countries, Baker, et al. (2013) adjusts the three categories of keywords to account for particularities of each country and its language. In this influential paper of Baker, et al. (2013), they discovered that the recent increase in uncertainty was as a result of the Great Recession. They also find that uncertainty had a significant negative effect on real GDP, aggregate investment, employment and consumption expenditures.

Baker et al. (2013) validated their methodology against potential concerns related to newspaper reliability, accuracy, bias, and consistency making their methodology free of newspaper related methodological issues. In terms of the usefulness of this index to decision makers, the market-use value of this index is validated through its use by major data providers like Bloomberg, FRED, Haver and Reuters to meet demands from banks, hedge funds, corporations and policy makers. Also, in the area of literature, a number of studies have deployed Baker, et al. (2013) index as a variable in their study, in an attempt to gain more insight into the impact of policy uncertainty on other economic variables. For example, Gulen and Ion (2013) find that EPU significantly reduces corporate investment, and this effect is greater for firms that have more irreversible potential investments. Using the policy uncertainty index of Baker, et al. (2013) as a proxy for political uncertainty, Pástor and Veronesi (2013) findings revealed that, higher political uncertainty leads to stocks volatility and political uncertainty is higher in weaker economies. Brogaard and Detzel (2015) used Baker, et al. (2013) measure to discover that EPU positively forecasts log excess market returns, EPU is an economically important risk factor for equities. Brogaard and Detzel (2012) created an EPU index similar to Baker, et al. (2013) using the Access World News database to test the impact of EPU on asset prices. In a panel of twenty-one countries, their findings revealed that, EPU reduced stock market returns, raised equity risk premiums, and increased market volatility. This implies that, EPU makes purchasing stocks more risky. Based on the above evidences, this study uses Baker, et al. (2013) EPU index as a proxy of EPU in countries.

Consumer Price Index: In this study, the inflation indicator- CPI is justified as a variable for monetary policy analysis. CPI is directly influenced by monetary policy and fiscal policy decisions by governments and thus a good proxy of the effectiveness of the government's economic policy (Baker, et al., 2016). According to Pesce (2010) it is very important to choose a monetary policy index that reflects the monetary policy's target of maintaining the purchasing power of domestic money. Thus, one must choose a price index that can measure the impact of price increases on the purchasing power of money and retail prices. Pesce (2010) added that inflation indicators are appropriate for monetary policy analysis since they grasp the persistent and generalised effects of price evolution on an economy. Pesce (2010) view is supported by Cecchetti (2010) whose study emphasised that Inflation measurement is fundamental to the conduct of monetary policy. The importance of CPI is also demonstrated by Baker et al. (2013) who used CPI forecast data along with federal expenditures, and state and local expenditures forecast data to compute a forecast disagreement measure. They chose these variables (including CPI) because they are directly influenced by monetary policy and fiscal policy decisions.

The CPI is the preferred index for monitoring inflation trends because it covers prices of items that enter into the representative consumption basket of the household (Al-Hamidy, 2010; Baker et al., 2013). Therefore, CPI is usually used as the best indicator of the performance of the purchasing power of money and retail prices, due to the relevance that CPI gives to the total traded goods and services in the market within an economy.

*Broad Money***:** In this study, broad money represents the measures of monetary policy stance in an economy. According to IMF (2014) and Schaechter (2001) most central banks of industrial countries as well as most transition and emerging market central banks prefer to target a short-term interest rate as their operating target (or instrument) and the result of the short-term interest rate target is evident in changes in the money supply in the economy. This implies that, a clear indictor of a central bank monetary policy is the amount of money it releases or withdraws in an economy.

Reserve rate (also termed as deposit holdings of central banks from commercial banks) in literature has been mostly used as a good indicator to reflect the outcome of implemented monetary policies because changes in the values of bank reserve has been known to be influenced by the targeted interest rate vales, making bank reserve endogenous (see, Christiano & Eichenbaum, 1992; Christiano, Eichenbaum & Evans, 1999; Saxegaard, 2006; Benes, Berg, Portillo, Dao, & Baldini, 2012; Davoodi, Dixit, & Pinter, 2013). However, Cartas and Harutyunyan (2017) in their recent study stated that central government deposit holdings is not largely influenced by changes in economic activity, interest rates and exchange rates, but rather these macroeconomic variables largely influence deposits of (money available to) the money-holding sectors in the economy. The money-holding sectors in the economy are available for making purchases of goods, services, financial and nonfinancial assets. When central banks use interest rate as the main tool to implement and control monetary policy actions, they closely monitor the level of money available to money- holding sectors in the economy because, the levels of money available to the money-holding sectors are seen as outcomes of the implementation of the monetary policy decision.

The best quantitative variable that clearly measures the amount of money at money- holding sectors in an economy is broad money. IMF defines broad money as the money holding sectors' total currency in circulation, plus financial instruments (including short-notice withdrawals) that are generally accepted alternatives for financial transactions (such as savings and term deposits). Broad money is similarly defined by OECD (2008) as the sum of "currency in circulation, sight deposits and time deposits as well as savings deposits at short-notice held by domestic non-banks". Therefore OECD (2020) concludes that broad money supply is considered as more stable than narrower definitions of money supply because there is less evidence of substitution between the various liquid asset categories.

Trade: The behavior of trade to uncertainty has become very important in recent times following the Great Depression, the global trade collapse during the 2008/2009 global economic crises, the collapse of Lehman Brothers and the European debt crisis. For example, the temporary increase in recession as a result of the Great Depression lead to an immediate drop in investment (Bernanke, 1983). Also, the Great Recession of 2008/ 2009 lead to a sharp drop in international trade (in both imports and exports) across the globe (Baldwin, 2009). The reduction in investment and trade was a result of a 'wait and see' attitude of investors to observe the uncertainty period for a while before making investment decisions (Bernanke, 1983; Dixit, 1989). Another cause of the decline in trade as a result of uncertainty is through the exchange rate channel. EPU increases exchange rate volatility (Krol, 2014; Beckmann & Czudaj, 2017a, 2017b) and according to Hlatshwayo and

Saxegaard (2016), EPU negatively affects the response of export to real effective exchange rates. This means that, EPU through exchange rate reduces the performance of export of a country.

According to the findings of a study conducted by Novy and Taylor (2014), international trade responds strongly to large uncertainty shocks. They explained that when uncertainty increases, firms reduce their foreign orders more than domestic orders due to the higher cost of foreign inputs. This eventually leads to a substantial drop in international trade. Taglioni and Zavacka's (2012) study also finds a significant negative relationship between uncertainty and trade. Thus, uncertainty is a great constraint to doing business (World Bank Development Report 2005). Focusing on the impact of EPU and trade, the few studies conducted have all proved that EPU negatively affects trade growth blobally (see, Armelius, Belfrage & Stenbacka, 2014; Han, Qi & Yin, 2016; Constantinescu, Mattoo & Ruta, 2017; Tam, 2018).

This study aims to extend the literature scope of the relationship between EPU and trade by focusing on EMEs and using novel methodologies. Also, to offer a richer account of trade flows in EMEs, the study conducts analysis for both exports of good and imports of goods. The study focuses only on the trade in goods rather than trade in goods and services because, since 2008, trade in goods and trade in services have each taken on different trajectories (Constantinescu, Mattoo and Ruta, 2017) and trade in goods makes up over 80% of total trade (Tam, 2018).

Gross Domestic Product: This study considers the relationship between uncertainty and GDP. GDP is a gauge of the level of economic development of a country. GDP is also used to measure the size of an economy and growth rate and serves as a key tool to guide policymakers and investors in their decision making (McCulla & Smith 2007). Most studies on the importance of uncertainty for economic growth examine how uncertainty affects investment, inflation, stock markets returns, stock market volatility, exchange rate, interest rates, commodity markets and foreign institutional investment. These studies examine how these variables indirectly affect economic growth. At the macro level the few examples of papers on the growth and uncertainty relationship we are very few (Lensink, Bo, & Sterken, 1999; Sušjan & Redek, 2008; Ali, 2001; Asteriou & Price, 2005).

Therefore, this study intends to investigate the relationship between EPU and economic deveopment in EMEs. Real GDP is used as proxy for the level of economic development of a country because this variable reflects the overall growth, performance and economic activities of a country. This includes all goods and services in the countries. The real GDP is used instead of normal GDP because the real GDP (also referred to as inflation-corrected GDP) unlike nominal GDP is adjusted for inflation. Real GDP accounts for changes in price levels which help to differentiate an actual increase in production from an increase in per-unit price. As such, the real GDP provides a more accurate figure of economic growth since it reflects GDP on a per quantity basis in an economy.

Share Price Index: An effective financial market is considered to be a good indicator for economic development and economic growth because firms are able to sell equities and/or borrow funds to finance their businesses and investment activities, which tends to promote growth in an economy (Bayraktar, 2014). Therefore, measuring the development level of financial markets across countries is very important since it helps in policy formulation and influences investors' decisions to invest in a country. The introduction of alternative measures of the development level of financial markets, particularly stock markets, has practical importance since there is evidence in literature concerning the inverse relationship between stock market and uncertainty. For example, Sum's (2012) investigation on the effect of EPU in the US on the stock market performance in Canada and Mexico shows that the increased changes in EPU in the US negatively affect stock market performance in Canada and Mexico. Arouri and Roubaud (2016) investigate the relationship between EPU and stock markets in China, India and the USA and findings revealed that an increase in EPU in the USA and India reduces stock returns and increases market volatility. Brogaard and Detzel (2012) test the impact of EPU on asset prices in a panel of twenty-one countries, and discovered that EPU reduced stock market returns, raised equity risk premiums, and increased market volatility. Yoon, Al Mamun, Uddin, and Kang (2019), investigate the net transmission and net return spillover between financial markets (stock, currency, and bond) and commodity markets (oil and gold). Their research findings revealed that, the US stock market is the most significant contributor of return spillover shock of the major stock markets in the Asia-Pacific belt.

This study focuses on stock market as a measure of the development level of financial markets because the stock market is able to provide information on the size of the equity market, and the market depth, in terms of its liquidity or the easiness to buy and sell shares. The SPX clearly reflects how a stock market is performing. This is because the price of a stock (which is determined by capitalisation and liquidity) is what determines the index of the stock. The SPX is thus an indicator that shows the movement of current share prices. This movement in share prices reflects whether the market conditions are active or lethargic (Suharsono, Aziza, & Pramesti, 2017). Donadelli, (2015) analysed the impact of policy- related uncertainty shocks on US macroeconomic conditions. Using SPX (also termed as stock price index) as a financial indicator, there was evidence of significant fall in share prices as a result of uncertainty shocks (see also, Brogaard, & Detzel, 2015). Therefore this study measures stock market activities using the SPX.

1.7 Significance and contributions to knowledge

The significance of this study is evident in the considerable contributions it makes to literature, policy makers, and investors. Economists have not arrived at a consensus on the possible explanations to what causes business cycles to comove and fluctuate. As such, research focused on business cycle analysis still battle with finding answers to this phenomenon (Christiano & Fitzgerald, 1998; Ludvigson, Ma, and Ng, 2015). In light of the real business cycle theory that views the fluctuations of the business cycle as the consequence of real external shocks (or exogenous changes to real economic activities), the study makes an important theoretical contribution by finding answers to why business cycles fluctuate. We specifically investigate if EPU is the cause or effect of business cycle fluctuations. This theoretical contribution is unique because, it deviates from traditional sources of fluctuations such as production technology and labour supply shocks and focus on uncertainty as a potential cause or effect of business cycle fluctuations. This is because there are proven evidence that uncertainty comoves with business cycle fluctuations (Bloom 2009, 2014; Leduc & Liu, 2016; Kraft, Schwartz, & Weiss, 2018). This finding is important because it seeks to bring more clarity on what causes business cycle fluctuations by investigating the directional sign of the relationship between uncertainty and the business cycle. Policy makers also get novel insights on the trends and patterns of EPU and macroeconomic variables which aids in the formulation and implementation of fiscal and monetary policies. The effective formulation and implementation of policies significantly reduces uncertainties and financial markets fluctuations.

We also contribute to the role EPU plays in the comovement of variables (GDP, CPI. SPX, import, export and broad money) by investigating if EPU has the potential to lead or follow the other variables within the selected EMEs. The inclusion of CPI, SPX, import, export and broad money is novel to the scope of study and has significantly altered the understanding on the relationship between EPU and business cycle fluctuations. The findings reinforce the necessity to test the relationship between EPU and business cycles by mediating numerous other variables that connect with EPU. We extend empirical work by using real data to provide evidence based quantitative estimates. The study introduces a wavelet methodology developed by Fernandez-Macho (2012) which is novel to the study of the relationship between uncertainty and business cycles. This methodology's measure of comovement simultaneously investigates how two or more (multivariate) time series variables move together continuously at both time and frequency domain. The study also adopts the Diks and Panchenko (2005, 2006) non-linear causality test which provides superior, consistent and robust results. We apply the MODWT with a wavelet filter of length L=3 to investigate evidence of causality. Thus, the causality results are divided into three scales which capture short-, medium-, and long-term dynamics. This helps to determine how variables vary over time and across frequencies.

Second, the study introduces the concept of economic distance and spatial distance into the study of EPU. It is worth noting that this is a novel contribution to the study on EPU. Spatial distance investigates if there is a relationship or pattern between the EPU as well as the macroeconomic variables of EME based on the geographical distance between them. Findings on the spatial analysis reveal that, neighbouring EMEs have strong relationships and patterns. This supports

Tobler's first law of geography that states that "everything is related to everything else, but nearer things are more related than distant things" (Tobler, 1970, p.236). The findings also provide robust information for policy makes and investors for international portfolio management, policy decision processes and international trade since the study offers country-specific features and characteristics of EMEs based on their geographical proximity from each other. The study on the economic dimension of distance explores and measures the empirical relationship between economic distance and EPU in the selected EMEs. It determines if EPU influences or is influenced by economic distance between EMEs. This helps in the identification of the differences and similarities between EMEs as a result of the distance between them. Likewise, we record relationship patterns between economic distance and EPU in the selected EMEs. The study provides another means of distinguishing one emerging country from another by way of how they react to uncertainty. We discover that macroeconomic variables were largely statistically significant and have explanatory power to explain the economic distance between the EMEs. Also, knowledge on how EPU relates with macroeconomic indicators can help policy makers control the occurrences of EPU. The dynamic linear regression method deals with distributional assumptions of variables while the local Moran's I spatial economic models deals with non-parametric geospatial analysis.

Third, although empirical studies have documented evidence of spillover effects within and beyond an economy, they were not able to address the amount and direction of the spillover effect. By exploring Baruník and Křehlík's (2018) methodology, this study extends the empirical research on the spillover effect of EPU within each of the EMEs and across the EMEs. This is achived by adopting the Baruník and Křehlík's (2018) methodology to investigate the amount and direction of EPU spillover in the selected EMEs. We further investigate the spillover effect pattern between EPU and key macroeconomic indicators. This finding offers new insight on country-specific spillover amounts and patterns "to" and "from" the selected EMEs. The findings also capture frequency domain as well as time-frequency dynamics and provide estimates in the short-, medium-, and long- term. Since investors are more concerned about the net transmitters, net recipients, and the amount of EPU spillover across economies, this methodology is specifically adopted to provide answers to these concerns. The findings throws more light the network connectedness across EMEs and hence aids investors to undertake precise investment decisions and intelligently plan their portfolio diversification strategies. The study also extends the literature on studies conducted on EMEs since studies on EPU spillover has mainly focused on developed (advanced) economies.

1.8 Structure of the thesis

In line with the specific objectives outlined in this thesis, the complete thesis report consists of six chapters. The organisation of the rest of the chapters is briefly outlined. Chapter Two focuses on the literature review for the three thematic areas. Chapter Three investigates the time-varying interdependence and comovement within and across EMEs. This study used the wavelet methodology proposed by Fernandez-Macho (2012) to examine the interdependence and co-movement between EPU and selected macroeconomic indicators. The study also adopts the Diks and Panchenko (2005, 2006) nonparametric causality test to answer the question of whether EPU is a cause or effect (or both) of business cycles fluctuations in selected EMEs. Findings from these analyses provides evidence of whether the selected EMEs comove and if EPU is the cause or rather effect (or both) of recessions across business cycles. Chapter Four seeks to introduce the idea of economic distance in addition to spatial autocorrelation among EMEs. In order to assess the relationship between economic distance and EPU, this study employs the dynamic linear regression method, where difference in GDP of EMEs is the proxy for economic distance. Secondly, to investigate if geographical proximity can influence the similarities or dissimilarities between EPU among EMEs, the study deploy the local Moran's I (Moran, 1984) as the measure of spatial autocorrelation. This study's investigation helps companies and investors to make well informed decisions when expanding their global market across countries by guarding against or reducing the occurrence of EPU caused by the economic distance between countries.

The objective of Chapter Five is to identify dynamic and network spillover between EPU and major macroeconomic indicators. This investigation used Baruník and Křehlík's (2018) methodology to measure total spillover, total directional spillover and pairwise directional spillover. This study conducted a country specific and cross border events analysis to examine the nature of spillover within and across EMEs. Knowing the value amounts of shocks been transmitted and received by each EME helps policy makers know the specific countries to monitor during the early signs of uncertainty fluctuations, as well as make well informed predictions and policy implementations. With these findings are investors are able to intelligently plan their portfolio diversification strategies with knowledge of the main transmitter and recipients of shocks at different frequencies. Chapter Six provides the summary, conclusion, policy implications and recommendations for investors, regulators and policy makers.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter covers the theoretical and empirical aspects of the literature. The literature review focuses on three distinct themes that affect EPU. The first theme which forms the basis of Chapter Three focuses on the interdependent relationship between EPU and macroeconomic indicators in EMEs. It explores the concept of the real business cycle theory, causes of business cycle fluctuations, measures of comovement and the inconsistent theories on the directional sign of the relationship between uncertainty and business cycle. The theory of psychic distance, economic distance and geographic distance and the various measures of distance are also examined. The third theme reviews literature on the spillover effect of EPU among EMEs. This theme focuses on the types of spillover methodologies and the effect of uncertainty shocks.

2.2 Theoretical Literature

This subsection of the literature review focuses on the theories and concepts that form the theoretical foundation of each of the three themes (namely, interdependence, distance and spillover effects in EMEs). The theoretical foundation is also intended to support the specific research objectives and questions of the study.

2.2.1 Measuring Interdependence

Despite proven facts that business cycles comove (Lucas, 1997; Long & Plosser, 1983; Christiano & Fitzgerald, 1998; Hornstein, 2000; Carlino & Sill,1998; and Kouparitsas, 2001), economists have not arrived at a consensus on the possible explanations to what causes most of the sectors in an economy to simultaneously move up and down at different time frames (also termed as comovement), and as such, research focused on business cycle analysis still battle with finding answers to this phenomenon (Christiano & Fitzgerald, 1998; Ludvigson, Ma, and Ng, 2015).

A natural starting point of a business cycle theory that forms a strong foundation for investigating why business cycles comove is termed as the real business cycle theory (see, Kydland & Prescott, 1982; Long & Plosser, 1983; and Prescott, 1986). According to Christiano & Fitzgerald (1998), the real business cycle theory views the fluctuations of the business cycle as the consequence of real external shocks, where production technology argues that real exogenous shocks to productivity leads to adjustments that cause the expansions and recessions in the business cycle. For example when there is a jump in productivity (caused by exogenous shock), employment increases because the jump in productivity will boost wages, thereby making it rational to work. On the other side, a decline in productivity (caused by exogenous shock) will make leisure more attractive thus reducing employment. This theory therefore classifies the ups and downs of the business cycle to be an efficient response to the exogenous changes to real economic activities (that is, the level of national output) (Plosser 1989).

The characteristic features of EPU during the Great Recession has led researchers to investigate the potential causes of business cycle fluctuations since traditional sources of fluctuations such as production technology and labour supply shocks, maybe less plausible in explaining the fluctuations of business cycles in this era (Redl, 2018). Why should uncertainty matter in the comovement of business cycles? There is proven evidence that uncertainty rises sharply during the downturns of the business cycle (also known as a recession (Bloom 2009, 2014). However, according to Ludvigson, Ma, and Ng (2015) the question of whether uncertainty is a source of the business cycle or an endogenous response to fluctuations in the business cycle is not fully understood. According to Ludvigson, Ma, and Ng (2015), one of the reasons is that there is no theoretical consensus on whether the uncertainty that accompanies recessions is primarily a cause or effect (or both) of decline in economic activities. For example, while classical theories affirm that economic uncertainties respond to market fluctuations (Ludvigson, Ma, & Ng, 2015), other theories proved that uncertainty is an exogenous shock to the fluctuations of some economic fundamentals (Bernanke, 1983; McDonald & Siegel 1986; Leduc & Liu, 2016; Arellano, Bai, & Kehoe, 2011). Other theories even postulate that macro uncertainty is the effect of a decline in economic growth (Van Nieuwerburgh & Veldkamp, 2006; Fajgelbaum, Schaal, & Taschereau-Dumouchel, 2017). Growth option theories believe that some types of uncertainty causes an increase in economic activities (Oi, 1961; Abel, 1983; Pastor & Veronesi, 2006; Segal, Shaliastovich, & Yaron, 2015; Kraft, Schwartz, & Weiss, 2018).

This thesis contributes to the literature on the importance of uncertainty in the comovement of business cycles. Following Ludvigson, Ma, and Ng's (2015) research on whether uncertainty is a source of the business cycle or an endogenous response to fluctuations in the business cycle, this study answers the same question by using real data to provide quantitative estimates (unlike Ludvigson, Ma, and Ng (2015) who used sampling simulation). This study also introduces a wavelet methodology which is novel to the study of the relationship between uncertainty and business cycles. The study also investigates if there is evidence of comovement and causality within the selected EMEs.

2.2.2 Economic Distance and Spatial Autocorrelation

Although the study of distance originated from geographical locations between units (such as countries), Beck, Gleditsch and Beardsley (2006) argued that distance does not only relate to geographical locations but rather the measure of distance is based on the connectivity between two locations. Beck et al. (2006) further explained that, the connectivity between countries exist as a result of trade partnership because trade partners influence each other. This section focuses on spatial distance and the economic dimension of non-geographical distance.

One of the early studies on non-geographical distance is the Uppsala model by Johanson and Vahlne (1997) that focused on psychic distance. Johanson and Vahlne (1997) argued that greater psychic distance between paired countries increases uncertainty for global business expansion. Their study also sparked interest in the research of different dimensions of distance beyond the scope of psychic distance by observing other characteristics of inter-country connectivity. Studies conducted discovered administrative or political distance, economic distance, language distance, industrial development distance, financial distance, and socioeconomic distance (see, for example, Ghemawat, 2001; Dow & Karunaratna, 2006; Berry, Guillen, & Zhou, 2010; Martin Martin & Drogendijk, 2014). The extent of dissimilarities of economic characteristics between units (or countries) is termed as economic distance (Dow & Karunaratna, 2006; Brewer, 2007; Johanson & Wiedersheim-Paul, 1975). In this era of globalisation and technological progress, the study of economic distance has become important because the trade and capital flows between countries are significantly determined by the economic distance between countries (Beck et al., 2006; Wilk, 2014). Secondly, the study of economic distance has been minimal (Tung & Verbeke 2010).

The theoretical argument for the study of distance is founded on Ghamawat's (2001) argument that "distance still matters". Ghamawat (2001) used this statement (distance still matters) to dispute literature that argued that globalisation has turned the world into a small place. To help companies make well informed decisions when expanding their global market, Ghamawat (2001) introduced a framework to help evaluate the dimensions of distance and their possible effect on their targeted new markets. Ghamawat (2001) proposed a framework that classified the various characteristics of countries into four dimensions - Cultural, Administrative/Political, Geographic, and Economic distance - termed the CAGE distance framework. Focusing on economic distance, Ghemawat (2001) classifies economic distance as the distance that reflects differences in the economic wealth, quality and cost of natural, financial and human resources. According to Ghamawat (2001), the most important trait that creates distance between countries is the income or wealth of their consumers because when businesses are on the same income level, it is very easy to replicate their existing business model with other similar businesses to exploit their competitive activity. According to Linder (1961), the economic distance between trade partners implies that the two countries have different demand structures when it comes to import and export. This implies that, the differences in economic distance can be reflected by economic indicators such as purchasing power, labour cost, macroeconomic stability, or the degree of openness of economies (Berry et al., 2010).

Another important theory underpinning economic distance is the gravity theory of trade flows. The gravity model in the simplest form proposes that the bilateral trade between two countries is positively related to the economic size of the trading partners and negatively related to the distance between them. The gravity model as a tool of explaining bilateral trade patterns was originally proposed by Tinbergen (1962). Although this theory was basically used to explain trade patterns, it has been employed in various research works. For example the gravity model was used by Flavin, Hurley, and Rousseau (2002) to explain stock market correlations. Findings showed that geographical variables still matter when examining equity market linkages. Portes and Rey (2000), and Portes, Rey, and Oh (2001), show that although the gravity model basically explains goods trade transaction, it is also able to effectively explain international transactions in financial assets. Theories that relate to studies on economic distance also include the behavioral theorists who conclude that distance creates uncertainty (Makino & Tsang, 2011) and the Linder (1961) effect who argue that as economic distance increases, bilateral trade reduces. The Heckscher-Ohlin effect also argues that higher economic distance foster inter-industry trade between countries. Higher economic distance between countries is an indication of the vast difference in their demand structures.

According to Krol (2018), there is a reduction in EPU when countries have similar international economic and trade policies. Likewise, the economic distance (or the dissimilarities) between a country’s trade policy and the trade policy of its neighbours can result in an increase in EPU for its trading partners. For example, the US' withdrawal from the Trans-Pacific Partnership agreement in January 2017 and President Trump's intention to withdraw from other trade agreements (such as the North American Free Trade Agreement), increased uncertainty in US trade partner countries. The increase in uncertainty prompted some of US' trade partner countries (such as Mexico) to diversify their trade partners (Baker 2017). This study contributes to the economic distance research area, with a focus on EPU. We ask if there exist a relationship between economic distance and EPU in the selected EMEs. Does distance still matter and can it be supported by empirical evidence?

As stated earlier, economic distance can exist if there is economic characteristic connectivity between countries. Do we have possible economic linkages between the selected EMEs? The EMEs in this research are members of the G20 and have strengthened trade, investment and financial linkages (Schaechter, 2001). These countries also have economic interdependence (Luckhurst, 2016) and have collaborations of common practices in some policy areas for effective policy coordination (Adler, 2008). Also, all the EMEs have international economic and trade policies to facilitate their trade, financial and international relations implying that there are policy linkages between the countries. It's important to note that, international economic and trade policies are components of economic policy of a country. It is clear that, there are obvious economic and policy linkages between these economies and this implies that they are not independent of each other (Mazurek, 2012). We conclude that, the economic distance between the selected EMEs can be measured.

This study therefore adds to the limited literature on economic distance by studying the relationship between economic distance and EPU in EMEs using the dynamic linear regression method. The proxy variable for economic distance must be a variable that can clearly reflect economic and trade policies in EMEs. We select GDP because, aside from the fact that GDP is a generally approved measure of economic distance (Malhotra, Sivakumar, & Zhu, 2009; Tsang & Yip 2007; Berry et al., 2010; Ghemawat, 2001), GDP also reflects economic and trade policies in an economy. Lindstrom (2008) proved that GDP is a strong economic policy indicator and a key quantifiable economic indicator for measuring and maximising economic policies in an economy. Lindstrom (2008) concluded that the growth and slowdown of an economy is as a result of economic policy implementations which are reflected in GDP. According to Wolverson (2013) economists have endorsed that GDP reflects the impacts of monetary policies, tax policies and spending policies in an economy and serves as a guide to policy making. For example the Federal Reserve use GDP to formulate monetary policies, China local officials' use GDP to judge policy decisions, and businesses uses GDP for investment decision making. He also stated that in this current era, GDP is a globally accepted measure for the comparison of economic progress between countries. Wolverson's (2013) view is in sync with OECD's (2002) argument that, short-term economic indicators of OECD Main Economic Indicators (MEI) such as GDP are essential instruments that are required when formulating national economic policies and they are also considered important for their use in the international context and by international organisations. There is monthly data for GDP making it a very good short-term indicator for our analysis. When we focus on trade polices' relationship with GDP, it is evident in literature that policies targeted at promoting foreign trade are important factors that significantly boost economic growth and convergence in EMEs(IMF,1997, Harrison, 1996). This makes GDP a very important indicator of trade policies. This is evident in the fact that, GDP positively correlates with the levels of trade flows and a country's trading partners (Ghemawat, 2001). Based on evidence from literature stated above, GDP clearly reflects economic and trade policies in an economy and is a perfect measure of economic distance with respect to EPU. Thus, there is a strong relationship between GDP and EPU. The study intends to provide empirical support for the relationship between economic distance and EPU.

The second aspect of distance focuses on the dependence between selected EMEs (with respect to their EPU measures) through spatial analysis. Tobler's first law of geography which forms the theoretical foundation of this investigation, also forms the theoretical foundation of geographical dependence between countries. The law states that "everything is related to everything else, but nearer things are more related than distant things" (Tobler, 1970, p.236). Ghemawat (2001) argued that the further the geographic distance between countries, the harder it will be for countries to conduct business. He concluded that geographic distance has a negative overall effect on investment, trade and equity flows. This means that, the level of investment, trade and equity flows between countries in geographical proximity are higher than geographically distant countries. Since the economies are neighbours, some events or factors such as common borders, transportation, communication links, physical remoteness, climates, common language, common regional trading bloc, and common currency connect these economies and create similarities between them. Therefore, countries that are closer to each other prefer to have trade and economic agreements with each other (Dell'Erba, Baldacci & Poghosyan, 2013) because, distance impedes the cross-border flow of economic activities (Kogut & Singh, 1988; Tsang & Yip, 2007), and also increases risk and transportation cost (Krugman, 1991; Ghemawat, 2011).

To investigate whether nearer countries are more related, the study uses the concept of spatial autocorrelation. Spatial autocorrelation measures the degree at which values of observations (in this study EPU index) at nearer geographical locations (measured by latitude-longitude coordinates) are related. The concept of spatial autocorrelation is applicable to EMEs because they exhibit many forms of similarities. Dell'Erba, Baldacci and Poghosyan's (2013) study show strong evidence of spillovers of sovereign spreads and macroeconomic fundamentals among neighbouring EMEs. Secondly, EMEs exhibit high returns in their equities than developed economies (Ghemawat, 2011; Eun & Lee, 2010). Thirdly, EMEs invest their transnational corporations (specifically, outward Foreign Direct Investment) in neighbouring (or adjacent) economies or markets (Dunning, Kim, & Park, 2008). Forthly, EMEs have strengthened trade and financial linkages (Schaechter, 2001). This means that EMEs are dependent and exhibit similarities which allows for the analysis of spatial autocorrelation between EMEs.

The concept of spatial autocorrelation is also applicable to EPU measures because, there are evidences of spillovers of EPU to EMEs, which leads to spatial autocorrelation (Haining, 2001). The spillover is an exogenous factor that causes spatial autocorrelation. For example, the spatial autocorrelation analysis has proven to help with the analysis of spillover to emerging economies (Dell' Ebra, Baldacci, & Poghosyan, 2013). Spillover is a process where an action at one location influences actions and outcomes at another location (Haining 1983, 1984). Carrière-Swallow & Céspedes's (2013) research findings showed evidence of EPU spillover to EMEs. Their study revealed that external uncertainty socks transmitted to EMEs cause severe falls in investment and private consumption. Choi (2018) study also show a significant impact of uncertainty shocks on EMEs' economic activities than advanced economies (see also, Matsumoto, 2011; Akıncı, 2013). In the financial context, financial variables in EMEs responds to policy uncertainty shocks (see, Choi, & Shim, 2019; Carri`ere-Swallow & C´espedes, 2013; Bhattarai, Chatterjee, & Park, 2017). According to Jiang, Zhu, Tian and Nie (2019) the evidence of EPU cross- country spillover is as a result of the interdependence between economic activities in EMEs (see also, Trung, 2019). Supported by literature, we therefore conclude that since EMEs have global factors, and economic linkages (such as geographic proximity, bilateral trade and financial exposure), and there exist an interdependent relationship between EPU and economic activities in EMEs the concept of autocorrelation analysis is applicable to EPU in EMEs. The study also suggests neighbourhoods of EMEs in terms of the distance between countries. This study is important to investors seeking to diversify their portfolio within neighbouring EMEs since they are able to understand the cross-country correlation of EMEs.

2.2.3 Spillover from Economic Policy Uncertainty

The theoretical framework focuses on addressing the spillover effect between EPU and key macroeconomic indicators (EPU, CPI, broad money, GDP, SPX, import and export) in EMEs and explores their time-varying characteristics. A theory that forms the basis and best explains the relationship between the key variables in this study is one done by Bloom (2009). Following two observations that (i) uncertainty escalates after major shocks and (ii) there is no model that analyses the effect of uncertainty shocks despite its consistency in occurrence, Bloom (2009) built a model with a time-varying second moment to analyse the impact of uncertainty shock and to prove his theory that uncertainty shocks has an impact on economic activities. According to Bloom (2009) theory, uncertainty shocks generate short sharp recessions and recoveries in economic activities such as a rapid drop and rebound in employment, output, and productivity growth. These short sharp recessions and recoveries are as a result of the ‘wait and see’ real option value firms demonstrate because of the increased volatility from the shock in the medium term temporarily paused investment, hiring and reallocation across units and overshoot in output, employment, and productivity.

2.3 Empirical Literature

2.3.1 Interdependence between Economic Policy Uncertainty and Macroeconomic variables.

Previous empirical studies have introduced various measures to analyse the comovement of the business cycle. Pearson correlation coefficient remained the most popular measure of comovement in early literature because it summarises the degree of comovement through time in a single value. Its short coming however is that, it is limited in describing the relationship between the variables at the frequency domain, thus one must resort to a spectral analysis to obtain insight about the relation between variables at the frequency level (see, for example, A'Hearn & Woitek, 2001; Breitung & Candelon, 2006; Croux, Forni, & Reichlin, 2001; Tripier, 2002; and Rua & Nunes, 2005).

Rua (2010) observed that both Pearson correlation and spectral analysis have limitations in addressing information about frequency level and time dependence respectively. To solve these limitations he proposed a wavelet based measure of comovement where one can access simultaneously how two variables (thus, a bivariate case) are related at both time and frequency domains. Rua, and Lopes (2015) afterwards decided to improve upon Rua (2010) measure of bivariate comovement by proposing a wavelet multivariate measure of cohesion over time and across frequencies simultaneously. Fernandez-Macho (2012) also extends the wavelet methodology to handle multivariate time series and called the tools the wavelet multiple correlation and the wavelet multiple cross-correlation. Fernandez-Macho (2012) used this tool to analyse the comovement between Eurozone stock markets. The wavelet multiple correlation analysis showed that there exist nearly exact similarities between Eurozone stock markets. The wavelet multiple cross-correlation analysis showed that the lead to the rest of the Euro markets is CAC40 from France. Notably, there is sufficient support in literature that applied the wavelet methodology in their research to find evidence of interdependence and co-movement (see, Tweneboah, Owusu Junior & Kumah, 2020; Owusu Junior, Tweneboah & Adam, 2019; Owusu Junior, Adam & Tweneboah, 2017; Tweneboah, Owusu Junior & Oseifuah, 2019; Owusu Junior, Boafo, Awuye, Bonsu & Obeng-Tawiah, 2018; Tweneboah & Alagidede, 2018; Tweneboah, 2019).

Various methodologies have been adopted in literature to investigate the comovement between EPU and business cycles. For example, Basu and Bundick's (2017) study argued that increased uncertainty likely played a role in worsening the Great Recession. They estimate the effects of uncertainty shocks on a number of business cycle indicators (output, consumption, investment, and hours worked) and observed their comovement as a result of uncertainty shocks. Using a linear Vector autoregression model, they find that, an unexpected increase in uncertainty generates comovements in the real activity indicators. Caggiano, Castelnuovo, and Pellegrino's (2017) used a nonlinear interacted-Vector Autogression framework to prove that consumption, investment and output reduce as a result of an unexpected increase in uncertainty. Caggiano, Castelnuovo, and Figueres (2017) also used a Smooth Transition Vector Auto Regression model to investigate how unemployment responses to an unanticipated increase in EPU during recessions or expansions. Findings showed that during recessions, uncertainty shocks explain a very high fraction of the volatility of unemployment at business cycle frequencies. Çekin, Hkiri, Tiwari, and Gupta (2020) study the comovement between interest rates and uncertainty for several advanced economies using the wavelet coherence under Morlet specification. In their study, they used daily uncertainty measure by Scotti (2016) and daily shadow interest rate as in Krippner (2013) as proxies for uncertainty related to the real economy. Their findings showed a significant comovement among all the countries across both time and frequency. Using a modified Dynamic Conditional Correlation-Mixed Data Sampling (DCC-MIDAS) model, Fang, Yu, and Li (2017) investigate the role of EPU in the time-varying long-term comovement of the stock and bond markets in the USA. Findings show that the comovement of stock and bond returns in the long-term is attributed to increase in EPU. Asgharian, Christiansen, Gupta, and Hou (2016) employed the mixed data sampling (MIDAS) method and discovered that US EPU shocks has a positive effect on the long-term market movements in the USA and the UK. These findings depict that EPU influences the comovement of business cycles.

This study is closely related to the reviewed literature since they all investigate the role of EPU in the comovement of business cycles. It is also evident from the literature review that, most of these studies used the Vector Auto Regression model. This work is similar to Çekin, Hkiri, Tiwari, and Gupta's (2020) study in that they used wavelet analysis under Morlet specification to analyse the comovement between interest rates and uncertainty for several advanced economies. Their study used wavelet coherence analysis which limits comovement investigations to a bi-variate framework. This thesis extends the works by adopting Fernandez- Macho's (2012) wavelet multiple correlation and wavelet multiple cross correlation techniques to examine the dynamic comovement and interdependence between uncertainty and key macroeconomic variables in EMEs. Fernandez-Macho's (2012) wavelet methodology goes further to address the limitation of accessing comovement via bivariate platforms by introducing a multivariate platform where the comovement of two or more variables can be analysed as a unit. This technique displays the correlations within the multivariate in just two plots of wavelet multiple correlation and wavelet multiple cross-correlation. This methodology does not only find evidence of comovement between variables but further determines leading or lagging variable.

2.3.2 Causal relationship between Economic Policy Uncertainty and Macroeconomic Variables.

Literature on the causal relationship between EPU and business cycles sought to investigate if EPU is the cause or effect of business cycle flustuations. In the event where uncertainty causes fluctuations in the business cycles, Bloom (2014) for example found uncertainty to be countercyclical. Bloom (2014) using a range of statistical evidence argued that recessions cause a strong rise in uncertainty because a rise from bad news shocks starts a recession, the resulting recession then triggers an increase in uncertainty. Yin, Zhang, Yu, and Xin (2017) investigate the causality between EPU and exchange rate (ER) using the quantile Granger causality test. The test revealed that when the value of EPU is extremely high, there exists a causal relationship from EPU to ER in China. Also, when ER is too high (or too low), a causal relationship exist from ER to EPU. Ludvigson, Ma, and Ng (2015) using a structural vector autoregression (SVAR) identification strategy proved that macroeconomic uncertainty is not the cause of the downturn in the business cycle but is rather caused by output shocks. These output shocks cause a rise in macroeconomic uncertainty which amplify the downturns already caused by output shocks in the business cycle. Karnizova and Li (2014) also proved that Baker et al. (2013) EPU index is statistically and economically significant in forecasting US recessions at the horizons beyond five quarters. Karnizova and Li's (2014) study proved that EPU indexes are able to predict economic recessions. Likewise, Liu and Zhang's (2015) paper investigates whether EPU can predict future market volatility. Both in-sample and out-of-sample findings suggest that EPU significantly influences market volatility.

According to Brogaard and Detzel (2015), EPU causes volatilities in economic activities. Their findings show that, a 1% increase in EPU results in a 2.9% drop in market returns and 18% increase in market volatility. Handley and Limao (2015) adopt a dynamic model of heterogeneous firms to investigate the impact of policy uncertainty on firm investment and export decisions. They demonstrate that trade policy uncertainty delays exporter' decisions to enter new markets and implement tariff reductions. Mumtaz and Surico (2018) investigate the effect of policy uncertainty on aggregate fluctuations (output, consumption, investment, consumer confidence, and business confidence) in the US economy. They suggest that shocks of uncertainty affect the real economy. They further show that about 25% of output fluctuations are accounted for by policy uncertainty. Creal and Wu (2017) developed a new macro finance affine term structure model with stochastic volatilities to study the empirical effect of uncertainty. They find evidence that uncertainty contributes negatively to the real economy. Despite the fact that the majority of studies have indicated that uncertainty plays a substantial role in business cycle fluctuations, some studies have found that uncertainty has little or no impact on economic activity (see, Bachmann & Bayer, 2013; Chugh, 2016; Popescu & Rafael Smets, 2010; Born & Pfeifer, 2014).

The paper adds to the recent causality analysis of EPU and business cycles. This study employs Diks and Panchenko's (2005, 2006) non-linear causality test, which is considered to be superior, consistent, and robust when compared to other non-linear test alternatives. In comparison to other causality tests, this methodology does not reject the null hypothesis at a high rate. Diks and

Panchenko's (2005, 2006) test was specifically used in the study of EPU interdependence. A study that is closely related to the empirical analysis of this section is Zhang (2019) who investigates the causality between EPU and investor sentiment. Similar studies focused on how EPU affects China's economy (Pan, Wang, & Wang, 2019), and the causality between EPU and systematic risk (Stolbov, Karminsky, & Shchepeleva, 2018). For further reading see, Ajmi, Aye, Balcilar, El Montasser, and Gupta (2015) and Ajmi, Gupta, and Kanda (2014). As evident, studies on EMEs is minimal and have not investigated EPU causality with respect to CPI, broad money, trade (export of goods and import of goods), and SPX although they are significantly affected by EPU in the selected EMEs (Survey, 2019). This study therefore addresses these limitations.

2.3.3 Measurement of Distance

The concept of distance is very important to uncertainty because, distance is associated with the creation of uncertainty, and the costs of transportation, communication, coordination, integration and monitoring. However, there is limited study on the relationship between distance and uncertainty. Ghemawat (2001) also introduced the CAGE distance framework to show the four dimensions of distance and their possible effect on businesses. The four dimensions of distance are cultural, administrative, geographic and economic distance. Cultural distance affects consumers' product preferences. Administrative distance affects historical and political links between countries. Geographic distance affects the costs of transportation and communications. And lastly the economic distance affects the incomes of consumers.

Some studies employed connectivity matrices in their study on distance. Dow (1984) for example, considers dependence from geographical distance and language similarity matrices by estimating a simultaneous autocorrelation effect for each matrix in an application to cultural diffusion. Significant linguistic and spatial autocorrelation was detected. Using a metric of economic distance, Conley (1999) empirical example uses transportation costs to measure the physical capital between countries in his study on economic growth. Other studies also focused on gravity model as a measure of distance. Boisso and Ferrantino (1997) use the gravity model to determine the effect of economic and cultural distance on international trade and found that the economic and cultural distance influence on international trade amplified until early- to mid-1970s, and began to decline afterward. Portes and Rey (2000) estimate gravity equations for trade flows and portfolio equity flows over the same period. The model revealed that gross asset flows and trade flows both depend on market size in both source and destination country, while geography of information is the main determinant of the pattern of international transactions. Portes, Rey, and Oh (2001) further show that a gravity model explains international transactions in financial assets at least as well as goods trade transactions. They investigate if distance influences the cross-border trade in corporate equities, corporate bonds, and government bonds and found a strong negative relationship between asset trade and distance.

2.3.4 Economic Distance

Some recent literature also investigated the empirial relationship between economic distance and economic activies. For example, Conley and Ligon (2001) measured the economic distance between a set of 18 selected countries. They utilised transportation cost to measure the physical capital between the countries, while airlines fare dealt with human capital distance measures between countries. Using UPS distance, the authors discovered that the closest country to the United States was Germany and the most distant was South Africa, whereas using air fare distance, the closest country to the United States was the United Kingdom and the most distant was South

Africa. Tsang and Yip (2007) investigate the effect of the economic distance bewteen a home and host country on the hazard rates of foreign direct investment. Their findings show that, when multinational corporations invest in a less developed country they exploit the country's resources. In contract, when they invest in more developed countries their resources face exploration.

Mazurek (2012) also proposed a new measure "relative economic distance" and "group relative economic distance" where correlations between two different countries' variables can be used to evaluate their economic distance. The author, investigated the relative economic distance of Poland, Slovakia, Austria, Germany, the USA and Japan with respect to the Czech Republic. The macroeconomic indicators used to measure distance were GDP and unemployment. Findings showed a strong convergence between these countries after the surge of the financial crisis. Wilk (2014) proposed the use of symbolic data analysis method to measure economic distance. The author compared the economic situations of 16 Polish regions on the basis of symbolic data and observed high territorial disparities between countries because of their economic situation. To solve the problem of dependence on a specific unit such as dollar, Le (2017) also use a modified gravity models and adopts the procedure of panel-corrected standard errors (PCSE) to examine the effect of relative economic distance between countries on bilateral foreign trade and foreign direct investment (FDI). Vietnam is used as a case study, and the difference in per-capita GDP is used as proxy for the relative economic distance between Vietnam and her partner countries. Findings revealed that, Vietnam's trade and FDI inflows shared a positive and significant relationship, and a significant positive influence of economic distance on bilateral trade and FDI inflow.

The literature review reveals that, while research has been done on the empirical relationship between economic distance and economic activities, no research has been done on economic distance and EPU. This study therefore investigates the relationship between EPU and economic distance in selected EMEs. Although no study has conducted this investigation, it's similar to Le (2017) who examined the effect of relative economic distance between countries on bilateral foreign trade and foreign direct investment (FDI). Using Vietnam as a case study, Le (2017) also use a modified gravity models and measures distance as the difference in per-capita GDP between Vietnam and her partner countries. Contrary to the latter paper, we do not use the gravity model. Instead, we adopt Le's (2017) concept of the measure of economic distance but employ the dynamic linear regression method (Zeileis, 2019) to investigate the empirical relationship between economic distance and EPU in the selected EMEs. The parameters of the explanatory variables (which are EPU, import, export, SPX, CPI and broad money) are tested using their t-value and p-values.

2.3.5 Spatial Distance

In the framework of spatial analysis, Baltagi and Liu (2008) develop a joint Lagrange Multiplier test to simultaneously investigate the absence of spatial lag dependence and random individual effects in a panel data regression model. This Lagrange Multiplier derives two standard and two conditional Lagrange Multiplier test. Dewachter, Houssa, and Toffano (2012) also implement a spatial vector autoregressive (SpVAR) model to account for both time and spatial dimensions of standard macroeconomic shocks. They study the interdependence between three key macroeconomic indicators namely, inflation, output and interest rate dynamics for eleven European countries. Findings showed a significant spatial dependence across countries in the transmission of macroeconomic shocks in Europe. Dewachter, Houssa, and Toffano (2012) adopt a spatial vector autoregressive model to investigate the time and the spatial dimensions of macroeconomic (inflation, output gap and interest rate) shocks in Europe. The authors find significant spatial dependence across European.

Dell'Erba, Baldacci, and Poghosyan (2013) investigate whether the geographical proximity and economic linkages between economies matter in the transmission of fundamental risks. The authors explore spillovers in the sovereign bond market by using a novel spatial econometrics technique (spatial autoregressive model) and selecting geographical proximity, trade and finance linkages as channels of spatial transmission. Analysing transmission of shocks across twenty four (24) emerging markets while controlling for the impact of global factors, reveal strong evidence of spillovers from both sovereign spreads and macroeconomic fundamentals in neighbouring emerging economies. Their findings further showed that global factors still explain more than half of the spread dynamics. Owusu Junior and Alagidede (2020) proposed the "Financial Distance" dimension as an extension of Ghemawat's (2001) CAGE distance framework, for use in time-invariant spatial risks analysis. To estimate time-invariant risk, the spatial analysis (nonparametric spatial autocorrelations), was founded on Tobler's first law of geography and the Bank for International Settlement's Global Liquidity Indicators served as measure for systemic market risk. For the 12 selected EMEs, the findings indicate that the overall spatial autocorrelation is positive and bigger for the period of the Eurozone and Global Financial Crisis while, smaller and negative for the period after the Global Financial Crisis.

The empirical analysis of this section is directly linked to Owusu Junior and Alagidede's (2020) time-invariant spatial risks analysis. This study adopts their concept of distance and well as the methodology they adopted, the local Moran's I (Moran, 1984) as the measure of spatial autocorrelation. This study, on the other hand, differs from the previous one in that it focuses on EPU. This study intend to investigate if the differences and similarities of EPU values among the selected EMEs are influenced by the distance between these economies. This is a novel empirical analysis in the distance framework and provides robust information for policy makes and investors for international portfolio management, policy decision processes and international trade. The study offers country-specific features and characteristics of EMEs based on their geographical proximity from each other.

2.3.6 Spillovers from Economic Policy Uncertainty

There are recent measures in literature that have been generally used to measure spillover connectedness. Diebold and Yilmaz (2012) proposed a method to measure total, directional and net pairwise spillovers between the CDS spreads and other credit risk determinants. They use a generalised vector autoregressive framework in which forecast-error variance decompositions are invariant to the variable ordering, and explicitly include directional volatility spillovers. Diebold and Yilmaz (2012) methodology is a further improvement of Diebold and Yilmaz (2009) methodology that introduced a volatility spillover measure based on forecast error variance decompositions from vector autoregressions (VARs) but had limitations in addressing only the total spillovers while one would also like to examine directional spillovers within and across countries. For more studies on variance decompositions, see, Diebold and Yilmaz (2014, 2015). Kang and Yoon (2019) investigated the spillover effect across the nine countries by applying Diebold and Yilmaz's (2014, 2015) spillover index model. Their results indicate that the total spillover index is on average 67.4%, which indicates a high level of interconnectedness across the nine indexes with the EU been the largest transmitter of uncertainty connectedness. Yoon, Al Mamun, Uddin, and Kang (2019) also applied Diebold and Yilmaz's (2012, 2014) methodology to investigate the pairwise and directional spillover between financial and commodity markets. Their research findings identified US stock market to be the main source of return spillover shocks transmitted into the Asia-Pacific belt stock markets and an increase in the different financial markets leads to a reduction in the size of the spillover effect. Baruník and Křehlík (2018) introduced a new connectedness framework as an improvement of Diebold and Yilmaz's (2012) measure of connectedness. They measured connectedness using generalised forecast error variance decomposition. With the objective of contributing to the understanding of connected between macroeconomic variables, they proposed a measure that can estimate connectedness in the short-, medium-, and long- term cycle. For an empirical demonstration, they investigate the connected of financial firms in the US. Their analysis obtained rich time-frequency dynamics of connectedness were high frequency connectedness are as a result of shocks that impact mainly in the short term and lower frequency connectedness implies that shocks are transmitted for longer terms. Recent studies have adopted the Baruník and Křehlík (2018) measure of connectedness. For example, Owusu Junior, Alagidede and Tweneboah (2020) applied this methodology to explore the connectedness in the top 9 emerging markets and the US equities. The results show evidence of spillover for both time and frequency domain across the whole system. They however found dominance in spillover by some emerging markets (South Korea, Brazil and Mexico) as against the US in the frequency-dependent spillovers (see also, Tiwari, Cunado, Gupta & Wohar, 2018; Ferrer, Shahzad, López & Jareño, 2018; Xia, Yao & Geng, 2020; Tiwari, André & Gupta, 2020).

Focusing on empirical evidence, most studies have focused on the effect of uncertainty shocks on the macroeconomic variables of an economy (see, Alexopoulos & Cohen, 2009; Bloom, 2009; Baker et al., 2013; Caggiano et al., 2013; Leduc and Liu, 2013; and Nodari, 2013). Although this is a good start and a natural approach, other studies have sought to investigate if the uncertainty shocks hitting these countries may very well spillover onto other countries. There are empirical studies that document that EPU shocks have spillover effects within and beyond an economy. The Vector autoregression model was used in a number of these investigations. For example, Colombo (2013) in his study answers the question of whether there are spillovers from the US economy to the Euro area due to EPU shocks. The authors use Baker et al. (2013) EPU index to model a Vector autoregression framework that includes both US and Euro area aggregates. The findings were positive, showing that, in the short-run a one-standard deviation shock to US EPU leads to a statistically significant fall in the European industrial production and prices. Employing a global Vector autoregression framework, Trung (2019a) examined how US EPU shock spills over to the rest of the world. Using 32 economies that constitute more than 90% of the world GDP, findings showed that US EPU shocks are significant. However, the spillovers varied across countries because of the various types of US policy uncertainty and the different characteristics of the countries receiving US EPU shock spillovers. This is in sync with the previous research Trung (2019b) conducted on 14 economies using a panel Vector autoregression model and Baker et al. (2016) EPU index. Findings revealed that US uncertainty shocks spills over to these 14 countries dropped their capital inflow, investment, export and consumption. Biljanovska, Grigoli, and Hengge (2017) employed heterogeneous panel structural vector autoregressions, to test for EPU spillovers on other countries' economic activity. The authors' findings show that EPU reduces growth in real output, private consumption, and private investment. Further they demonstrate that EPU spillovers from foreign countries (especially United States, Europe and China) account for about two-thirds of the negative effect on an economy. Luk, Cheng, Ng, and Wong (2020) in their study on spillover effects, used a non-structural network-connectedness method to investigate the impact of major economies' EPU shocks on the economic activities of small economies. With the focus on Hong Kong, their findings revealed that Hong Kong's trading partners were the main source of its EPU (recorded to be over 40%) and these shocks had a significant negative effect on the growth rate of economic output.

Other strands of studies on EPU adopted Diebold and Yilmaz's (2012) spillover methodology. For example, Balli, Uddin, Mudassar, and Yoon's (2017) study investigates the determinants of cross-country EPU spillovers among 16 countries. The authors' adpoted Diebold and Yilmaz (2012) spillover methodology and measured spillovers in the generalised VAR framework of Pesaran and Shin (1998). Findings showed that, bilateral trade plays a highly significant role in explaining EPU spillovers. Furthermore, countries having higher vulnerability in terms fiscal, trade, or financial liability imbalances experience higher EPU shocks. Klößner and Sekkel (2014) estimate the spillovers of policy uncertainty among six developed countries. They also used Diebold and Yilmaz (2009) spillover methodology with an algorithm created by Klößner and Wagner (2014) to calculate the spillover measures. The authors find that spillovers account for a high share of the dynamics of policy uncertainty. Further, the author's findings show that Unites States and the United Kingdom are responsible for a large fraction of the spillovers of policy uncertainty shocks. Recent studies have used Barunk and Kehlk's (2018) methodology to investigate the spillover connectedness between EPU and crude oil returns (Zhang & Yan, 2020), the Chinese stock and housing markets (Xia, Yao, & Geng, 2020), financial markets (Albulescu, Demirer, Raheem, & Tiwari, 2019), commodities (Balli, Naeem, Shahzad, & de Bruin, 2019), and gold returns (Gozgor, Lau, Sheng & Yarovaya, 2019). This study is in line with these recent EPU literature. However, this thesis extends the literature on EPU by examining the spillovers of EPU and key macroeconomic variables (which have not been studied previously) within and across selected

EMEs. Because recent studies have focused on advanced economies, this study focuses on EMEs. It further investigates the transmitters and recipients of the shocks. This study follows latter papers by adopting the Baruník and Křehlík (2018) methodology. This is because, the Baruník-Křehlík methodology could be classified as a time-frequency version of the Diebold-Yilmaz spillover index (Ji, Geng, & Tiwari, 2018; Ji, Liu, Nehler, & Uddin, 2018). It not only reflects the degree and direction of systematic and pairwise spillover in a connectedness network, but it also reveals the evolutionary pattern over time and across frequencies (Ji, Li, & Sun, 2019; Ji, Liu, Zhao, & Fan, 2018; Ji, Marfatia, & Gupta, 2018; Ji, Zhang, & Geng, 2018; Luo & Ji, 2018).

2.4 Conclusion

We have reviewed the theoretical and empirical framework of the three themes in this chapter. Firstly, despite proven facts that uncertainty and business cycle comove, researchers have not been able to have a consensus on the question of whether uncertainty is a source of the business cycle movement or rather an endogenous response to the fluctuations in the business cycle. This study aims to reduce this inconsistency as it focuses on the importance of uncertainty and it's comovement with business cycles. The study uses real data to provide quantitative estimates (unlike sampling methods) and adopts Fernandez-Macho's (2012) wavelet methodology. Furthermore, the review shows that the study of distance has been neglected in the area of uncertainty and more specifically, EPU. Given the significant negative impact of distance on uncertainty and trade (Makino & Tsang, 2011; Linder 1961), the exclusion of EPU presents an important gap since EPU strongly correlates with the microeconomic environment. We intend to investigate if the differences and similarities of EPU among EMEs can be influenced by the distance between these economies. The last review focused on the dynamic and network spillover between EPU and major macroeconomic indicators. We see from the theoretical and empirical review that previous studies on this subject have addressed total spillovers but have not been able to address the directional spillover as well as the exact amount of spillover among economies (Colombo, 2013; Zhu & Yan, 2015; Luk, Cheng, Ng, &Wong, 2020; Trung, 2019a; Diebold & Yilmaz, 2009). However, a recent methodology developed by Baruník and Křehlík's (2018) can help address this limitation. This is an important investigation in EMEs because Carrière-Swallow and Céspedes (2013) study on the impact of uncertainty shocks revealed that emerging economies suffer much more from uncertainty spillover shocks since findings showed that exogenous uncertainty shocks to EMEs reduce investment and private consumption. With the above theoretical foundation and empirical studies, the study is well grounded for a detailed and robust investigation.

CHAPTER THREE

NON-LINEAR INTERDEPENDENCE AND CAUSALITY BETWEEN ECONOMIC POLICY UNCERTAINTY AND MACROECONOMIC INDICATORS IN EMERGING MARKET ECONOMIES

3.1 Introduction

The study on the interdependence between EPU and macroeconomic indicators has become essential in this era where researchers argue that heightened EPU has a significant harmful effect on an economy and its activities (see, Wang, Chen, & Huang, 2014; Arouri & Roubaud, 2016; Economic Survey, 2019; Chowdhury, Bayar, & Kiliç, 2013; Nguyen et al., 2018; Gulen & Ion, 2016; Sum, 2012; Baker, et al., 2013; Colombo, 2013; and Ghirelli, Gil, Pérez, & Urtasun, 2019b). The objective of this chapter is to investigate the interdependence and the non-linear causality between EPU and macroeconomic indicators in emerging market economies. As discussed in the literature review section, several studies in theoretical literature have attempted to theoretically explain why EPU comoves with business cycles (macroeconomic indicators). The real business cycle theory which forms the foundation of this study classifies the ups and downs of the business cycle to be an efficient response to the exogenous changes to real economic activities (that is, the level of national output) (Plosser 1989). Some theories further proved that uncertainty is a type of exogenous change (shock) to the fluctuations of some economic fundamentals (Bernanke, 1983; McDonald & Siegel 1986; Leduc & Liu, 2016; Arellano, Bai, & Kehoe, 2011). Although some studies identify uncertainty as an exogenous shock, other studies argue that uncertainty is rather a response to the decline in economic growth (Bachmann & Moscarini, 2011; Fostel & Geanakoplos, 2012; and Pástor & Veronesi, 2013). The growth option theories also argue that some types of uncertainty cause fluctuations in economic activities (Oi, 1961; Abel, 1983; Pastor & Veronesi, 2006; Segal, Shaliastovich, & Yaron, 2015; Kraft, Schwartz, & Weiss, 2018). Other theories also argue that macro uncertainty shocks are the cause of fluctuations in real economic activities (Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, & Terry, 2018). Various studies have therefore theoretically explained the relationship between uncertainty and business cycles.

First, the study intends to investigate if business cycles comove as argued by Lucas (1977). Lucas (1997) argues that business cycles are all alike. Various literature have proved that business cycles of different sectors (Long and Plosser, 1983; Christiano & Fitzgerald, 1998), different industries (Hornstein, 2000), different regions and different countries (Carlino & Sill, 1998; Kouparitsas, 2001) comove and this chapter hopes to investigate this argument with respect to EPU and its related variables. This study explicitly selects specific variables to serve as proxy for business cycle. The selected variables clearly reflect the outcome of economic activities in developing economies and also reflect the outcome of economic policy actions as well as EPU shocks. Amongst the various measures of economic activities (business cycles), industrial production has been widely used as a measure of real economic activity at both country and global level (Ciccarelli & Mojon, 2010; Mackowiak, 2007; Kim, 2001; Kim & Roubini, 2000; Grilli & Roubini, 1996; Gerlach, 1988; Mullineaux, 1980). Up until April 2012, OECD used the index of industrial production as a measure of overall economic activity (Fulop & Gyomai, 2012). The index of industrial production was chosen over other measures (such as GDP) because, unlike quarterly statistics, industrial production is available on a monthly basis. Second, industrial production displayed strong co-movement with GDP. However, recent findings have caused OECD to generate monthly GDP based on the quarterly estimate to replace the use of the industrial production index (Fulop & Gyomai, 2012). First, industrial production measures the value added by industrial production, which has historically contributed significantly to GDP. However, in recent decades, shares of service in economies also account for a substantial part of economic activities. As a result industrial production and GDP in this decade are not sufficiently synchronised (for empirical evidence, see, Steindel, 2004; Herrera, Lagalo & Wada, 2011; Kilian, 2009). The second critique of the industrial production is that it excludes Iceland, China, Brazil, India, Indonesia, Russia and South Africa who have become major contributors to world output (Engel & Rogers, 2006; Crucini, Kose & Otrok 2011; Kose, Otrok & Prasad, 2012). Hence, industrial production is not a robust the measure of economic activity. According to a recent study by Chirwa and Odhiambo (2016), the key macroeconomic determinants of economic growth in developing economies include foreign aid, foreign direct investment, fiscal policy, investment, trade, human capital development, demographics, monetary policy, natural resources, reforms, and geographic, regional, political, and financial factors. This study therefore selects CPI, broad money, export, import, GDP and SPX as proxy for business cycles. The GDP represents aggregate output and is also a measure of economic development, import and export represent trade activities, broad money represents monetary policy activities, CPI is an inflation indicator as well as a measure of economic policy activities related to the purchasing power of domestic money, and SPX represents the movement of current share prices and stock market activities. The study investigates if EPU commoves with business cycles variable, within each of the selected EMEs. The study further investigates the group integration of each variable across the selected EMEs.

The characteristic features of EPU during the Great Recession have led researchers to investigate the potential causes of business cycle fluctuations. Researchers have argued that EPU comoves with a recession (Leduc & Liu, 2012; Redl, 2018; Ludvigson, Ma, & Ng, 2015). However, according to Ludvigson, Ma, and Ng (2015), the question of whether uncertainty is a source (cause) or an endogenous response (effect) to fluctuations in the business cycle is not fully understood because there is inconsistency in econometric analysis conducted and no theoretical harmony on whether uncertainty is a cause or effect of fluctuations in economic activities (see, for example, Ludvigson, Ma, & Ng, 2015; Bernanke, 1983; McDonald & Siegel 1986; Leduc & Liu, 2016; Arellano, Bai, & Kehoe, 2011; Van Nieuwerburgh & Veldkamp, 2006; Fajgelbaum, Schaal, & Taschereau-Dumouchel, 2017; Oi, 1961; Abel, 1983; Pastor & Veronesi, 2006; Segal, Shaliastovich, & Yaron, 2015; Kraft, Schwartz, & Weiss, 2018). This study then tries to investigate whether uncertainty is a cause or effect (or both) of the recession phase in the business cycle (also referred to as economic activities). This study intends to bring more clarity to this inconsistency by i) using EPU as a measure of uncertainty, ii) introducing novel methodologies (the Fernandez-Macho's, (2012) wavelet methodology and, Diks and Panchenko's, (2006) non-linear causality test), and iii) selecting EMEs that are members of the G20. This makes the analysis more informative. We employ the two methodologies because the comovement (or strong correlation) between two variables does not imply causality. Correlation is used to investigate the dependence between variables. However the variables could be moving together not because of each other but because of an external factor that simultaneously influences both variables. Causality plays the role of investigating whether one variable has predictive power to forecast outcomes of the other variable (see, for example, Nazlioglu, Soytas, & Gupta, 2015; Tweneboah & Alagidede (2019).

The study adopted the Fernandez-Macho (2012) wavelet methodology and Diks and Panchenko (2006) non-linear causality test because these methods are able to deal with time series which exhibit non-linear behaviours. Table 2 reveals that, all the selected variables significantly depict non-normality. Hence, using a linear model to examine interlinkages in this study will be a flaw, as heavily criticised in literature (Pan, Wang, & Wang, 2019). The Fernandez-Macho (2012) wavelet methodology applied the Maximal Overlap Discrete Wavelet Transform (MODWT) which is a mathematical technique which transforms a signal into multilevel wavelet and scaling coefficients. According to literature, the MODWT is an effective tool that deals with time series which exhibit non-linear and non-stationary behaviors and also provides exact scale-based decomposition results (Serroukh, Walden, & Percival, 2000). The MODWT is also able to quantify certain characteristics of both non-stationary and non-linearity time series. According to Shan and Li (2010), the MODWT is capable of analysing non-linear and nonstationary signals because the wavelet transform is complete, orthogonal (in the district form) and local. Zhu, Wang and Fan (2014) also argued that, because the wavelet transform has a good time-frequency localisation capacity, the wavelet decomposition of the time series at different scales is able to separate the multiple near-periodicity, long-range dependence, non-stationary and nonlinearity in a series. We also adopt the Diks and Panchenko (2005, 2006) non-linear causality test because Diks and Panchenko's (2005, 2006) non-liner (nonparametric) causality test effectively analyses non-linear time series data and is considered a more superior, consistent and robust test as compared to other non-linear test that reject the null hypothesis at very high rates when other checks conducted showed otherwise.

The significance of this study is the clarity it brings to the possible role EPU plays in economic fluctuations. These contributions can unearth robust findings that can help policy makers regulate and curtail EPU and recessions in an economy. Robust information about the role EPU plays in a recession helps policy makers to implement predictable fiscal and monetary policies that will reduce the occurrence of uncertainty and stabilise central banks' interest rate regulations. Once investors know the cause of uncertainty, they can predict the occurrences of uncertainty and recessions in an attempt to maximise returns on investment. The findings from this study indicate that Lucas's (1979) argument that business cycles comove has been proved. However, the scale by scale analysis has further proved that the level of integration is strongest in the long-term. Secondly, we discover that EPU is both a cause and effect of business cycles fluctuations in the selected EMEs except for India where business cycle fluctuations rather cause EPU fluctuations.

3.2 Theoretical Models and Empirical Methodology

The modelling approaches adopted in this chapter are described in this section. The objective of this chapter is to investigate non-linear interdependence and causality between economic policy uncertainty and macroeconomic indicators in emerging market economies. To investigate comovement of the selected variables within and across the six EMEs, Fernandez-Macho (2012) wavelet methodology is employed. This comovement analysis intends to prove or disprove the argument that "business cycles comove together" (Lucas, 1997; Long & Plosser, 1983; Christiano & Fitzgerald, 1998; Hornstein, 2000; Carlino & Sill, 1998; and Kouparitsas, 2001). Secondly, following the wide range of ambiguous findings on the directional sign of the relationship between uncertainty and the business cycle, (for further details see, section 2.2.1) this study tries to close the inconsistency gap by employing Hill's causality test approach to ascertain if EPU is the cause of business cycle fluctuations.

3.2.1 Wavelet-based measure of Interdependence

To examine the co-movement between EPU and selected macroeconomic indicators, and investigate the relationship between EPU and business cycles, this study used the wavelet multiple correlation and wavelet multiple cross-correlation proposed by Fernandez-Macho (2012). Although wavelet analysis are robust for non- linearity and structural breaks (Aloui & Hkiri, 2014), Fernandez-Macho's (2012) wavelet methodology is superior and unique as compared to other wavelet methodology in several ways. First, the wavelet multiple correlation and wavelet multiple cross-correlation goes further to address the limitation of accessing comovement via bivariate platforms by introducing a multivariate platform where the comovement of two or more variables can be analysed as a unit. This eliminates the complexity in analysing multivariate time series. This methodology's measure of comovement also goes further to simultaneously investigate how two or more (multivariate) time series variables move together continuously at both time and frequency domain. This technique accesses the significance of correlations at each scale and moderate against type 1 errors which could be omitted when assessing the significance of the correlation coefficients (Tweneboah, Owusu Junior, & Oseifuah, 2019). Finally, this methodology displays the correlations within the multivariate in just two plots of wavelet multiple correlation and wavelet multiple cross-correlation and the leading/ lagging variable can also be determined at once in one plot.

This study used the wavelet multiple correlation method to find evidence of comovement between EPU index, CPI, broad money, trade (export of goods and import of goods), GDP, and SPX within each EME. We then estimated the wavelet multiple cross-correlation analysis to determine which variable is the leading or lagging variable of the system (or economy) within the various timescales. To find evidence of EPU comovement across EMEs, the wavelet multiple correlation investigate group integration of EPU by capturing all EPU indices of the six EMEs as a unit within various timescales. This same investigation is be conducted for the macroeconomic variables (CPI, broad money, trade (export of goods and import of goods), GDP, and SPX) across all the selected EMEs. The wavelet multiple cross-correlation was conducted to find the leading or lagging country of the whole system for each variable.

The Maximal Overlap Discrete Wavelet Transform (MODWT) developed by Gençay, Selçuk, and Whitcher (2001), and Percival and Walden (2000) commences the analysis of wavelet multiple correlation (WMC) and wavelet multiple cross-correlation (WMCC). Let $X_t = x_{1t,} x_{2t,}, \dots, x_{nt}$ be a real-valued multivariate random process and let $W_{jt} = w_{1jt,} w_{2jt,}, \dots, w_{njt}$ denote the corresponding scale λ_j wavelet coefficients obtained by applying the MODWT. Fernández-Macho (2012) defines the wavelet multiple correlation denoted by $\Phi X(\lambda_j)$ as a single set of multiscale correlations from equation (3.1) subsequently.

$$\Phi X(\lambda_j) = \sqrt{1 - \frac{1}{\max diagP_j^{-1}}} \quad (3.1)$$

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 $R_i^2 = 1 - {}^{1}/_{\rho^{ii}}$, where ρ^{ii} is the 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; denote the fitted values of z_i as $\hat{z}_i$ WMC can also be expressed as equation (3.2), 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;

$$\Phi X(\lambda_j) = \frac{Corr(w_{i\,jt}, \widehat{w}_{i\,jt}) Cov(w_{i\,jt}, \widehat{w}_{i\,jt})}{\sqrt{Var(w_{i\,jt}) Var(\widehat{w}_{i\,jt})}} \qquad (3.2)$$

The WMCC in equation (3.3) is generated by allowing a lag τ between observed and fitted values of the variable at each scale λ_j:

$$\begin{aligned} \Phi X, \tau\,(\lambda_j) &= Corr(w_{i\,jt}, \widehat{w}_{i\,jt+\tau}) \\ &= \frac{Cov(w_{i\,jt}, \widehat{w}_{i\,jt+\tau})}{\sqrt{Var(w_{i\,jt}) Var(\widehat{w}_{i\,jt+\tau})}} \end{aligned} \qquad (3.3)$$

Confidence intervals (CI) from wavelet multiple correlation are calculated using the Fisher (1915) transformation defined as $arctanh(r)$, where $arctanh(*)$ is the inverse hyperbolic tangent function.

3.2.2 Testing for non-linear causality

We specifically adopt the Diks and Panchenko (2005, 2006) causality test which is introduced in a bivariate setting is considered a more superior, consistent and robust test as compared to other non-linear test alternatives because some causality methodologies where rejecting the null hypothesis at very high rates when undeniably, checks conducted showed otherwise. Diks and Panchenko's (2005, 2006) test has also been widely used in a wide scope of disciplines (see Diks & Wolski, 2016).

This nonparametric test answers the question of whether EPU is a cause or effect of business cycles fluctuations in selected EMEs. The study pairs EPU with each of the selected macroeconomic variables serving as proxy for the business cycle (CPI, broad money, trade (export of goods and import of goods), GDP, and SPX) within each EME to investigate their interdependence. Diks and Panchenko's (2005, 2006) test have been specifically applied in the study of the interdependence of EPU. For example, Zhang (2019) investigates the causality between EPU and investor sentiment. Ajmi, Aye, Balcilar, El Montasser, and Gupta (2015) also focused on the interdependence between EPU and the Equity market. Studies on EPU causality have also focused on EPU across countries (Ajmi, Gupta, & Kanda, 2014), how EPU affects China's economy (Pan, Wang, & Wang, 2019), and the causality between EPU and systematic risk (Stolbov, Karminsky, & Shchepeleva, 2018). As evident, studies have not investigated EPU causality with respect to CPI, broad money, trade (export of goods and import of goods), and SPX although they are significantly affected by EPU in the selected EMEs (Survey, 2019).

The description of the Diks and Panchenko's (2005, 2006) test approach is explained in this section. Let X_t and Y_t represent a bivariate stationary and dependent time series. Let $F_{X,t}$ and $F_{Y,t}$ denote the information sets of past observations of X_t and Y_t, before time t −1 respectively, and let '~' symbolise the equivalence in distribution, then the time series X_t Granger causes series Y_t, for some k ≥1,

$$(Y_{t+1}, \ldots, Y_{t+k})|(F_{X,t}, F_{Y,t}) \sim (Y_{t+1}, \ldots, Y_{t+k})|F_{X,t} \tag{3.4}$$

To test for conditional independence, finite lags, thus l_r and l_s are used under the null hypothesis:

$$H_0: Y_{t+1}|(X_t^{l_r}; Y_t^{l_s}) \sim Y_{t+1}|Y_t^{l_s}, \qquad (3.5)$$

where, $X_t^{l_r} = X_{t-l_r+1}, \dots, X_t)$, $Y_t^{l_s} = Y_{t-l_s+1}, \dots, Y_t)$ and (l_r, $l_s \geq 1$)

For a strictly bivariate time series, the null hypothesis in equation (3.5) is basically an assertion about the invariant distribution of the $l_r + l_s + 1)$ -dimensional vector $Q_t = (X_t^{l_r}, Y_t^{l_s}, Z_t)$, where vector $Z_t = Y_{t+1}$. In order to keep the notation compact and clarify that the null hypothesis depicts the invariant distribution Q, the time index is dropped and rewritten as $Q = (X, Y, Z)$, and $l_r = l_s = 1$, with $k = 1$ and assume that Q is a continuous random variable. The null hypothesis is Eqn (4.14) can be restated in terms of a joint probability function $\mathrm{f_{X,Y,Z}(x, y, z)}$and the condition stated below must be stratified by its marginal:

$$\frac{\mathrm{f_{X,Y,Z}(x,y,z)}}{\mathrm{f_Y(y)}} = \frac{\mathrm{f_{X,Y}(x,y)}}{\mathrm{f_Y(y)}} * \frac{\mathrm{f_{Y,Z}(y,z)}}{\mathrm{f_Y(y)}} \qquad (3.6)$$

for each fixed value of y, X and Y are independent conditionally on Y=y. With the reformulated null hypothesis, the employed weight function by Diks and Panchenko (2006) was

$\mathrm{g\,(x, y, z\,) = f_Y^2(y)}$ and defined:

$$q \equiv E\left[f_{X,Y,\mathrm{Z}}\,(X, Y, \mathrm{Z}) f_Y(Y) - \; f_{X,Y}\,(X, Y) f_{Y,\mathrm{Z}}(Y, \mathrm{Z})\right] = 0 \qquad (3.7)$$

A natural estimator of q was deduced by Diks and Panchenko (2006) and it was expressed as:

$$T_n(\varepsilon_n) = \frac{(2\varepsilon_n)^{-d_X - 2d_Y - d_{\mathrm{Z}}}}{n(n-1)(n-2)} * \sum_i \left[\sum_{k,k\neq i} \sum_{j,j\neq i} \left(I_{ik}^{XY\mathrm{Z}}\, I_{iJ}^{Y} - \, I_{ik}^{XY}\, I_{iJ}^{Y\mathrm{Z}}\,\right)\right] \qquad (3.8)$$

I(•) represents an indicator function, where $I_{ij}^{Q} = I\left(\left\|Q_i - Q_j\right\| \, < \varepsilon_n\right)$ and ε_n is the bandwidth parameter dependent on the sample, if a consistent test is necessary. Through the representation of the local density estimators of a d_Q – variate random vector Q at Q_i;

$$\hat{f}_Q(Q_i) = \frac{(2\varepsilon_n)^{-d_Q}}{n-1} * \sum_{j,j\neq 1} I_{ij}^{Q} \quad (3.9)$$

The test statistics $T_n(\varepsilon_n)$ of the Diks and Panchenko (2006) test is simplified to:

$$T_n(\varepsilon_n) = \frac{(n-1)}{n(n-2)} * \sum_i \left(\hat{f}_{X,Y,Z}(X_i, Y_i, Z_i)\, \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i)\, \hat{f}_{Y,Z}(Y_i, Z_i)\right) \quad (3.10)$$

For $d_X = d_Y = d_Z = 1$, if $\varepsilon_n = Cn^{-\beta}$ for $(c > 0, \beta \in (0.25, 0.67))$, then Diks and Panchenko (2006) highlighted that $T_n(\varepsilon_n)$ converges in distribution to the standard normal

$$\sqrt{n} * \frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{d} N(0,1) \quad (3.11)$$

Where the asymptotic variance of $T_n(\bullet)$ is denoted by S_n.

3.3 Data, sample, and preliminary analysis

The series used in the wavelet multiple correlation, wavelet multiple cross-correlation and causality analysis are monthly data which covers the period from 1st January 1999 to 31st December 2018. The EMEs selected for analysis are Brazil, China, India, Korea, Mexico and Russia. The selections of the EMEs in this study are based on IMF country classification of EMEs and the availability of continuous time series of the selected varables. In addition, these selected EMEs are members of the G20 and have strengthened trade, investment, policy and financial ties (Schaechter, 2001; Adler, 2008). They therefore serve as footprints for other EMEs as well as developing countries. The selected variables are EPU, CPI, broad money, trade (export of goods and import of goods), GDP, and SPX. The EPU indices were obtained from www.policyuncertainty.com. The macroeconomic variables data was obtained from the Organisation for Economic Co-operation and Development (OECD) database. Since business cycles specifically focus on the up and down movements of activities in an economy, the analysis in this chapter focuses on "within" EMEs rather than "across" EMEs to investigate if EPU comoves with business cycles and whether EPU is the cause of business cycle fluctuations in an economy.

Table 3.1: Interpretation of wavelet scales & frequencies

WAVELET MULTIPLE CORRELATION AND WAVELET MULTIPLE CROSS-CORRELATION SCALES		
Scale	**Frequency Range (Months)**	**Interpretation**
w_{i1}	2 ~ 4	Monthly to quarterly
w_{i2}	4 ~ 8	Quarterly to biannual
w_{i3}	8 ~ 16	Biannual to annual

For the maximum level of scales, this study decompose the monthly data by applying the MODWT with a wavelet filter of length L = 3. Thus, the decomposition level "J" for analysis is 3. The study chose J=3 to avoid small wavelet coefficients that occur at high "J" levels Fernández-Macho, 2015). The study produced three wavelet coefficients for each monthly series, w_{i1} w_{i2} w_{i3} respectively. For each J=1, 2, 3 the frequency range, the corresponding time periods are $(2^{j}, 2^{j+1})$ time units as displayed in Table 3.1 at the frequency range session (Whitcher, Guttorp, & Percival, 2000). The three scales λ_j, j = 1, 2, 3 corresponds to periods 2–4 months (which includes monthly to quarterly scales), 4–8 months (which mostly includes quarterly to biannual scales), 8–16 days (mostly includes biannual to annual scales) respectively. The scales therefore capture short-, medium-, and long-term dynamics.

To compare the wavelet multiple correlation findings with the causality analysis, the three scale frequency range are also applied to the non-linear causality. To conduct the non-linear causality test the study chooses optimal values of lag length $l_s = l_r$ ranging from 8-10. The optimal values for lag lengths at the different scales in the tests have been selected using the Akaike, Hannan-

Quinn, and Schwarz Information Criteria; AIC, BIC, and HQIC, respectively. The optimal lag among the three outputs was selected. In all cases, the length scale ε, is set to 1.5 and the study follows all other test protocols of Diks and Panchenko (2006).

3.3.1 Descriptive statistics

The basic summary statistics for the log-returns of EPU, trade (export and import), GDP, SPX, CPI and broad money for each EME is presented in Table 3.2. Kurtosis indicates how the peak and tails of a distribution differ from the normal distribution. The statistics show evidence of excess kurtosis values, at different magnitudes. This depicts a leptokurtic behavior of the log-returns of the selected variables. This implies that the distribution is not normally distributed but rather, has heavier tails and a sharper peak than the normal distribution. This implies that the log-returns of the selected variables (EPU, GDP, SPX, CPI, export, import and broadmoney) have a relatively high probability to generate higher returns which indicate a heavy degree of risk and volatility. However, investments can generate hefty returns to compensate for the risk. The kurtosis values are also a reflection of the time-varying property of volatility.

Skewness is a measure of symmetry or asymmetry of a distribution. The results depict that the variables are not symmetrical. The statistical results shows record of both positive and negative skewness. Positive skewness values are recorded for broad money log-returns (with the exception of Russia), EPU log-returns (with the exception of India and Russia), and CPI log-returns (with the exception of Mexico). This indicates the possibility of positive returns for these variables. The EPU variable clearly shows a large right tail of positive return growth, confirming arguments that EPU is constantly increasing over time. Negative skewness values are recorded for GDP, SPX (with the exception of China), Import (with the exception of Brazil and China), and export (with the exception of Brazil and India). This results also indicate the possibility of negative returns. The skewness results depict non-normality. Skewness is used along with kurtosis to assess the likelihood of a normal probability distribution. Hence, the kurtosis and skewness values depict non-normality. Hence, the use of time-varying analysis and the test for non-linear interdependence can be conducted with these variables. It is evident from the Shapiro-Wilks test that, at all conventional levels of significance the hypothesis of normality was rejected except for Russia's EPU index, India's import values, Korea's CPI values and Russia's broad money. Focusing on standard deviation which measures the dispersion (or variations) in a series, it is evident that EPU recorded the highest variations when compared to the other variables used in the study. Russia (0.2874%) has the most volatile EPU series, while China's (0.0005%) GDP is the least volatile series. This summary statistics is also applicable to Chapter Four and Chapter Five since the same variables are used for analysis in Chapter Three, Chapter Four and Chapter Five. Hence, the summary statistics will not be repeated for Chapter Four and Chapter Five.

Table 3.2: Summary statistics of EPU and macroeconomic varabiables in the selected EMEs

EME	Observations	Mean (%)	Std. Dev (%)	Skewness	Kurtosis	Shapiro-Wilks Test (P-value)	Sum
EPU							
Brazil	239	-0.0006	0.2338	0.0674	0.8303	0.0589	23593.382
China	239	0.003	0.1736	0.1977	3.9364	0.0000	34357
India	239	-0.0003	0.163	-0.1767	1.273	0.0149	22259.977
Korea	239	0.002	0.1559	0.379	0.7865	0.0035	30160.367
Mexico	239	-0.0026	0.207	0.4579	1.6158	0.0033	20931.938
Russia	239	0.0016	0.2874	-0.2243	0.2733	0.1696	30035.325
Export							
Brazil	239	0.0031	0.0307	0.4625	1.0747	0.0131	3152.9496
China	239	0.0048	0.0298	-1.2025	10.9616	0.0000	26852.867
India	239	0.0041	0.0305	0.3138	0.922	0.0007	3658.4242
Korea	239	0.0027	0.0246	-0.4567	2.2925	0.0001	7742.8715
Mexico	239	0.0024	0.0122	-0.9921	4.2694	0.0000	5637.3586

EME	Observations	Mean (%)	Std. Dev (%)	Skewness	Kurtosis	Shapiro-Wilks Test (P-value)	Sum
Russia	239	0.0036	0.0281	-0.3892	0.7707	0.0076	6193.5069
Import							
Brazil	239	0.0023	0.0309	0.0156	0.2428	0.5993	2641.045025
China	239	0.0047	0.0299	0.5079	5.0604	0.0000	22607.03107
India	239	0.0045	0.0332	-0.1836	0.2749	0.3438	5454.639945
Korea	239	0.0029	0.0204	-0.532	1.6225	0.0002	7033.533459
Mexico	239	0.0023	0.0119	-1.7062	11.742	0.0000	5789.3834
Russia	239	0.0034	0.0216	-1.3	9.1484	0.0000	3747.121502
GDP							
Brazil	239	0.0000	0.0009	-1.3462	3.1593	0.0000	23979.88302
China	239	0.0000	0.0005	-1.218	3.5723	0.0000	23978.13483
India	239	0.0000	0.0007	-0.4452	0.322	0.0000	24019.90085
Korea	239	0.0001	0.0007	-0.2081	2.7703	0.0000	24009.67506
Mexico	239	0.0000	0.0007	-1.9025	7.3911	0.0000	24028.22976
Russia	239	0.0001	0.0008	-1.3566	4.8398	0.0000	24001.66765
SPX							
Brazil	239	0.0046	0.029	-0.3193	1.4297	0.0173	20823.53268
China	239	0.0015	0.0282	0.2543	1.5147	0.0003	15431.87179
India	239	0.0043	0.0251	-0.6864	2.6762	0.0000	13394.02829
Korea	239	0.0023	0.0241	-0.1205	1.2535	0.0004	17742.13693
Mexico	239	0.0044	0.0222	-0.616	1.8258	0.0001	14708.38129
Russia	239	0.0072	0.0367	-0.3494	6.7268	0.0000	16608.71445
CPI							
Brazil	239	0.0023	0.0017	2.0398	8.6113	0.0000	17068.24027
China	239	0.0007	0.0028	0.3942	0.6373	0.0145	20500.72427
India	239	0.0022	0.0034	0.5684	3.1479	0.0000	15814.74929
Korea	239	0.0009	0.0016	0.1966	-0.1354	0.4171	20710.208
Mexico	239	0.0017	0.0016	-0.2248	0.8301	0.0025	19058.23513
Russia	239	0.0038	0.0031	1.4257	2.6241	0.0000	14653.60656
Broad money							
Brazil	239	0.0051	0.0026	0.8964	2.4408	0.0000	12907.064
China	239	0.0052	0.0023	1.2106	2.6617	0.0000	12492.43836
India	239	0.0057	0.0021	0.6445	1.7165	0.0000	3428.596862
Korea	239	0.0028	0.0014	0.6754	1.0355	0.0000	15930.29383
Mexico	239	0.0042	0.004	2.5023	15.4812	0.0000	13406.31591
Russia	239	0.0084	0.0086	-0.0789	0.233	0.339	11125.38219

3.4 Empirical Results

The empirical results intend to prove or disprove if the variations in the movement of business cycles within and across EMEs are interdependent and if uncertainty dictates such interconnectedness. This session is therefore divided into two sessions. The first session investigates if business cycles in the selected EMEs comove as argued by Lucas (1997). Do the different sectors in the economy simultaneously move up and down at different time frames? We further investigate the role EPU plays in the comovement of variables within and across the selected EMEs. The second session investigates if EPU causes business cycle fluctuations or vice versa.

As stated earlier on in Chapter One, to study the comovement or dependence in a country over the business cycle, a measure of economic activities in the economy is required as an economic indicator of the business cycle. Although previous studies have used variables such as output, employment, consumption, investment, industrial production and gross output as a proxy for business cycle, this study explicitly select specific macroeconomic variables that represent real economic activities in various sectors of the economy, and also reflect the outcome of EPU shocks and economic policy actions as proxy for the business cycle. These six variables all serve as proxy for business cycle (thus movement of economic activities). Henceforth, GDP represents aggregate output and a measure of economic development, import and export represent trade activities, broad money represents monetary policy activities, CPI is an inflation indicator as well as a measure of economic policy activities related to purchasing power of domestic money and lastly SPX represents the movement of current share prices and stock market activities.

3.4.1 Intra-country comovement of EPU and Macroeconomic variables for selected EMEs.

The study selects each EME and uses the bivariate and multivariate wavelet methodology (proposed by Fernandez-Macho, (2012)) to investigate the intensity of the comovement between paired variables and the whole set of the seven variables on a scale by scale basis.

3.4.1.1 Comovement of EPU and Macroeconomic variables in Brazil

We first analyse the bivariate wavelet correlation of the selected variables in Brazil. Figure 3.1A displays the corresponding heat maps, with the magnitude of contemporaneous correlations displays by the scale on the right of the figure. The colors are from blue to wine moving in an ascending order. The x-axis displays the paired variables and the y-axis displays the wavelet scales. The correlation coefficient of each paired variable is displayed in the figure for each scale with corresponds to the appropriate heat map. From Figure 3.1A, there is evidence of both positive and negative correlation. The strongest positive association recorded is the pairwise relationship between export and import (C2C3) with a coefficient value of 0.47 within 4 ~ 8 months (medium-term frequency range). Likewise, the strongest degree of negative linkage is recorded between "EPU and broad money" in the long-term with a coefficient value of 0.21(negative). The varying results in the relationships between the macroeconomic variables are supported by Dew-Becker and Giglio (2020). Their findings also showed a mixed relationship between coss-sectional uncertainty and overall economic activity. The negative relationships recorded between EPUand the macroeconic varibles supports Basu, and Bundick's (2017) study. They identified that, uncertainty shock in the data causes significant declines in output, consumption, investment, and hours worked. They futher discovered that, uncertainty shocks can easily generate comovement with countercyclical markups through sticky prices. These findings also support previous studies that argue that EPU correlates with economic variables (Government of India, 2019; Carrière-Swallow and Céspedes, 2013; and Ghirelli et al., 2019b).The values of the coefficients of the paired variables are consistent across the scales increasing as the time scale increases. This means that the longer the time period, the higher the level of interdependence (for both positive and negative values).

Figure 3.2A and Figure 3.3A show a graphical presentation of the wavelet multiple correlation and wavelet multiple cross-correlation respectively. Table 3.3A which corresponds to Figure 3.2A and Figure 3.3A represent the numerical versions of the outputs. The wavelet multiple correlation graph (Figure 3.2A) displays three lines; the middle line represents the correlations at the different scales and the two other lines sandwiching the correlations represent the upper bound (gray line) and the lower bound (blue line) of the corresponding 95% confidence level. All wavelet multiple correlation coefficients are significant at the various scales. Although there is an increase in the overall culmination of 44% similarities within 2 ~ 4 to 66% similarity level in the medium term (4 ~ 8 months), the level of similarity dropped to 57% in the long-term. This signifies a correlation increase from monthly to biannual time scale and a decrease in correlation between 8 ~ 16 months. In the long-term, the selected variables culminating are 0.57 implying that the outcomes of in variable can be determined by the remaining six variables at a degree of 57%. Although there is evidence of overall comovement (0.57), the level of interconnected or comovement among the selected variables is weak with discrepancies between variables amounting to about 43%. In terms of diversification, short-term portfolio diversification is a better option.

Likewise, the dashed-lines in the wavelet multiple cross-correlation heat map (displayed in Figure 3.3A) indicate localisations which represents the time lag at which the potential leader or follower of each specific scale maximise the multiple correlation against a linear combination of the rest the variables. Table 3.3A outlines the localisations, time lag and lead or lag potentials for each scale. The lags are up to 12 months which indicates a year length. We find import to be the potential leader or follower of the whole system within the short-term and long-term with lag (0). Import dominates with no lead or lag tendencies because localisation is located at the point of symmetry (0). However, within the biannual and annual frequency, GDP (-1) is the leader of the whole system. It is clear that, in the long-term, GDP maximises the multiple correlation against a linear combination of the rest of the variables.

3.4.1.2 Comovement of EPU and Macroeconomic variables in China

Figure 3.1A displays the pairwise comovement between the selected variables. Once again export and import (C2C3) have the record of the strongest positive correlation of 0.57 within the long-term. The second strong pair of variables is import and GDP (C3C4) (as also recorded in the case of Brazil) with a coefficient value of 0.49 within the long term (8 ~ 16 months). The negative relationship recorded for EPU and the macroeconomic variables are between; EPU and GDP (C1C4) on the biannual to annual scale with a coefficient value of 0.16 (negative), EPU and import (C1C3) within the medium- term with a value of 0.05 (negative), EPU and broad money also within the medium- term of coefficient value 0.05 (negative) , EPU and CPI (C1C6) with a coefficient value of 0.19 (negative) but at the short- term (2 ~ 4 months scales) and EPU and SPX (C1C5) which has the strongest negative correlation coefficient value (-0.32) recorded in China in the long- term.

These outputs buttress arguments that EPU negatively correlates with the economic activities in an economy (see for example Friedman, 1968; Rodrik, 1991; Higgs, 1997; Hassett & Metcalf, 1999; Rafiq & Mallick, 2008; Gupta, Jurgilas, & Kabundi, 2010; Frankel, 2006; Xu & Chen, 2012; Handley & Limao, 2015; Brogaard & Detzel, 2015). Specifically the negative relationship between EPU and SPX is supported by Bianchi, Ilut, and Schneider (2018). Their study showed that, an increase in uncertainty about profits lowers stock prices, causes firms to substitute away from debt and reduces shareholder payout. It is interesting to note that import and GDP (C3C4) have a negative correlation in the medium- term although it increased to 0.49 in the long- term. This implies that an increase in import is associated with a decrease in GDP (vice versa). This finding is however in contrast to previous literature that argue that import positively relates to GDP (see for example Hye, 2012; Çetintaş, H., & Barişik, S., 2009; Herrerias, & Orts, 2011). However, across the graph the pairwise comovement between the variables are generally weak with evidence of no correlation for GDP and SPX (C4C5) and GDP and CPI (C4C6) all within the medium term (4 ~ 8 months scales).

The wavelet multiple correlation output on China (see, Figure 3.2A) revealed that the correlations are increasing as the timescale increases reaching an overall coefficient value of 0.76 in the log-term. The short-term recorded an overall culmination of 46% similarities and the medium- term recorded 47% degree of similarities. The results imply that in the long- term, 76% of the outcome of one variable is jointly determined by the remaining six variables. This proves Lucas (1997) argument that business cycles comove. To investigate the potential leaders or followers of the whole system, we employ wavelet multiple cross-correlation. Figure 3.3A displays the wavelet multiple cross-correlation of China while Table 3.3A provides the numerical information of the point of localisation and the EMEs that have the potential to lead or follow. It is evident that for all the scales CPI, export and import dominate the whole system in an ascending scale order. However, they do not have lead/lag tendencies because there is no evidence of skewness at lag (0). All wavelet multiple cross-correlation coefficients are significant at the various scales. Clearly, for the multivariate analysis of the seven variables there is strong evidence of comovement which increases as the scales increase (which proves Lucas, 1997 agreement of comovement). In China, EPU has no lead/lag potential across all the wavelet scales and therefore does not dictate or play a role in the interconnectedness of all the seven variables.

Table 3.3A: Wavelet multiple correlations and cross-correlations for Brazil and China

	WAVELET MULTIPLE CORRELATION			**WAVELET MULTIPLE CROSS-CORRELATION**		
Scale	Lower	Correlation	Upper	Localisation	Time lag	Leading/Lagging
BRAZIL						
w_{i1}	0.282199	0.439852	0.574374	0.43985221	0	IMP
w_{i2}	0.479984	0.655496	0.780554	0.655496116	0	IMP
w_{i3}	0.258444	0.570876	0.775189	0.614379037	-1	GDP
CHINA						
w_{i1}	0.309496	0.463662	0.594078	0.463662	0	CPI
w_{i2}	0.248291	0.474221	0.65122	0.474221	0	EXP
w_{i3}	0.550087	0.762804	0.882568	0.762804	0	IMP

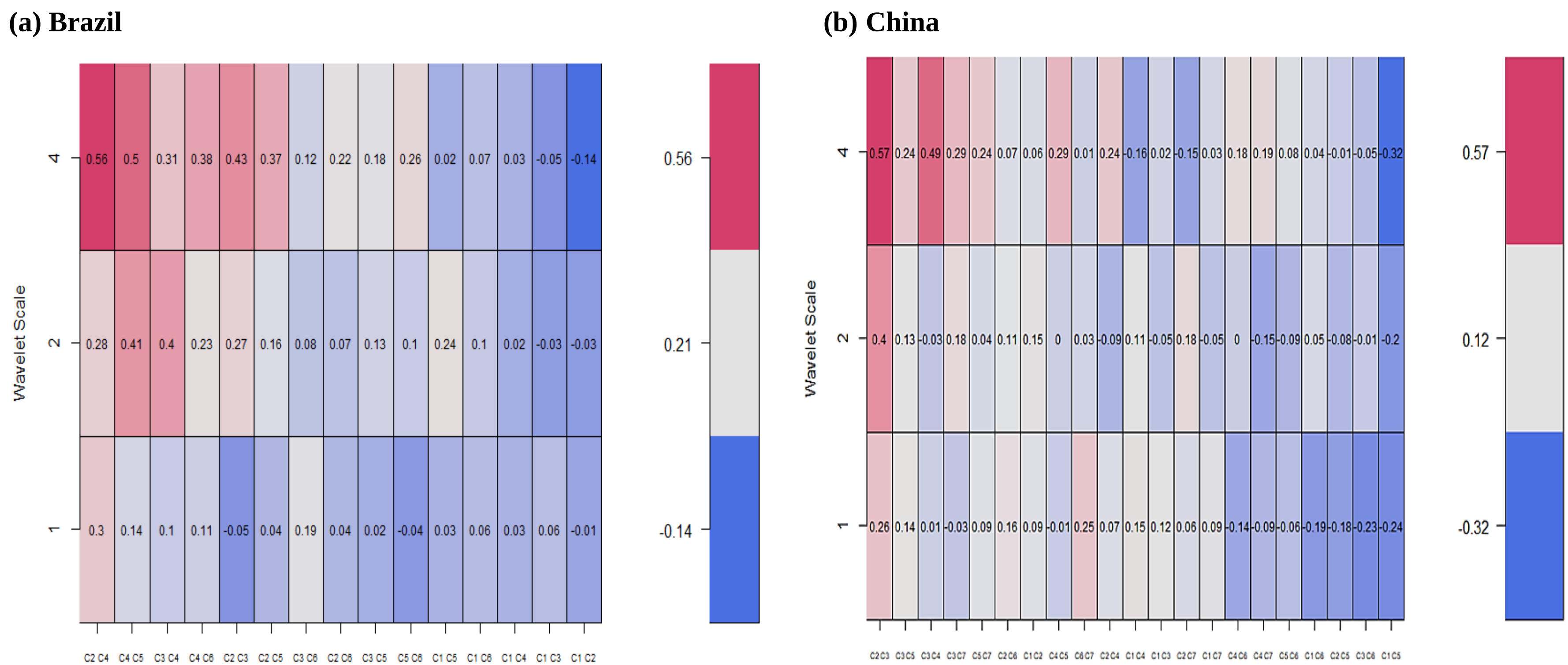
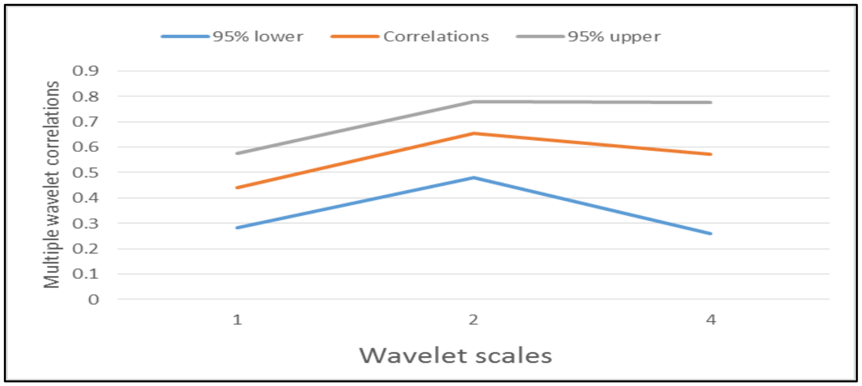


Figure 3.1A: Bivariate correlation of selected variables for Brazil and China

Note: C1-economic policy uncertainty; C2- export; C3-import; C4- gross domestic product; C5-share price index; C6-consumer price index; C7-broad money.

(a) Brazil **(b) China**



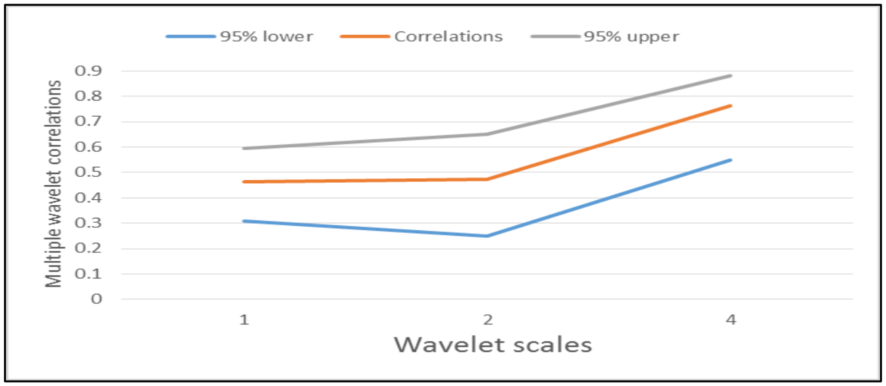
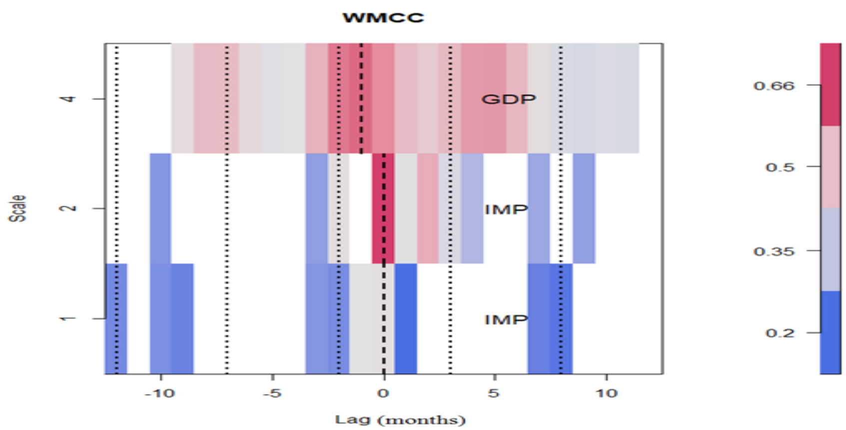


Figure 3.2A: Wavelet multiple correlation of selected variables for China and Brazil

(a) Brazil **(b) China**



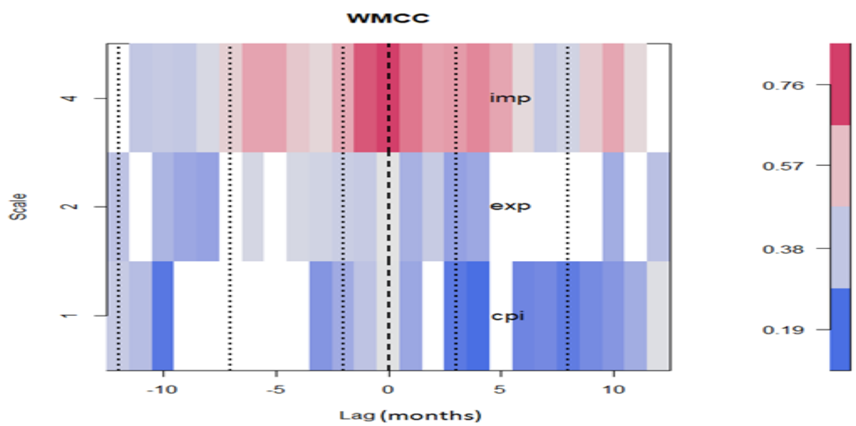


Figure 3.3A: Wavelet multiple cross correlation of selected variables for China and Brazil

Note: Dashed-lines indicate localisations. Selected variables are economic policy uncertainty, export, import, gross domestic product, share price index, consumer price index, and broad money.

3.4.1.3 Comovement of EPU and Macroeconomic variables in India

The investigation of India proceeds with the pairwise comparison of the variables within India. As shown in Figure 3.1B, export and import (C2C3) records the strongest positive linkage within biannual to annual frequency, with a coefficient value of 0.57. The second strong positive relationship that exists in India is between import and SPX (C3C5) of coefficient value 0.33 in the long- term. Focusing on evidence of negative correlation, the strongest negative correlation coefficient (-0.4) is the relationship between EPU and SPX (C1C5) recorded within 4 ~ 8 months. The general, the evidence of comovement within India is low although the bivariate wavelet correlations generally increase in degree and bearing. Also the bivariate correlation between EPU and the macroeconomic variables were all negative across all the scales except for two cases. Firstly, EPU and CPI (C1C6) that recorded positive coefficient values from the short- term (0.16) to the medium- term (0.07) and secondly, EPU and export (C1C2) recorded a positive coefficient value in the long- term (0.07). Clearly, the comovement between EPU and the macroeconomic variables supports claims that EPU and economic activities have a negative relationship (Gupta et al., 2010; Handley and Limao, 2015; Brogaard and Detzel, 2015; Basu & Bundick, 2017). However, there is a positive correlation between EPU and CPI (C1C6) from the short term (0.16) to the medium term (0.07), as well as EPU and export (C1C2) in the long run (0.07). This finding is also supported by previous studies that argue that EPU has a positive relationship with economic activities (Segal et al., 2015; Kido, 2016; Kung and Schmid, 2010; Gilchrist and Williams, 2005; Kraft et al., 2018).

For the multivariate analysis, we first consider wavelet multiple correlation to investigate comovement of the selected variables as one whole system. From Figure 3.2B, it is observed that the correlation between the seven variables are significant at the different time scales but is averagely low since only 66% of the performance of one of the variables can be influenced by the rest of the six variables. The correlation coefficient consistently increased across the scale with coefficient values of 0.44, 0.54 and 0.66 in ascending order of the wavelet scale. We further interpret the output for the wavelet multiple cross-correlation for India displayed in Figure 3.3B. Within 4 ~ 8 months and 8 ~ 16 months, there were no spillover effects since the localisations 0.54459 and 0.664708 respectively occurred at the point of symmetry (thus 0 time lag) (see Table 3.3B). Although SPX and import dominates the medium-, and long- term respectively, they have no lead or lag trends. However, at scale w_{i1} (short- term), import with a negative time lag of -1 is the actual leader of the whole system at the first month. There is evidence of bivariate and multivariate wavelet correlation although it is not an exact linear relationship. There is therefore evidence of comovement as argued by Lucas (1997). Clearly, EPU has no lead/lag potential across all the wavelet scales and therefore does not dictate or play a role in the interconnectedness of all the seven variables in India.

3.4.1.4 Comovement of EPU and Macroeconomic variables in Korea

The bivariate wavelet correlation of the selected variables in Korea (see Figure 3.1B) records the strongest positive correlation coefficient of 0.81 for the pair "export and import" (C2C3) within 8 ~ 16 months. For negative correlation, EPU and SPX (C1C5) recorded a value of 0.48 (negative) also within 8 ~ 16 months. The bivariate wavelet correlation coefficients all increase as the scale increase excerpt for export and broad money (C2C7) whose correlation coefficient decline in the long-term after rising consistently in the short-, and medium- term. Generally, there is strong evidence of comovement of the paired variables in Korea. There is evidence of negative correlation between EPU (C1) and the macroeconomic variables across all scales. Once again, these findings support arguments for a negative relationship between EPU and economic activity (Gupta et al., 2010; Handley and Limao, 2015; Brogaard and Detzel, 2015).

As evident in Figure 3.2B and Table 3.3B, the wavelet multiple correlation coefficients are all significant at the various time scales. Figure 3.2B also shows strong evidence of comovement of the multivariate set of seven variables. Although the level of similarities in the short- term was 54%, it gradually rose to 88% in the long- term with their corresponding upper and lower bounds displayed accordingly. In the long- term, 88% of the values of on variable can be determined by the remaining six (6) variables in the system. This information is very beneficial to policy makers who wish to predict the possible outcome of a change in one of these variables in relation to the rest of the variables. Interestingly, the localisation (see, Table 3.3B) at all the time scales occurred at the point of symmetry, which is at a time lag of (0). We can therefore only infer that the potential leader or follower of the whole system at short-, medium-, and long- term are export (0.53586), import (0.623559) and export (0.883017) respectively with the localisation in parenthesis. Despite evidence of comovement of the seven variables in Korea, EPU lacks the potential to lead or lag at any of the wavelet scales. This implies that, EPU does not influence the movement of business cycles Korea.

Table 3.4B: Wavelet multiple correlations and cross-correlations for India and Korea

	WAVELET MULTIPLE CORRELATION			**WAVELET MULTIPLE CROSS-CORRELATION**		
Scale	Lower	Correlation	Upper	Localisation	Time lag	Leading/Lagging
INDIA						
w_{i1}	0.235558	0.398651	0.539906	0.398846	-1	IMP
w_{i2}	0.335263	0.54459	0.702677	0.54459	0	SPX
w_{i3}	0.39425	0.664708	0.829204	0.664708	0	IMP
KOREA						
w_{i1}	0.393852	0.53586	0.652883	0.53586	0	EXP
w_{i2}	0.437307	0.623559	0.758519	0.623559	0	IMP
w_{i3}	0.763652	0.883017	0.944011	0.883017	0	EXP

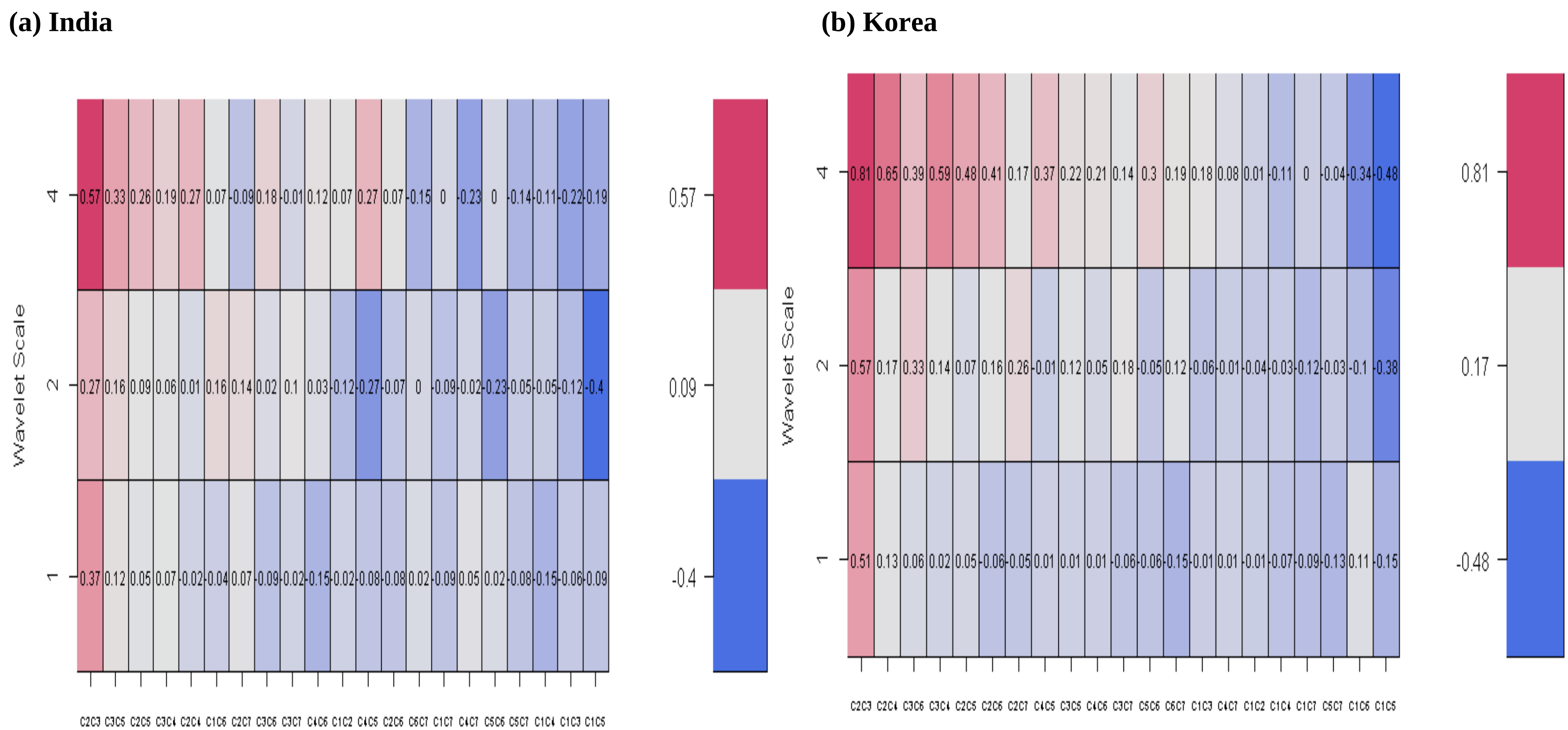
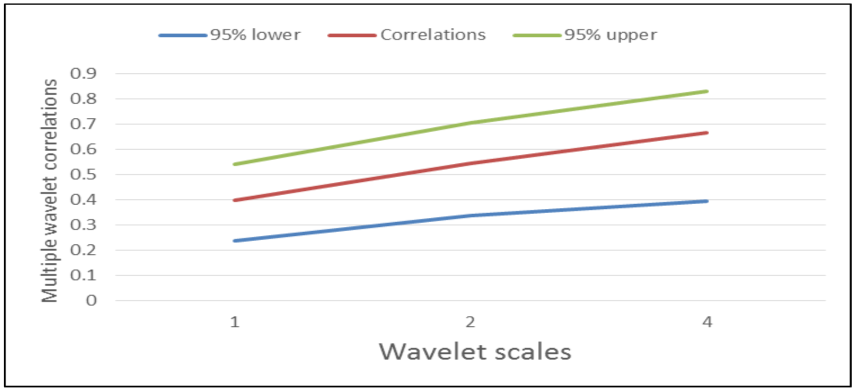


Figure 3.1B: Bivariate correlation of selected variables for India and Korea

Note: C1-economic policy uncertainty; C2- export; C3-import; C4- gross domestic product; C5-share price index; C6-consumer price index; C7-broad money.

(a) India



(b) Korea

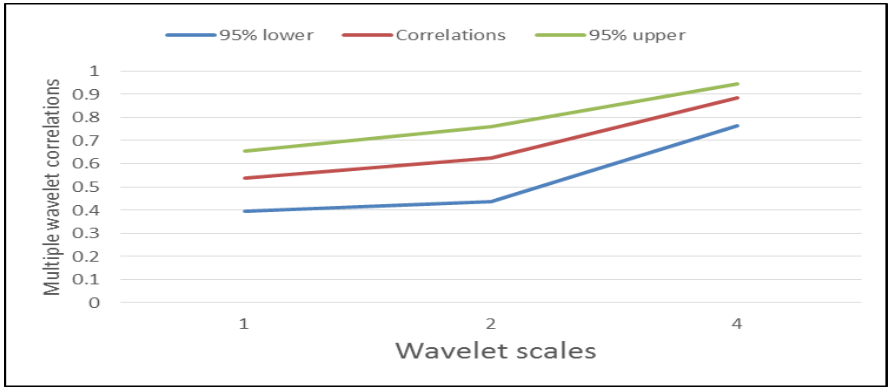
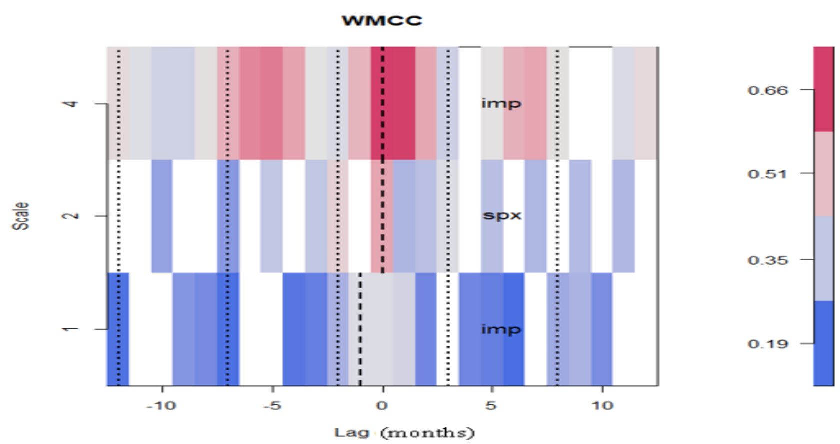


Figure 3.2B: Wavelet multiple correlation of selected variables for India and Korea

(a) India



(b) Korea

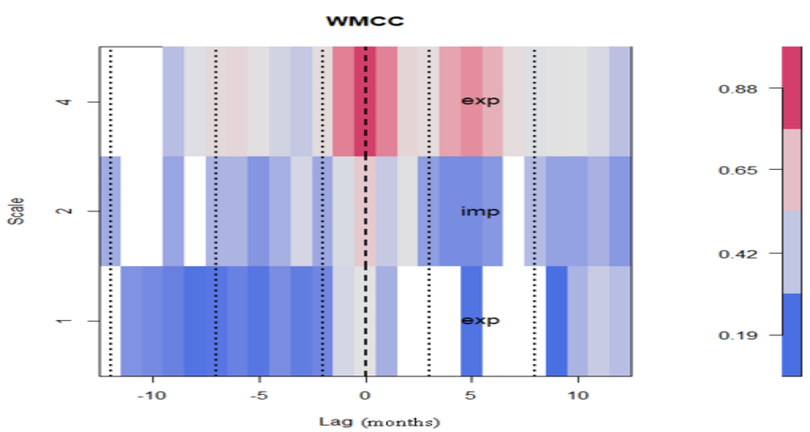


Figure 3.3B: Wavelet multiple cross correlation of selected variables for China and Brazil

Note: Dashed-lines indicate localisations. Selected variables are economic policy uncertainty, export, import, gross domestic product, share price index, consumer price index, and broad money.

3.4.1.5 Comovement of EPU and Macroeconomic variables in Mexico

The observations drawn from Korea are applicable to Mexico. Mexico shows strong evidence of interdependence for both bivariate and multivariate wavelet correlation analysis. The bivariate analysis as evident in Figure 3.1C displays the strongest pairwise positive association (with coefficient value of 0.81) to be between export and import (C2C3) while the strongest negative linkage between EPU and SPX (C1C5) has a coefficient value of -0.49 all in the long- term. Despite evidence of negative association between EPU and the macroeconomic variable, it was observed that EPU positively correlates with broad money (0.37) and GDP (0.16) in the long-term. This implies that although EPU is generally known to negatively correlate with macroeconomic variables, country specific analysis could turn out different as evident in the case of Mexico.

Likewise for wavelet multiple correlation as displayed in Figure 3.2C and Table 3.3C the overall correlation for the multivariate set on a scale by scale basis increase per scale to a long- term coefficient value of 0.88. The disparities between the variables are small in the long- term but the differences between the variables are evident in the short- to medium- term. The gradual increase in the correlation over longer time frame is as a result of information asymmetry and the integration into an era of globalisation and trade. Markets and sectors of the economy are more integrated resulting in the comovement of EPU and the macroeconomic variables. The wavelet multiple cross-correlation (see Figure 3.3C and Table 3.3C) for the whole multivariate set recorded lag (0) across all the frequency ranges. However, the potential leader or follower of the system which is the variable that maximises the multiple correlation against a linear combination of the rest of the variables are export (0.577647), import (0.619186), and import (0.881364) for short-, medium-, and long-term respectively with localisations in parenthesis. Once again, we note that EPU does not pose as any lead or lag power in Mexico.

3.4.1.6 Comovement of EPU and Macroeconomic variables in Russia

Figure 3.1C displays the various combinations of the paired variables. Export and import (C2C3) show evidences of the strongest positive association (0.62) occurring in the long- term. As recorded in the other EMEs export and GDP (C2C4) have strong associations (0.43). EPU and SPX (C1C5) have strong negative linkages across all scales with the long- term culmination coefficient value of 0.44 (negative). In the case of Russia there were large records of positive relationship between EPU and macroeconomic variables (in contrast to previous negative relationships). As evident from Figure 3.1C, EPU has a weak but positive relationship between broad money with a coefficient value of 0.04 and 0.23 in the medium-, and long- term respectively; import with a coefficient value of 0.06 and 0.13 in the short-, and medium- term respectively; GDP with a coefficient value of 0.07 and 0.05 in the medium-, and long- term respectively; export with a coefficient value of 0.08 and 0.03 in the short-, and medium- term respectively; and SPX with a coefficient value of 0.15 and 0 in the small-, and medium- term respectively. There is also evidence of positive associations between EPU and macroeconomic indicators in Russia. This finding is in contrast to previous findings that EPU negatively correlates with macroeconomic variables (Gupta et al., 2010; Handley and Limao, 2015; Brogaard and Detzel, 2015). As a result, more EPU research on a country-specific dimension should be conducted.

The graphical wavelet multiple correlation output and its numerical correspondence is displayed in Figure 3.2C and Table 3.3C respectively. Starting with a coefficient value of 0.47 in the short- term, there is a decline in the overall correlation in the medium- term with a value of 0.44.

However, in the long-term there was a significant increase to a coefficient value of 0.75. This implies that in the long- term, the seven variables have a high degree of comovement and 75% outcomes of one variable is determined by the remaining six variables. The wavelet multiple cross-correlation (see Figure 3.3C) revealed that CPI lags the whole system at 1 month in the short- term. Within 4 ~ 8 months, import dominates with no lead or lag tendencies and thirdly, import also lags the whole systems at 1 month in the long- term. In the long- term, discrepancies between the variables in Russia are small amounting to about 25%. This implies that, portfolio diversification will be less profitable in the long- term because the outcome of one variable is significantly determined by the overall performance of the other variables. This finding implies that over the years, the selected variables have become more similar. One possible reason for this is the integration of sectors as a result of trade, investment and portfolio diversification. We therefore conclude this session by stating that EPU comoves with macroeconomic actives across the selected EMEs. However, although there were some similarities across the EMEs, the movements were mostly specific to each EME. It was also observed that EPU has no lead or lag potential across all time scales in the selected EMEs under study.

Table 3.5C: Wavelet multiple correlations and cross-correlations for Mexico and Russia

	WAVELET MULTIPLE CORRELATION			WAVELET MULTIPLE CROSS-CORRELATION		
Scale	Lower	Correlation	Upper	Localisation	Time lag	Leading/Lagging
MEXICO						
w_{i1}	0.443795	0.577647	0.686287	0.577647	0	EXP
w_{i2}	0.431528	0.619186	0.755478	0.619186	0	IMP
w_{i3}	0.760528	0.881364	0.943194	0.881364	0	IMP
RUSSIA						
w_{i1}	0.32193	0.474434	0.602941	0.58448	1	CPI
w_{i2}	0.204251	0.437453	0.623669	0.437453	0	IMP
w_{i3}	0.532725	0.752339	0.877019	0.76266	1	IMP

(a) Mexico **(b) Russia**

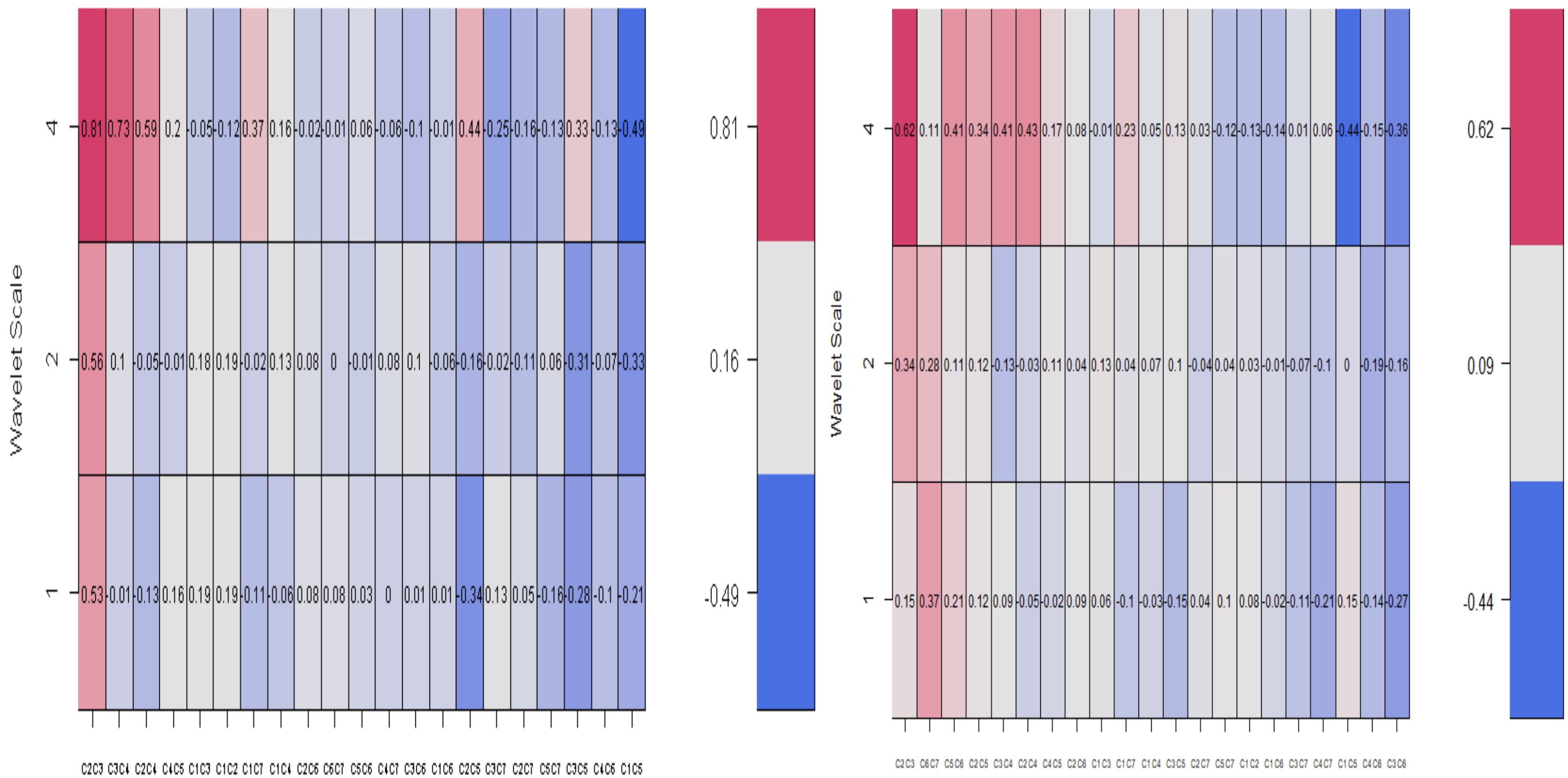
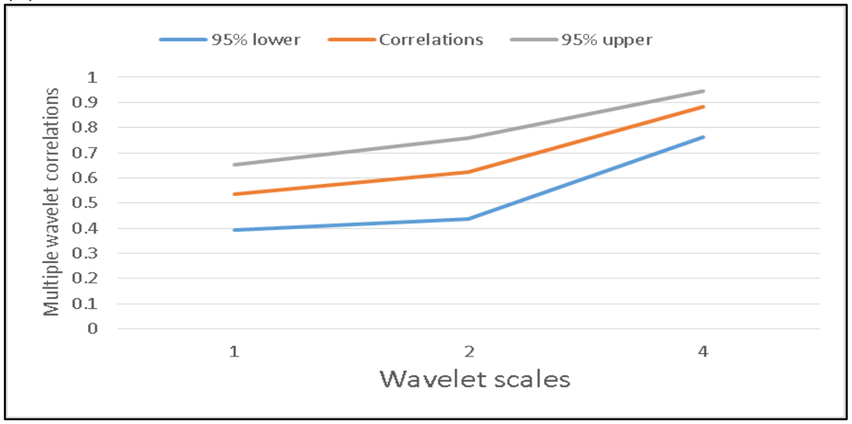


Figure 3.1C: Bivariate correlation of selected variables for Mexico and Russia

Note: C1-economic policy uncertainty; C2- export; C3-import; C4- gross domestic product; C5-share price index; C6-consumer price index; C7-broad money.

(a) Mexico



(b) Russia

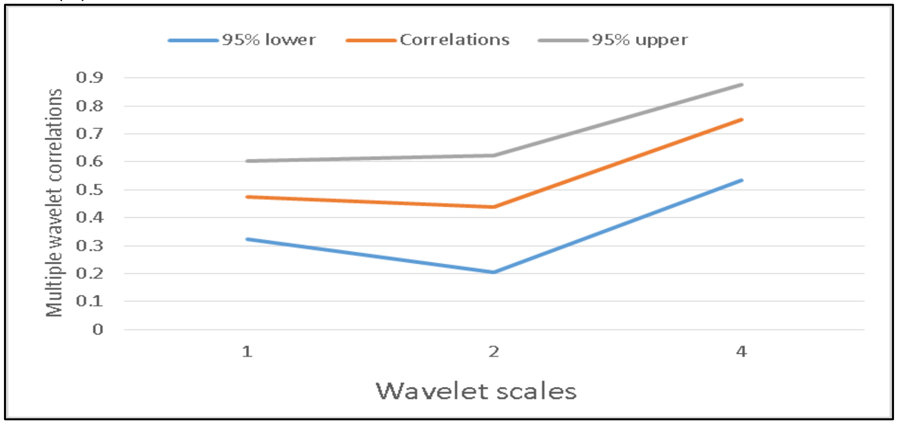
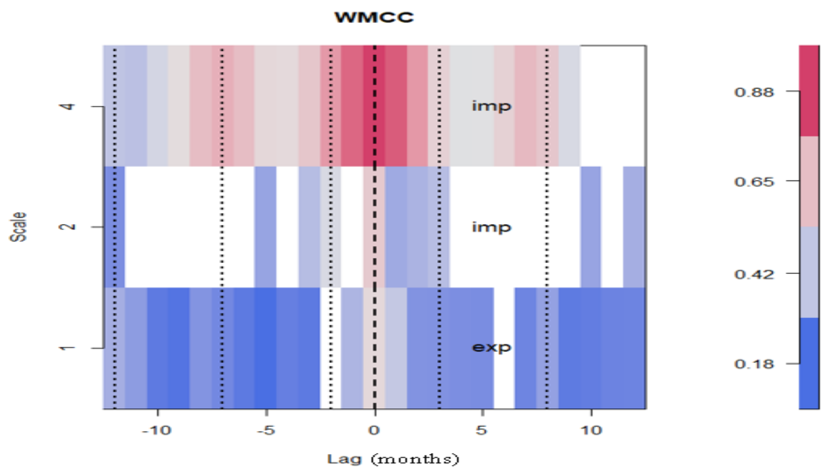


Figure 3.2C: Wavelet multiple correlation of selected variables for Mexico and Russia

(a) Mexico



(b) Russia

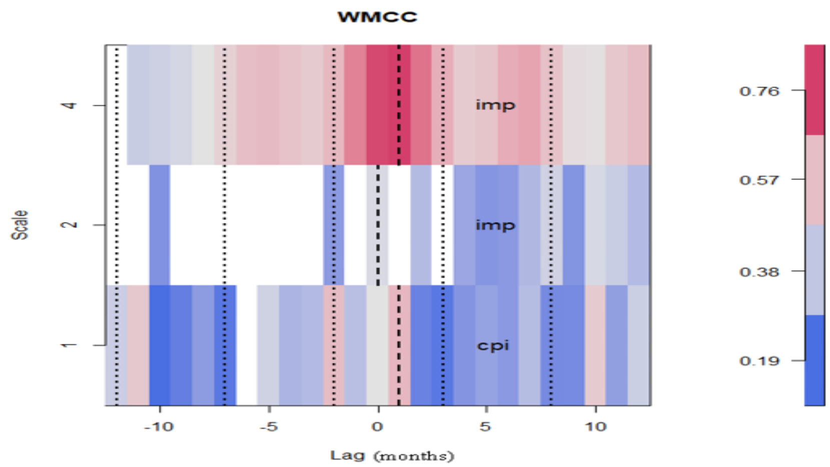


Figure 3.3C: Wavelet multiple cross correlation of selected variables for Mexico and Russia

Note: Dashed-lines indicate localisations. Selected variables are economic policy uncertainty, export, import, gross domestic product, share price index, consumer price index, and broad money.

3.4.2 Inter-country comovement of EPU and Macroeconomic variables for selected EME.

This session focuses on the evidence of comovement of each variable across the selected EMEs. To prove or dispute the argument that business cycles (when compared with the same measure) comove across economies (see Lucas, 1977; Carlino & Sill, 1998; Kouparitsas, 2001), the study conducted a group integration investigation of each variable across the selected EMEs.

3.4.2.1 Comovement of EPU across selected EMEs.

The bivariate comovement of EPU across the EMEs is displayed in Figure 3.4A. The pairwise series with the strongest correlation (value of 0.56) is China and Korea (C2C4) with 8 ~ 16 months. Also, the strongest negative pairwise association is Brazil and China (C1C2) with a value of -0.14 in the long- term. The comovement of the pairwise series generally increased as the scale increased except for Brazil and Korea's (C1C4) and Braziland Mexico (C1C5). Brazil and Korea's (C1C4) drops from 0.03 in the short- term to 0.02 in the medium- term. Furthermore, the comovement between Brazil and Korea does not change significantly since the coefficient difference between each scale is 0.01. In the case of Brazil and Mexico (C1C5), the coefficient value rise from 0.03 in the short- term to 0.24 in the medium- term and drops drastically to 0.02 in the long-term falling below the value obtained in the short term. The highest level of integration between Brazil and Mexico is in the medium term while the short-, and long- term show high levels of discrepancies. Therefore, portfolio diversification in these two economies is effective within 2 ~ 4 months and 8 ~ 16 months.

The wavelet multiple correlation output in Figure 3.5A and Table 3.4A shows that the whole multivariate EPU set increases scale by scale, starting at 0.35 within the short- term and climaxing with a coefficient value of 0.68 in the long term. This implies that the EPU of the selected EMEs get more interconnected as the time period increases beyond eight (8) months. The wavelet multiple cross-correlation (Figure 3.6A and Table 3.4A) shows that the different scales with leads and lags are up to 12 months (equivalent to 1 year). It is evident that Korea- EPU is the potential leader and follower across all the wavelet scales. The Korea- EPU maximised the multiple correlation against a linear combination of the rest of the variables at lag (3), lag (0) and lag (-1) within the short- (0.385396688), medium- (0.580450752), and long- term (0.72288102) respectively with the localisation in parenthesis. This implies that, within the short- term Korea-EPU is the follower of the whole system and within the long- term, Korea-EPU is the leader of the whole system. However, in the medium- term Korea- EPU dominates with no lead/lag tendencies because it records a lag value (0).

3.4.2.2 Comovement of export across selected EMEs.

The bivariate analysis displayed in Figure 3.4A reveals a strong interdependence between the paired series of the export values of the selected EMEs. All correlation coefficients in the long-term are positive and generally large with coefficient values ranging from 0.25 to 0.75. However, there are few records of negative correlation in the short-, and medium- term. We can conclude that, in the long-term paired export of the selected EMEs comove in the same direction. The gradual rise in the correlation over longer time frame is as a result of information asymmetry. This is a situation where markets dynamics affecting one variable takes some time to dissipate into other variables.

The wavelet multiple correlation for export which is displayed in Figure 3.5A and Table 3.4A shows strong evidence of comovement of export across the selected EMEs in the long- term. The short- term (2 ~ 4 months scales) recorded a very low degree of interdependence (0.29) but recorded a level of 82% similarity in the long- term. The drastic increase in the long- term is largely as a result of globalisation and the increase in international trade fostered by trade agreements and trade policies. The wavelet multiple cross-correlation output as shown in Figure 3.6A and Table 3.4A indicates the lead and lag for the various time scales. In the short- term, Russia-export with localisation 0.343321315 is the leader of the whole system and the time lag at which Russia-export as the leader maximises the multiple correlation against a linear combination of the rest the variables is month 2. The localistaion value of 0.427140903 in the medium term falls at the point of symmetry (lag 0), which signals that Korea-export dominates in the medium-term but has no lead/lag potentials in the whole system. Thirdly, Mexico-export with a localisation value of 0.824980111 leads the whole system in the long-term at time lag 1 (negative). This implies that across all the wavelet scales, there is no one leader or follower of the whole system. However, attention must be given to Russia-export, Korea-export and Mexico-export for prediction and decision making purposes since these three economies have the potentials to maximise the multiple correlation against a linear combination of the rest of the export values in the selected EMEs.

Table 3.4A: Wavelet multiple correlations and cross-correlations of macroeconomic variables among selected EMEs

	WAVELET MULTIPLE CORRELATION			**WAVELET MULTIPLE CROSS-CORRELATION**		
Scale	Lower	Correlation	Upper	Localisation	Time lag	Leading/Lagging
EPU						
w_{i1}	0.184188	0.352498	0.500723	0.385396688	3	KOREA- EPU
w_{i2}	0.381002	0.580451	0.728279	0.580450752	0	KOREA-EPU
w_{i3}	0.415107	0.678401	0.836837	0.72288102	-1	KOREA-EPU
EXPORT						
w_{i1}	0.116028	0.289968	0.446651	0.343321315	-2	RUSSIA-EXP
w_{i2}	0.192068	0.427141	0.615859	0.427140903	0	KOREA-EXP
w_{i3}	0.654591	0.823524	0.914123	0.824980111	-1	MEXIO-EXP

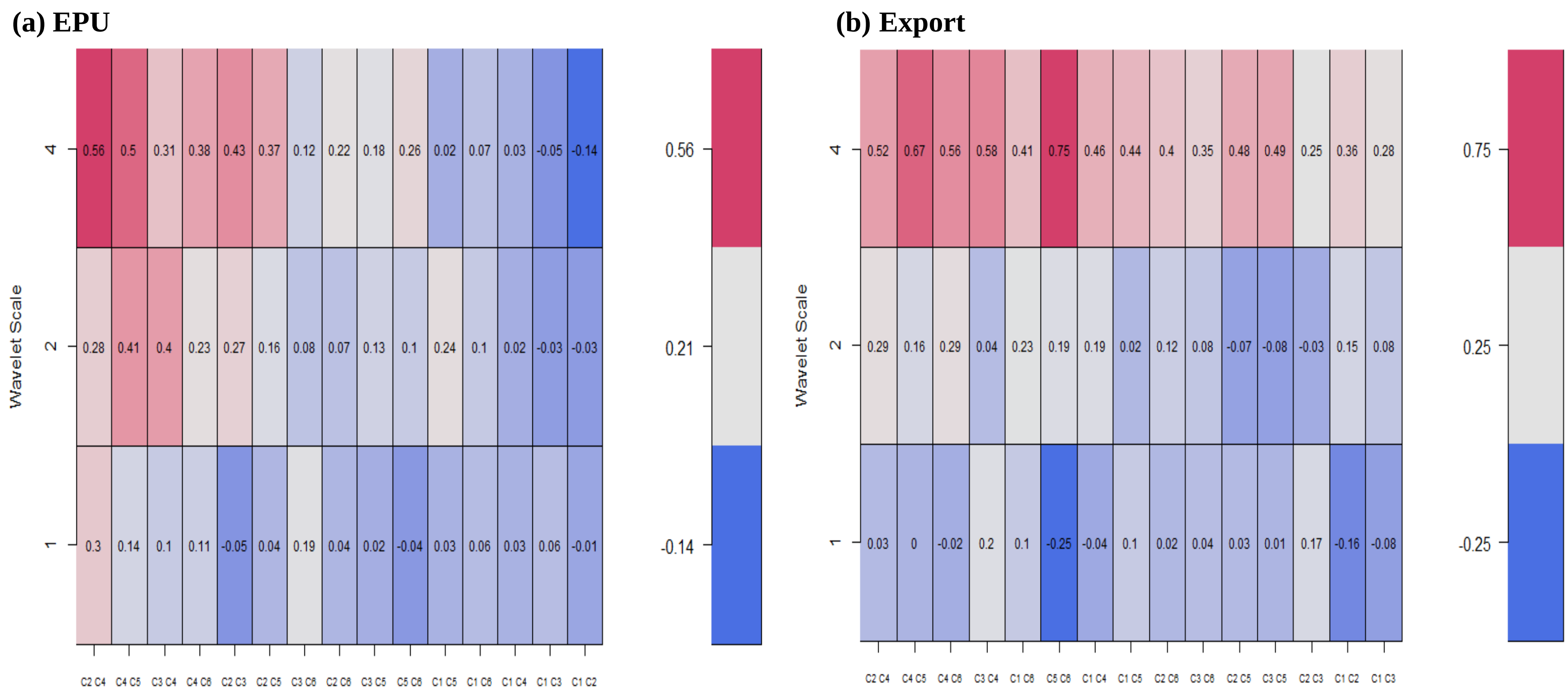


Figure 3.4A: Bivariate correlation of EPU and Export among selected EMEs.
Note: C1- Brazil; C2- China; C3-india; C4- Korea; C5-Mexico; C6-Russia.

(a) EPU (b) Export

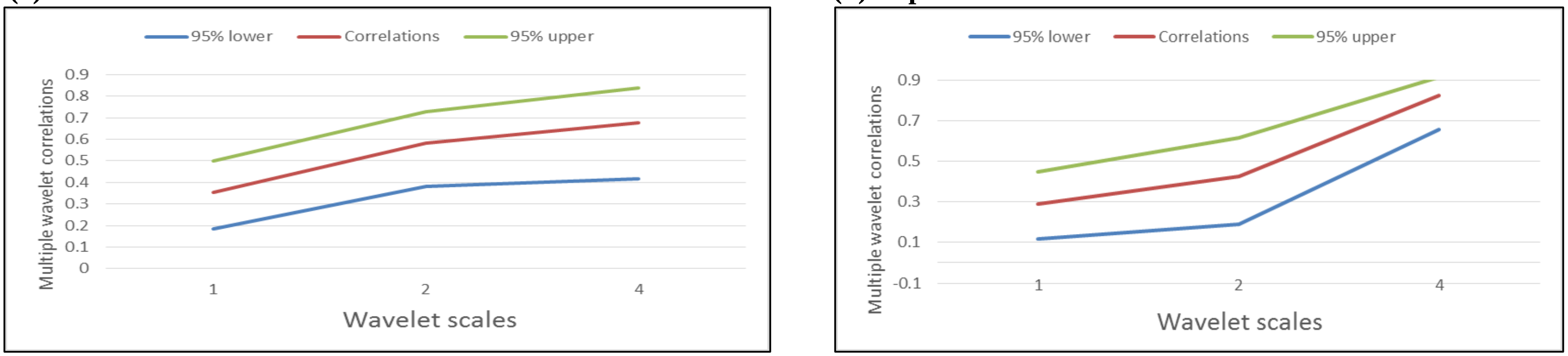


Figure 3.5A: Wavelet multiple correlation of EPU and Export among selected EMEs.

(a) EPU (b) Export

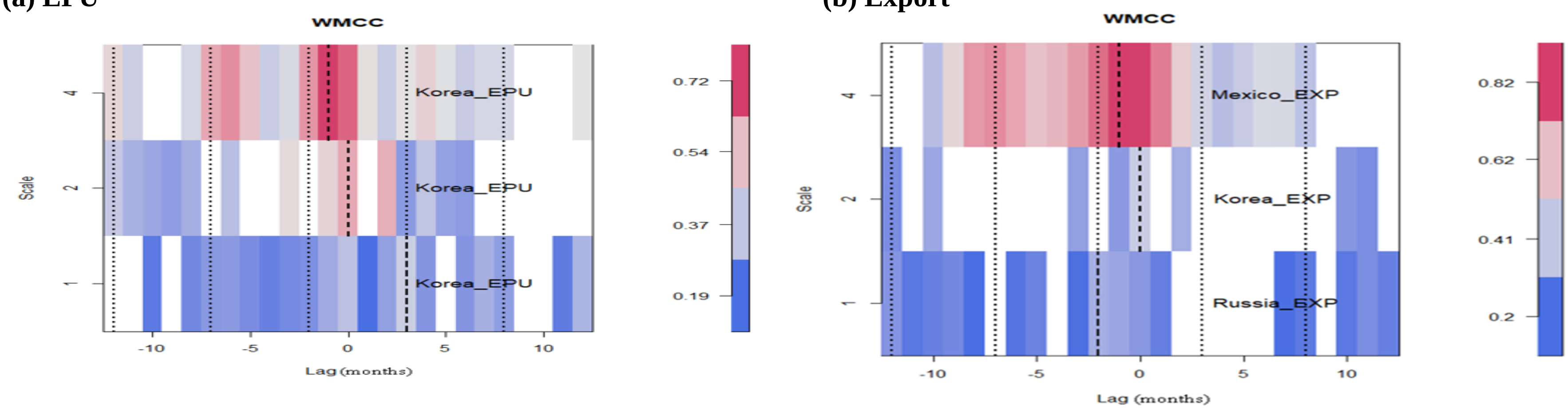


Figure 3.6A: Wavelet multiple cross correlation of EPU and Export among selected EMEs.

Note: Dashed-lines indicate localisations. Note: C1- Brazil; C2- China; C3-india; C4- Korea; C5-Mexico; C6-Russia.

3.4.2.3 Comovement of import across selected EMEs.

The bivariate autocorrelation as displayed in Figure 3.4B are extremely high in the long- term. China and Korea (C2C4) are the strongest pair with coefficient values of 0.45, 0.48 and 0.79 in the short-, medium-, and long- term respectively. Clearly, these economies are major trading partners and this has resulted in their high level of interconnectedness. As recorded, there exist a positive pairwise relationship between all pairs across all time scales except for India and Russia (C3C6), Brazil and Korea (C1C4), Brazil and Russia (C1C6), China and India (C2C3), and Brazil and China (C1C2) in the short term and Brazil and India (C1C3) in the medium term. Mexico and Russia (C5C6) and Brazil and Mexico (C1C5) had no evidence of comovement in the short- term but recorded a coefficient value of 0.72 and 0.68 respectively in the long-term. It implies that in the short-term these economies were not trade partners.

The wavelet multiple correlation for import (displayed in Figure 3.5B and Table 3.4B) shows a gradual rise in correlation over the time sales. The short- term recorded a value of 0.555301 which dropped to 0.542227 in the medium- term. However, there is strong evidence of comovement in the long- term with a coefficient value of 0.883226. It is therefore evident that there is a strong evidence of comovement between export values across the selected EMEs. However, there were no lead/lag tendencies in the case of import for wavelet multiple cross-correlation as displayed in Figure 3.6B and Table 3.4B. This is because all the localisations for the various scales recorded lag 0. In the short- term and medium- term, the potential lead/ lag of the system at localistion 0.555301215 and 0.542227201 respectively was CHINA-IMP. In the long- term the potential leader or follower of the system is KOREA-IMP at localisation 0.883226113. We can conclude that although there is strong evidence of correlation of import values across the selected EMEs, only China and Mexico dominates the whole system but with no lead/lag tendencies.

3.4.2.4 Comovement of GDP across selected EMEs.

The bivariate correlation results for GDP as displayed in Figure 3.4B clearly show evidence of comovement. The strongest positive association was recorded between China and Korea (C2C4) in the long-term followed by Brazil and Korea (C1C4) also in the long-term. The strongest negative association was recorded between India and Mexico (C3C5). Mexico and Russia (C5C6) had no evidence of correlation in the medium-term. The degree of correlation is generally low except for eight (8) pairs in the long-term.

The wavelet multiple correlation results are also displayed in Figure 3.5B and Table 3.4B. We record very low levels of group integration in the short-term (0.185001). However, the coefficient value increased from 0.314312 in the medium-term to 0.779402 in the long-term. The wavelet multiple cross-correlation output in Figure 3.6 with their localisation displayed in Table 3.4B reveal that Mexico leads the whole system in the short-term at lag 10. Likewise Korea is the leader of the whole system in the medium-term at lag -6. In the long-term, Korea dominates but Korea is potential leader or follower of the whole system because the localisation is at point 0.

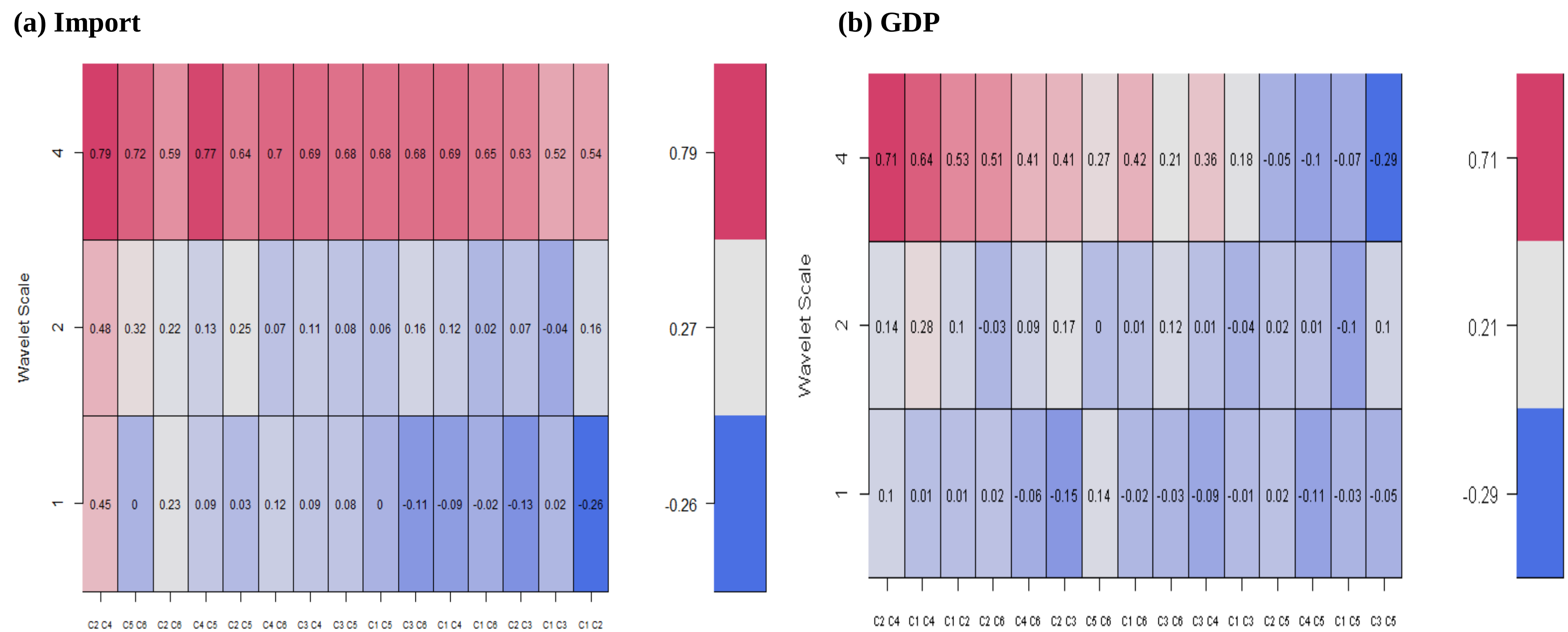
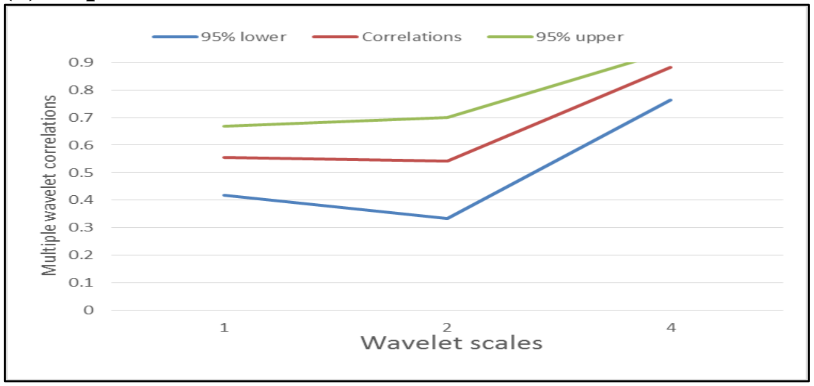


Figure 3.4B: Bivariate correlation of Import and GDP among selected EMEs.
Note: C1- Brazil; C2- China; C3-india; C4- Korea; C5-Mexico; C6-Russia.

(a) Import



(b) GDP

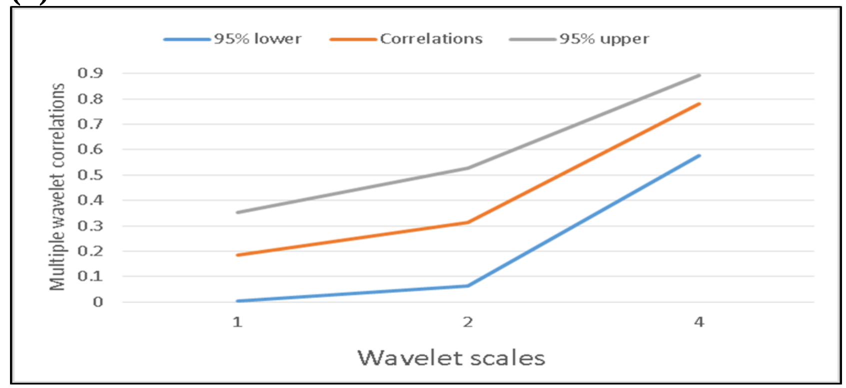
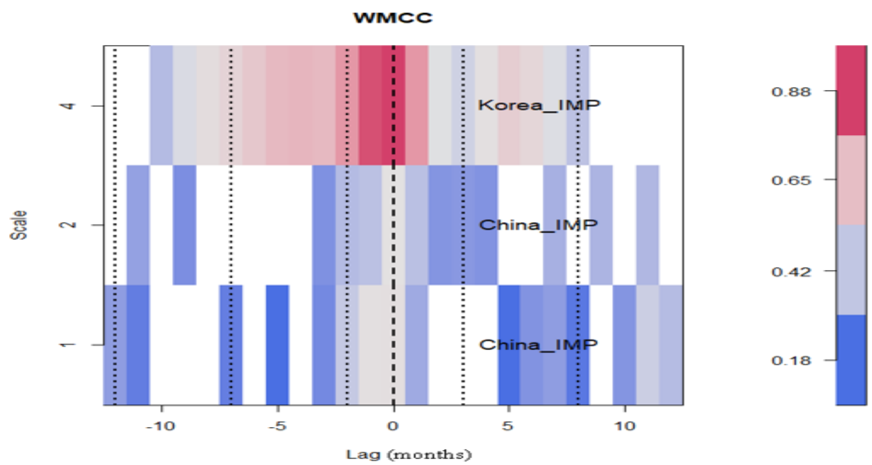


Figure 3.5B: Wavelet multiple correlation of Import and GDP among selected EMEs.

(a) Import



(b) GDP

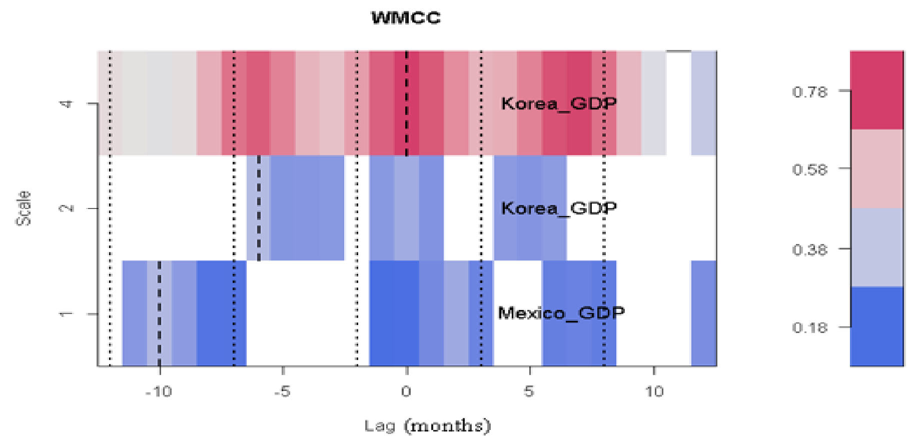


Figure 3.5B: Wavelet multiple cross correlation of Import and GDP among selected EMEs.

Note: C1- Brazil; C2- China; C3-india; C4- Korea; C5-Mexico; C6-Russia.

Table 3.4B: Wavelet multiple correlations and cross-correlations of Import and GDP among selected EMEs

	WAVELET MULTIPLE CORRELATION			WAVELET MULTIPLE CROSS-CORRELATION		
Scale	Lower	Correlation	Upper	Localisation	Time lag	Leading/Lagging
IMPORT						
w_{i1}	0.416984	0.555301	0.668481	0.555301215	0	CHINA-IMP
w_{i2}	0.332284	0.542227	0.700976	0.542227201	0	CHINA-IMP
w_{i3}	0.764049	0.883226	0.944115	0.883226113	0	KOREA-IMP
GDP						
w_{i1}	0.005178	0.185001	0.353234	0.344933199	-10	MEXICO-GDP
w_{i2}	0.063327	0.314312	0.527904	0.350562791	-6	KOREA-GDP
w_{i3}	0.578008	0.779402	0.891303	0.779402435	0	KOREA-GDP

3.4.2.5 Comovement of SPX in selected EMEs.

The bivariate correlation heat map is displayed in Figure 3.4C. The SPX is the only variable that shared a positive pairwise relationship across the whole wavelet scale. In other words, there was no record of negative correlation. The pairwise series also shows a high degree of comovement of SPX across the selected EME with the highest coefficient value of 0.81 between Korea and Mexico (C4C5) in the long- term. They also have the strongest relationship for short-, and medium- term in the wavelet scale. This implies that Korea and Mexico have been integrated in the financial markets right from 2 ~ 4 months to the long- term. It can be inferred that their stock markets have a lot of similarities which creates an opportunity for innovation and expansion of this financial sectors. The SPX values across the EMEs strongly prove Lucas (1977) argument that business cycles move together.

The wavelet multiple correlation (Figure 3.5C) of SPX across the selected EMEs are quite high with the level of similarities increasing as the time scale increase. Starting with a value of 0.75 in the short- term, the correlation coefficient consistently increased as the time scale increased reaching a value of 0.87 in the long- term. The SPX values obtained in any of the selected EMEs can be determined by the overall performance of the rest of the EMEs by a degree of 87% in the long- term. Figure 3.6C and Table 3.4C displays the wavelet multiple cross-correlation where the leads and lags are up to 12 months across all the wavelet scales. All the localisation values fall at the point of symmetry for each wavelet scale. This means that MEXICO-SPX (0.754683) in the short- term is a potential leader or follower at lag 0. BRAZIL-SPX (0.798331) is the potential leader or follower within the medium- term and KOREA-SPX (0.874029) is the potential leader or follower of the system in long- term with a lag value of 0. There is therefore no singular EME that leads or follows the whole systems across all the wavelet scales, but it's important for policy makers and investors to highlight the trends in the SPX of Mexico, Brazil and Korea during their decision making process since they dominate the whole system in the short-, medium-, and long- term respectively.

3.4.2.6 Comovement of CPI selected EMEs.

The pairwise series shows strong evidence of CPI comovement across EMEs. Figure 3.4C shows the bivariate correlation of the CPI of the six (6) EMEs. The strongest positive correlation recorded was 0.71 for China and Mexico (C2C5) within 8 ~ 16 months. With respect to negative correlation, India and Russia (C3C6) recorded a correlation coefficient value of -0.66 in the long- term which is also the highest negative correlation recorded for the selected variables. All the pairwise series in the long- term are quite high. This means that there is a high level of integration between paired CPI values in EMEs.

To investigate multivariate comovement across the EMEs the study adopts the wavelet multiple correlation. Figure 3.5C and Table 3.4C shows the plot for the interdependence of CPI across

EMEs. It is observed that the evidence of the comovement of CPI across EMEs is high. It consistently rose from 0.43 in the short- term to 0.65 in the medium- term. In the long term, the level of similarities increased to 79%. Figure 3.6C and Table 3.4C also show that the leader of the whole system within the short- term at a time lag of 5 months is INDIA-CPI. The localisation of CHINA-CPI (0.651752667) within the medium- term was located on the point of symmetry. This makes CHINA-CPI a potential leader or follower. However, in the long- term, CHINA- CPI (0.847489601) follows the whole system.

Table 3.4C: Wavelet multiple correlations and cross-correlations of SPX, CPI and Broad money among selected EMEs

	WAVELET MULTIPLE CORRELATION			WAVELET MULTIPLE CROSS-CORRELATION		
Scale	Lower	Correlation	Upper	Localisation	Time lag	Leading/Lagging
SPX						
w_{i1}	0.665024	0.754683	0.822897	0.754683	0	MEXICO-SPX
w_{i2}	0.681593	0.798331	0.87544	0.798331	0	BRAZIL-SPX
w_{i3}	0.746728	0.874029	0.93956	0.874029	0	KOREA-SPX
CPI						
w_{i1}	0.271878	0.430792	0.566835	0.407856584	-5	INDIA-CPI
w_{i2}	0.474939	0.651753	0.777987	0.651752667	0	CHINA-CPI
w_{i3}	0.590248	0.786591	0.89506	0.847489601	10	CHINA CPI
BROAD MONEY						
w_{i1}	0.1488747	0.32028759	0.4730137	0.357802946	-12	RUSSIA-BRM
w_{i2}	0.1006717	0.34778795	0.5544864	0.402039162	-1	RUSSIA-BRM
w_{i3}	0.0710633	0.42646177	0.6857796	0.467565538	5	INDIA-BRM

(a) SPX (b) CPI

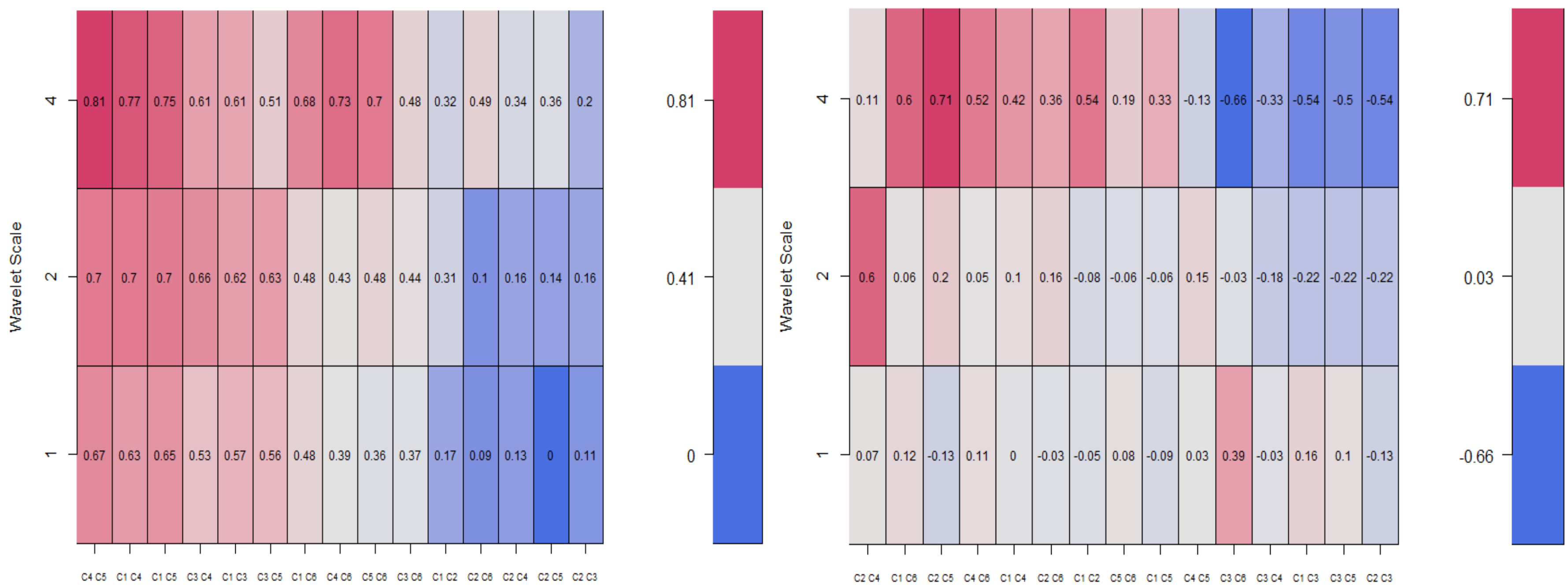
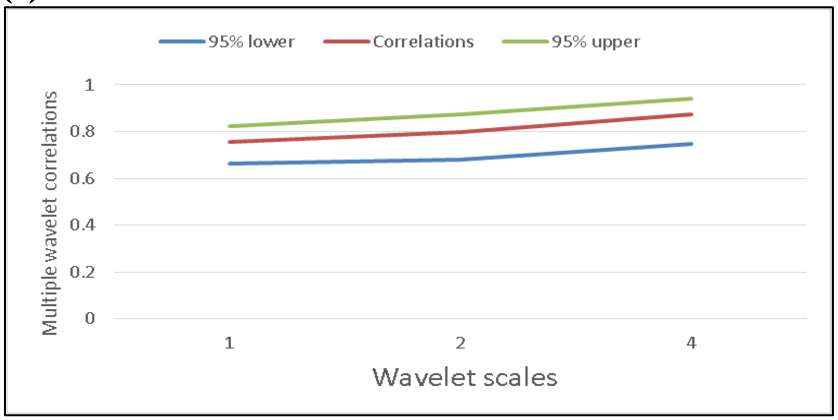


Figure 3.4C: Bivariate correlation of SPX and CPI among selected EMEs.

Note: C1- Brazil; C2- China; C3-india; C4- Korea; C5-Mexico; C6-Russia.

(a) SPX



(b) CPI

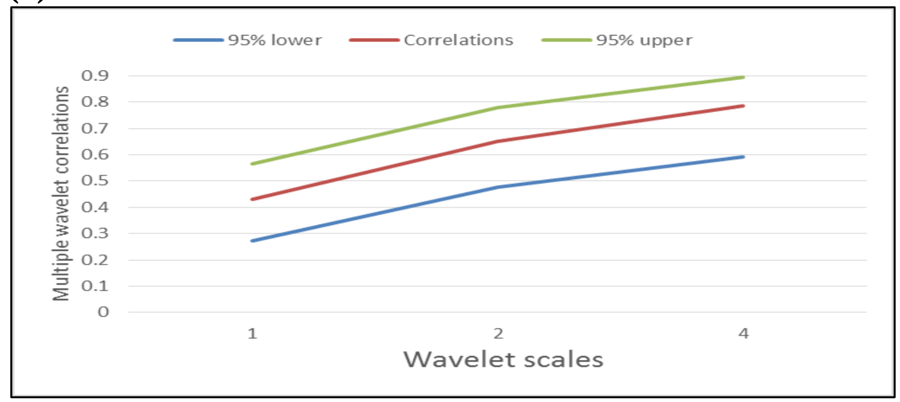
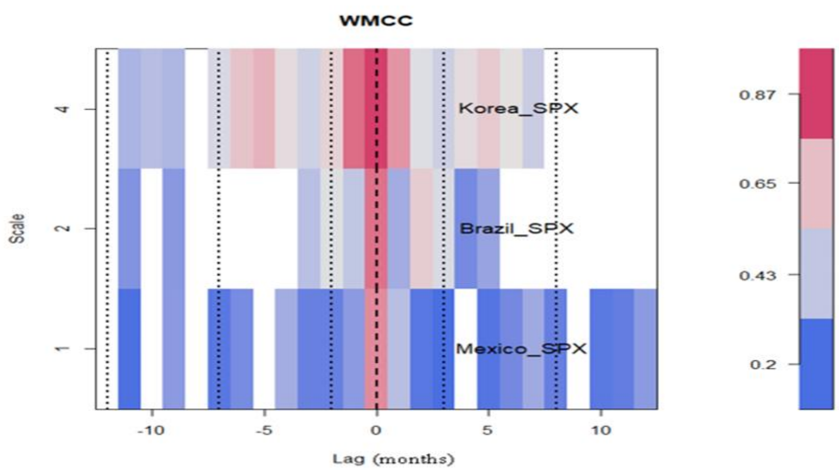


Figure 3.5C: Wavelet multiple correlation of SPX and CPI among selected EMEs.

(a) SPX



(b) CPI

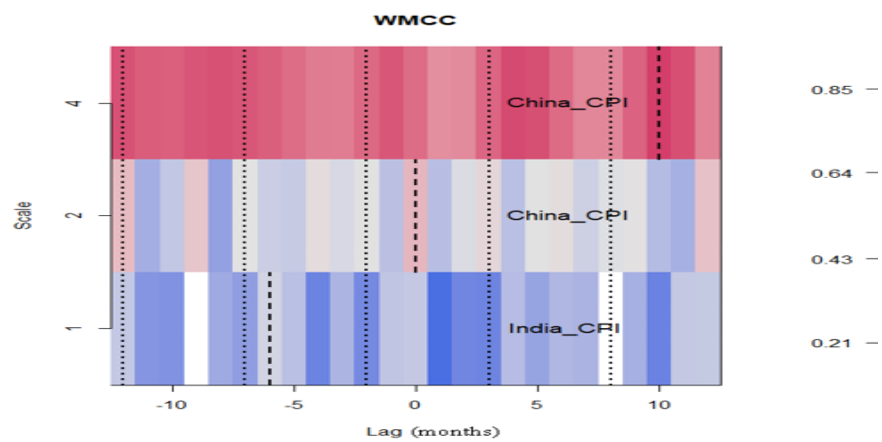


Figure 3.5C: Wavelet multiple cross correlation of SPX and CPI among selected EMEs.
Note: C1- Brazil; C2- China; C3-india; C4- Korea; C5-Mexico; C6-Russia.

3.4.2.7 Comovement of broad money across selected EMEs.

The pairwise series of the comovement across EMEs as evident in Figure 3.4D is very low across all scales. The strongest positive comovement recorded a coefficient value of 0.28 for India and Mexico (C3C5) while the strongest inverse relationship recorded was -0.31 between India and Russia (C3C6). It was also observed that unlike other variables that increased as the time scale increased, broad money across the selected EMEs experienced multiple fluctuations in correlation right from medium- term to the long- term. This clearly depicts that the interdependence between broad money in EMEs are unpredictable and this largely explains the low level of interdependence n the bivariate wavelet analysis.

The wavelet multiple correlation (see, Figure 3.5D) of broad money across the EMEs is relatively low as previously recorded in the bivariate analysis. The short- term recorded 32% degree of similarities, and the medium- term recorded 35% level of similarities. The long- term recorded the highest comovement coefficient of 43% which shows a very high level of discrepancies between the variables even after 1 (one) year. Although there is evidence of comovement across EMEs, the interdependence between the economies is generally low since only 43% of the changes in one variables is influenced by the rest of the broad money across the EMEs. To investigate the potential leader or follower of the whole system, we adopt the wavelet multiple cross-correlation (see Figure 3.6D and Table 3.4C). Within the short- term, Russia-BRM (0.357802946) leads the system at lag 12 (thus, at 12 months). Secondly, within the medium- term Russia –BRM (0.402039162) is the leader of the whole system at lag 1 (one month). India-BRM (0.467565538) is the follower of the system at lag 5 within the long- term. Localisation is in parenthesis. Only Russia and India have the potential to maximise the multiple correlation against a linear combination of the rest of the

EMEs. Policy makers and investors should therefore observe the broad money trends in these EMEs as a means to predict outcomes in other economies.

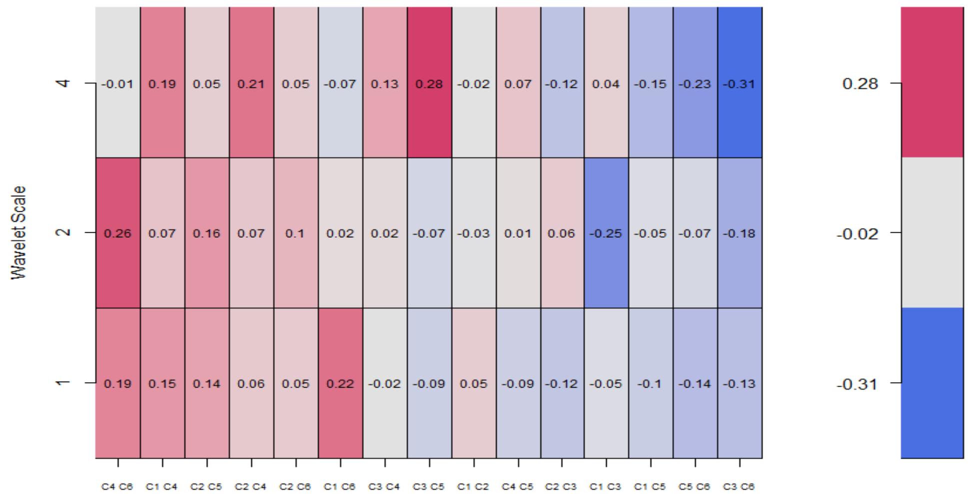


Figure 3.4D: Bivariate correlation of broad money among selected EMEs.
Note: C1- Brazil; C2- China; C3-india; C4- Korea; C5-Mexico; C6-Russia.

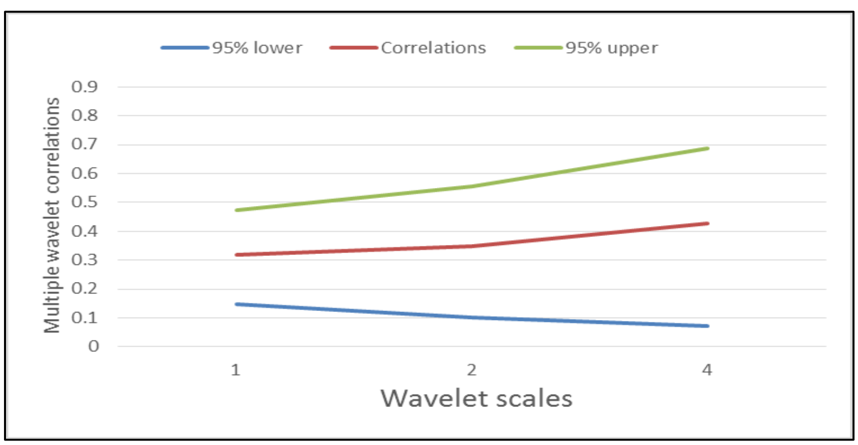


Figure 3.5D: Wavelet multiple correlation of broad money among selected EMEs.

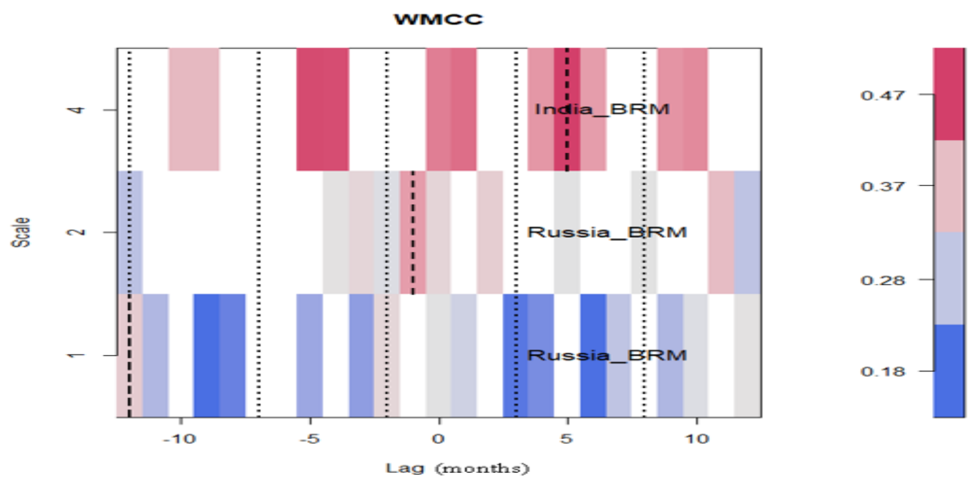


Figure 3.6D: Wavelet multiple cross correlation of macroeconomic variables among selected EMEs.
Note: Dashed-lines indicate localisations. Note: C1- Brazil; C2- China; C3-india; C4- Korea; C5-Mexico; C6-Russia.

3.5 Pairwise Non-linear time-sample causality test

The nonparametric test helps answer the question of whether EPU is a cause or effect of business cycles fluctuations in selected EMEs. The study therefore paired EPU with each of the selected macroeconomic variables which served as proxy for the business cycle (CPI, broad money, trade (export of goods and import of goods), GDP, and SPX) within each EME to investigate their causality linkages. It is evident from the Shapiro-Wilks test that, at all conventional levels of significance, Table 3.2 significantly depicts non-normality. This finding motivates our choice of adopting the non-linear causality test method of Diks and Panchenko (2005, 2006). The directional causality is interpreted as changes in EPU i is likely to cause changes in macroeconomic variable j or vice versa. This implies that, information on EPU i to an extent can be used to forecast macroeconomic variable j and vice versa.

Table 3.5 displays the causality test results for the selected EMEs. To be able to compare the causality findings with the intra-country wavelet multiple cross-correlation results, we use

MODWT with a wavelet filter of length L=3 to investigate evidence of causality. Thus, the causality results are divided into three scales. The three scales λ_j, j = 1, 2, 3 corresponds to periods 2–4 months (which includes monthly to quarterly scales), 4–8 months (which mostly includes quarterly to biannual scales), 8–16 days (mostly includes biannual to annual scales) respectively. The scales therefore capture short-, medium-, and long-term dynamics. Clearly, there were just a few evidence of causality for the pairs of EPU and macroeconomic variables even from the 10% significance level. We observe that except in some few cases, EPU does not cause business cycles. Secondly, it is evident that the variable serving as proxy for business cycle influences the outcome. Although evidence from previous studies have been robust to the use of proxy variables such as Industrial production which is a widely watched economic indicator of business cycles (Ludvigson, Ma, and Ng, 2015), the selected macroeconomic variables in this study shows robust findings of integration and causality with EPU. Despite the fact that these variables reflect real economic activities, it is evident that these variables respond differently to EPU in each EME. Thus, causality with respect to the economic indicator of business cycles is specific to each EME.

Specifically for Brazil, Brazil-EPU cause Brazil-GDP (in Scale 2) and Brazil-SPX (in Scale 2) at 5% and 10% significance level respectively. This implies that in the medium-term, Brazil's EPU has a positive predictive power for GDP and SPX. The positive causal relationship indicates that an increase (decrease) in Brazil's EPU leads to an increase (decrease) in GDP and SPX in the medium term. The findings that EPU causes economic activities (including GDP) supports the work of Liu and Zhang's (2015), Karnizova and Li (2014), Yin, Zhang, Yu, and Xin (2017), Brogaard and Detzel (2015), and Mumtaz and Surico (2018). The positive and negative causal relation between EPU and GDP as well as SPX can be attributed to good uncertainty (growth options) and bad uncertainty (real options). They argue that a good uncertainty shock is characterised by the positive movement in economic variables (such as output, consumption and investment growth) as a result of uncertainty shocks, whereas negative movement indicates a bad uncertainty shock. On the other uni-directional linkage, CPI (in Scale 1and Scale 3), import (in Scale 1, Scale 2 and Scale 3) and export (in Scale 2) cause Brazil-EPU. This implies that Brazil's CPI has a positive predictive power in determining EPU values in the short- and long-term. Also, Brazil's EPU has a positive causal impact on import across all scales. Third, Brazil's EPU positively causes export in the medium-term. This finding clearly supports literature that argue that EPU significantly impacts inflation and trade (Baldwin, 2009; Hlatshwayo & Saxegaard, 2016; Novy & Taylor, 2014). However, contrary to studies who proved that EPU negatively affects trade growth globally (see, Armelius, Belfrage & Stenbacka, 2014; Han, Qi & Yin, 2016; Constantinescu, Mattoo & Ruta, 2017; Tam, 2018) the causality test shows a positive causality that runs from EPU to trade. This can be attributed to growth theory that argues that uncertainty drives economic agents to work harder inorder to sevure more capital stock for future insurance.

In the case of China, only China-EPU cause China-CPI (in Scale 3) at 5% significance level. This implies that changes in China's EPU have predictive power in determining the future dynamics of CPI in the long-term. In this case a positive (negative) change in EPU leads to a positive (negative) change in CPI. These findings are in support of the growth option that good uncertainty leads to a fall in CPI and bad uncertainty causes a rise in CPI. On the other hand, China-broad money (in Scale 2 an Scale 3), China-import (in Scale 3) and China-export (in Scale 3) cause China-EPU all at 5% significance level except for China-broad money in scale 2 which falls within the 10% level of significance. Thus, in the case of China, the following variables have a positive causal impact on the variations of EPU. Specifically, in the medium-term, an increase (decrease) in broad money causes an increase (decrease) EPU. Second, in the long-term, broad money, import and export cause EPU. . To the best of the author's knowledge this is the first study that adopted broad money as a proxy of business cycles and it's worth noting that it causes variations in EPU n the medium- and long-term. It therefore implies that, broad money which represents the measure of monetary policy stance in an economy causes EPU. More studies must therefore be conducted on broad money as a measure of business cycle. It is also clear that there are no records of causality in the short-term. These findings can help investors to forecast the future values of EPU and business cycles to aid investors in their investment strategies.

India recorded only one causality link, India-GDP cause India EPU (in Scale 2) at 10% significance level. This implies that, in the medium-term India's GDP has a positive causal impact on EPU. In India, EPU does not cause business cycles, but rather business cycles cause EPU. GDP is also used to measure the size of an economy and growth rate and serves as a key tool to guide policymakers and investors in their decision making (McCulla & Smith 2007). The findings imply that in India investors should focus their attention on the outcomes of GDP since it will aid them in forecasting EPU values. Also, policy makers should focus on policies that will keep growth of GDP stable in order to stabilise uncertainty in the economy. Per the growth theory, it can also be argued that a rise in GDP causes a rise in good uncertainty. As argued by Segal et al. (2015), good uncertainty significantly and positively associated with higher output. These are uncertainties that result from an optimistic view that an incident would provide an opportunity for growth. One noticeable example is the introduction of World Wide Web in the 1990s.

Table 3.5: Non- linear causality between EPU and macroeconomic variables in selected EMEs.

Direction	Scale 1	Scale 2	Scale 3
BRAZIL			
BRA-EPU ≠> BRA-BRM	0.356(0.36075)	-0.426(0.66508)	0.615(0.26920)
BRA-EPU ≠> BRA-CPI	0.143(0.44314)	0.451(0.32594)	0.459(0.32315)
BRA-EPU ≠> BRA-GDP	0.347(0.36439)	**1.764(0.03885)**	0.836(0.20162)
BRA-EPU ≠> BRA-IMP	-0.526(0.70044)	0.454(0.32486)	0.706(0.23996)
BRA-EPU ≠> BRA-EXP	-0.355(0.63865)	-0.219(0.58683)	0.634(0.26312)
BRA-EPU ≠> BRA-SPX	0.705(0.24039)	**1.300(0.09674)**	-0.694(0.75627)
BRA-BRM ≠> BRA-EPU	1.489(0.93177)	-1.055(0.85423)	0.449(0.32674)
BRA-CPI ≠> BRA-EPU	**1.644(0.05007)**	0.415(0.33900)	**1.518(0.06447)**
BRA-GDP ≠> BRA-EPU	-0.214(0.58454)	1.019(0.15404)	-0.124(0.54935)
BRA-IMP ≠> BRA-EPU	**1.309(0.09528)**	**1.590(0.05594)**	**1.659(0.04852)**
BRA-EXP ≠> BRA-EPU	0.904(0.18300)	**1.774(0.03807)**	0.033(0.48680)
BRA- SPX≠> BRA-EPU	0.047(0.48128)	0.415(0.33909)	-0.048(0.51927)
CHINA			
CHI-EPU ≠> CHI-BRM	0.652(0.25729)	0.156(0.43814)	0.701(0.24153)
CHI-EPU ≠> CHI-CPI	0.880(0.18949)	0.886(0.18784)	**1.710(0.04360)**
CHI-EPU ≠> CHI-GDP	-0.175(0.56947)	0.626(0.26568)	0.587(0.27845)
CHI-EPU ≠> CHI-IMP	-0.474(0.68225)	0.797(0.21273)	-0.981(0.83667)
CHI-EPU ≠> CHI-EXP	0.572(0.28351)	-0.365(0.64261)	1.020(0.15397)
CHI-EPU ≠> CHI-SPX	-0.230(0.59102)	0.628(0.26513)	0.315(0.37633)
CHI-BRM ≠> CHI-EPU	-0.726(0.76616)	**1.391(0.08216)**	**1.616(0.05299)**
CHI-CPI ≠> CHI-EPU	0.764(0.22243)	0.675(0.24981)	1.050(0.14689)
CHI-GDP ≠> CHI-EPU	0.293(0.38480)	1.066(0.14320)	0.587(0.27845)
CHI-IMP ≠> CHI-EPU	0.398(0.34519)	0.512(0.30449)	**1.545(0.06114)**
CHI-EXP ≠> CHI-EPU	-0.372(0.64510)	0.381(0.35159)	**1.791(0.03664)**
CHI- SPX≠> CHI-EPU	0.331(0.37022)	-1.282(0.90005)	0.410(0.34076)
INDIA			
IND-EPU ≠> IND-BRM	-0.544(0.70666)	0.729(0.23302)	0.757(0.22463)
IND-EPU ≠> IND-CPI	-008(0.65826.4)	-0.801(0.78837)	0.296(0.38358)
IND-EPU ≠> IND-GDP	1.166(0.12171)	-0.062(0.52482)	0.844(0.19924)
IND-EPU ≠> IND-IMP	-1.140(0.87293)	-0.742(0.77083)	1.127(0.12985)
IND-EPU ≠> IND-EXP	-0.127(0.55056)	-0.233(0.59224)	0.536(0.29598)
IND-EPU ≠> IND-SPX	-1.005(0.84248)	0.910(0.18139)	0.651(0.25751)
IND-BRM ≠> IND-EPU	-0.415(0.66108)	0.065(0.47415)	0.711(0.23860)
IND-CPI ≠> IND-EPU	-0.447(0.67258)	-1.493(0.93226)	0.269(0.39413)
IND-GDP ≠> IND-EPU	-0.264(0.60421)	**1.428(0.07667)**	0.244(0.40361)

Direction	Scale 1	Scale 2	Scale 3
IND-IMP ⇏ IND-EPU	0.239(0.40544)	-0.020(0.50783)	0.141(0.44408)
IND-EXP ⇏ IND-EPU	0.972(0.16563)	-0.051(0.52028)	-0.197(0.57804)
IND- SPX⇏ IND-EPU	0.143(0.44332)	-0.197(0.57800)	0.387(0.34946)
KOREA			
KOR-EPU ⇏ KOR-BRM	0.599(0.27467)	0.790(0.21467)	**1.454(0.07291)**
KOR-EPU ⇏ KOR-CPI	-0.955(0.83013)	**1.646(0.04991)**	**2.174(0.01484)**
KOR-EPU ⇏ KOR-GDP	0.893(0.18584)	-0.396(0.65402)	0.810(0.20902)
KOR-EPU ⇏ KOR-IMP	-0.671(0.74888)	**1.556(0.05985)**	0.863(0.19394)
KOR-EPU ⇏ KOR-EXP	0.270(0.39347)	0.369(0.35609)	0.457(0.32381)
KOR-EPU ⇏ KOR-SPX	1.227(0.11000)	-0.609(0.72867)	**1.498(0.06707)**
KOR-BRM ⇏ KOR-EPU	0.109(0.45654)	1.110(0.13348)	**1.323(0.09290)**
KOR-CPI ⇏ KOR-EPU	0.567(0.28537)	0.504(0.30717)	**1.791(0.03663)**
KOR-GDP ⇏ KOR-EPU	-0.627(0.73466)	1.054(0.14590)	0.290(0.38573)
KOR-IMP ⇏ KOR-EPU	0.968(0.16660)	-0.198(0.57852)	0.726(0.23390)
KOR-EXP ⇏ KOR-EPU	0.764(0.22241)	0.086(0.46579)	**1.349(0.08868)**
KOR- SPX⇏ KOR-EPU	-0.212(0.58408)	0.417(0.33838)	0.773(0.21986)
MEXICO			
MEX-EPU ⇏ MEX-BRM	0.032(0.48741)	-0.071(0.52842)	0.437(0.33089)
MEX-EPU ⇏ MEX-CPI	0.040(0.48408)	0.374(0.35431)	-0.579(0.71865)
MEX-EPU ⇏ MEX-GDP	-0.577(0.71789)	-0.367(0.64312)	**1.435(0.07560)**
MEX-EPU ⇏ MEX-IMP	-0.327(0.62816)	-0.427(0.66537)	-0.718(0.76374)
MEX-EPU ⇏ MEX-EXP	-0.246(0.59711)	**1.313(0.09453)**	0.987(0.16171)
MEX-EPU ⇏ MEX-SPX	-0.750(0.77324)	**1.468(0.07107)**	0.780(0.21779)
MEX-BRM ⇏ MEX-EPU	0.005(0.49811)	0.505(0.30682)	1.045(0.14799)
MEX-CPI ⇏ MEX-EPU	-0.532(0.70250)	-0.282(0.61097)	-0.324(0.62718)
MEX-GDP ⇏ MEX-EPU	0.576(0.28232)	0.947(0.17171)	0.636(0.26245)
MEX-IMP ⇏ MEX-EPU	0.752(0.22592)	**1.369(0.08557)**	0.061(0.47588)
MEX-EXP ⇏ MEX-EPU	-0.404(0.65673)	1.042(0.14878)	-0.558(0.71143)
MEX- SPX⇏ MEX-EPU	-1.091(0.86227)	0.371(0.35521)	1.119(0.13158)
RUSSIA			
RUS-EPU ⇏ RUS-BRM	-0.592(0.72312)	-0.190(0.57528)	0.214(0.41514)
RUS-EPU ⇏ RUS-CPI	-0.366(0.64267)	0.604(0.27278)	1.081(0.13991)
RUS-EPU ⇏ RUS-GDP	-0.425(0.66466)	0.451(0.32605)	0.485(0.31385)
RUS-EPU ⇏ RUS-IMP	0.794(0.21367)	**1.698(0.04476)**	-0.200(0.57925)
RUS-EPU ⇏ RUS-EXP	-0.267(0.60528)	**1.329(0.09200)**	0.935(0.17497)

Direction	Scale 1	Scale 2	Scale 3
RUS-EPU ≠> RUS-SPX	-1.345(0.91074)	-0.958(0.83089)	**1.827(0.03387)**
RUS-BRM ≠> RUS-EPU	0.049(0.48038)	-0.126(0.55027)	**1.597(0.05516)**
RUS-CPI ≠> RUS-EPU	-0.197(0.57800)	0.246(0.40300)	1.258(0.10419)
RUS-GDP ≠> RUS-EPU	-0.794(0.78630)	0.457(0.32386)	**1.319(0.09355)**
RUS-IMP ≠> RUS-EPU	0.235(0.40727)	0.114(0.45477)	0.016(0.49343)
RUS-EXP ≠> RUS-EPU	0.342(0.36627)	0.433(0.33240)	-0.779(0.78192)
RUS- SPX≠> RUS-EPU	-0.103(0.54120)	1.049(0.14711)	0.968(0.16642)

Korea recorded the highest causality linkages. Korea-EPU cause Korea-broad money (in Scale 1), Korea-CPI (in Scale 2 and Scale 3), import (in Scale 2), and Korea- SPX (in Scale 3). Findings show that except for GDP and export, Korea positively causes all the proxy business cycles from the short-term to the long-term. These imply that economic activities in Korea strongly respond to uncertainties related to economic policy. Therefore, reducing and stabilising economic policy uncertainties in Korea is very essential for the voidance of extremely high CPI values and extremely low values for broad money, export, import and SPX. Controlled EPU enhances investor confidence and promote overall economic growth is important. For investors, investing in Korea is risk because EPU has a positive causal impact on most of the proxy business cycles but they can gain revenues when uncertainty is high. This is because an increase in uncertainty leads to increase in import, SPX and broad money. Likewise, the uni-directional linkage shows that Korea-broad money, Korea-CPI and Korea- export cause Korea-EPU all at scale 3. This implies that, in the long-term the causal relationship between Korea's EPU and CPI is bidirectional. Hence in the long-term, Korea causes EPU and EPU causes CPI. Also broad money and export cause EPU in the long-term. Policy makers should therefore consider long-term monetary and trade policies since the implementation of these polices can control the predictive power of broad money, CPI and export.

In the case of Mexico, Mexico- EPU cause Mexico-GDP (in Scale 3), Mexico- Export (Scale 2) and Mexico- SPX (in Scale 2) all at 10% level of significance. This implies that in the medium-term, Mexico's EPU has predictive power over export and SPX and in the long-term, EPU causes GDP. The implicatons of Mexico applies to the implications discussed on Brazil. The uni-directional causal realtionship from business cycles to EPU shows that Mexico- import causes Mexico-EPU (in Scale 2) at 10% level of significance. Hence, in Mexico, the only variable that causes EPU is import. Policy makers should therefore focus on economic policies that promote import. For Russia, the significant uni-directional linkages was recorded as, Russia-EPU causes Russia-import (in Scale 2), Russia-export (in Scale 2) and Russia-SPX (in Scale 3). Russia-broad money and Russia-GDP cause Russia EPU all in the long term. Clearly all the proxies for business cycles at one point or another either cause EPU or vice versa. Although there is evidence that EPU causes business cycles fluctuations, the type of business cycle indictor that influences these fluctuations is specific to each EME. For example in Brazil and Mexico, "EPU causes GDP" but "EPU does not cause GDP" in China, India, Korea and Russia.

For some of the EMEs the wavelet multiple cross-correlation and causality results have some similarities. For example Brazil's wavelet multiple cross-correlation records import, import and GDP as potential leaders and followers of the whole system at Scale1, Scale 2 and Scale 3 respectively. Import also has causality linkage with EPU. Specifically, Brazil-import causes Brazil-EPU in Scale1, Scale 2 and Scale 3. Likewise China-export and China-import are potential leaders/followers of the whole system in Scale 2 and Scale 3 respectively and the causality test also show that China-import causes China- EPU in Scale 3 and China-export causes China-import at Scale 3 all at 5% significance level. The wavelet multiple cross-correlation shows that the Korea-export is the potential leader/follower of the whole system at Scale 1 and Scale 3 and Korea-export also causes EPU in Scale 3. It can be inferred that been the potential leader or the follower of the whole system doesn't mean that the variable cases the fluctuations in the other variables. We conclude that EPU is both a cause and effect of business cycles fluctuations in the selected EMEs except for India where business cycle fluctuations rather cause EPU fluctuations.

3.6 Conclusion and recommendations

The first two empirical sections investigated if business cycles in the selected EMEs comove as argued by Lucas (1997). The study elected to use the bivariate correlation, wavelet multiple correlation and cross-correlation to measure the overall statistical relationship that might exist at differing scales. Sub-session 3.4.1 focused on intra-country analysis. Lucas's (1979) argument that business cycles comove has been proved, however the scale by scale analysis has further proved that the level of integration is strongest in the long-term. The varying results in the relationships between the macroeconomic variables are supported by Dew-Becker and Giglio (2020). Their findings also showed a mixed relationship between coss-sectional uncertainty and overall economic activity. The negative relationships recorded between EPU and the macroeconomic variables supports Basu, and Bundick's (2017) study. They identified that, uncertainty shock in the data causes significant declines in output, consumption, investment, and hours worked. They further discovered that, uncertainty shocks can easily generate comovement with countercyclical markups through sticky prices. It is evident in the bivariate analysis that export and the import are the variables that recorded the highest positive coefficient values within each EME. We further investigate the role EPU plays in the comovement of variables within each EME and discovered that evidence of positive correlation was generally recorded between EPU and CPI within each

EME. This clearly implies that high inflation rate and the purchasing power of domestic money positively correlates with high EPU. Likewise, evidence of negative correlation for EPU was recorded between EPU and SPX across all EMEs. We must also note out that China's findings contradict earlier research that claims imports are positively associated to GDP (Hye, 2012; etintas and Barisik, 2009; Herrerias and Orts, 2011). There are numerous examples of positive correlations between EPU and macroeconomic factors in Russia. Similarly, EPU shows a long-term positive association with both broad money and GDP in Mexico. These findings are supported by studies (Segal et al., 2015; Kido, 2016; Kung and Schmid, 2010; Gilchrist and Williams, 2005; Kraft et al., 2018) that show EPU has a positive association with economic activity. Therefore, to make effective decisions, policymakers should carefully consider the specific positive and negative relationships between EPU and business cycles within each EME.

All wavelet multiple correlation are significant with strong degrees of interdependence. With respect to wavelet multiple cross-correlation, we note that EPU has no lead/lag potential across all the time scales within each EME. Although there is strong evidence of comovement between EPU and the macroeconomic variables, EPU does not pose any leading or lagging power in all the six EMEs. However, import has records of dominates within each EME. Investors and policymakers should consider these variables in their decision-making processes because the findings indicate that the seven variables are interrelated, with a change in one variable potentially causing a change in the other six variables. The findings also show that correlations generally increase in degree with scale, implying that long-term integration levels are highest. As a result, when integration of variables within and between EMEs is weak in the short term, investors can hedge their portfolios, trade, and reduce market risk. Investors should keep in mind that portfolio diversification is less profitable in the long-term, and they should avoid investing in the selected EMEs for more than six months.

Inter-country analysis (Sub-session 3.4.2) also shows evidence of comovement. China and Korea recorded the highest positive correlation pair for EPU, import and GDP. For negative relationship, India and Russia recorded the highest inverse relationship for GDP, CPI and broad money. We further investigate the role EPU plays in inter-country comovement. Evidence of bivariate comovement of EPU across the selected EMEs shows the China's EPU and Korea's EPU have the strongest positive relationship while Brazil and China show evidence of a strong negative association. The wavelet multiple cross-correlation shows that Korea's EPU dominates the whole system across all the scales. Within the short- term Korea-EPU is the follower of the whole system, in the medium- term Korea- EPU dominates with no lead/lag tendencies because it records a lag value (0), and within the long- term, Korea-EPU is the leader of the whole system. We observe in the intra-country analysis that EPU does not dominate any variable and has no lead/lag potential across all timescales. On the otherhand we find that import, export, CPI, GDP, and SPX have lead/lag potentails. This means that, while EPU correlates with business cycles, EPU is not an indicator of EPU-business cycle comovement; rather, business cycles drive EPU-business cycle comovement. As a result, our paper is consistent with classical theory and empirical literature, which acknowledge that uncertainty can be endogenous and driven by the business cycle (Ludvigson et al., 2015; Van Nieuwerburgh and Veldkamp, 2006; Fajgelbaum et al., 2017). In this perspective, policies targeted at reducing or stabilising business cycle comovement, particularly with EPU, must extend policies to account for these indicators (import, export, CPI, GDP ans SPX) of EPU-business cycle comovement. Since we have discovered that EPU fluctuations are endogenous, we highlight the importance of public authorities to maintain transparency and stability during the implementation of economic policies to control EPU fluctuations.

The last session of this Chapter (Sub-session 3.5) investigates whether EPU is a cause or effect of business cycles fluctuations in selected EMEs using Diks and Panchenko (2005, 2006) nonparametric test. We find few evidence of causality for the pairs of EPU and macroeconomic variables at 5% and 10% significance level. The selected proxy for business cycles are import, export, GDP, broad money, CPI and SPX. All these variables showed evidence of causal but depending on the EME, some proxy variables did not show evidence of causality. Specifically, in Brail, there is a causal relationship between EPU and GDP, SPX, CPI, import as well as export. In the case of China, EPU has a causal relationship with CPI, broad money, import and export. For India, a causal relationship exists between EPU and GDP. In Korea a causal link exist between EPU and broad money, CPI, import, export as well as SPX. Mexico EPU has a causal link with GDP, export, import and SPX. And last, Russia has a causal link with EPU and import, export, broad money, GDP and SPX. Causality was recorded in the medium-term and long-term (except for Brazil where we find evidence of causality in the short-term. Economic policy makers are therefore advised to focus on short-, medium- and long-term measures to regulate EPU outcomes in the economies. Economic policy makers are therefore advised to focus on short-, medium- and long-term measures to regulate EPU outcomes in the economies as well as control the predictive power of GDP, SPX, CPI, broad money, import and export.

The causality results for all the selected EMEs are positive which implies that, an increase (decrease) in EPU (business cycles) leads to rise in business cycles (EPU). The reason for the positive causality between EPU and business cycles can be attributed to good uncertainty. Good uncertainties are uncertainties that trigger a rise in economic growth through trade, investment and consumption. This implies that, investors can gain revenues when uncertainty is high. This is because an increase in uncertainty leads to an increase in GDP, SPX, import, export and broad money. Policymakers should also start to take into account the possible positive effects of EPU on economic activities in the selected EMEs by investigating the types of good and bad uncertainty that affect economies. We further discover that in the long-term the causal relationship between Korea's EPU and CPI is bidirectional. These findings can help investors to make well informed investment strategies since they are able to forecast the future values of EPU and the variations in business cycles investment strategies. In the study, the results show that broad money has a causal relationship with EPU in China, Russia and Korea. This implies that, for these EMEs, tight monetary policies may be one of the solutions to control uncertainty since broad money represents the measure of monetary policy stance in an economy causes EPU.

The findings clearly demonstrate that EPU causes business cycles and at the same time business cycles cause EPU. This may account for the inconsistent findings in literature, since some studies argue that EPU causes business cycles while others argue that business cycles cause EPU. For example the evidence of causality in this study was sometimes in the short-, medium- or long-term. Hence the time period of the analysis of the other literature may have influenced the causal relationship between EPU and business cycle. Second, this study selected six macroeconomic variables as proxy for business and although they all showed evidence of positive causality, the characteristics of the selected macroeconomic variables are unique to each scale and EME. Hence, the variable selected as proxy for business cycles in previous literature will most likely affect the results differently, since each macroeconomic variable responds differently to EPU and economies. In other words, depending on the macroeconomic variable selected and its relationship with EPU, EPU can either cause the variations in business cycles or vice versa. For a robust comparison of literature on the causal link between EPU and business cycles, the above differences (scale and proxy variable) should be considered. It is evident that the selected macroeconomic variables respond differently to EPU in each EME. It is therefore recommended that studies on EPU in EMEs should focus more on intra-country than inter-country. It is evident that, just a handful of evidence proved that EPU causes business cycle fluctuation and vice versa. We therefore need to explore if other variables can explain the causal link between EPU and business cycles.

CHAPTER FOUR

RELATIONSHIP BETWEEN DISTANCE AND ECONOMIC POLICY UNCERTAINTY IN EMERGING MARKET ECONOMIES

4.1 Introduction

The objective of this chapter is to investigate the level of interdependence between selected EMEs' EPU and macroeconomic variables based on their geographical proximity and economic similarities and dissimilarities. We intend to investigate if the differences and similarities of EPU values among the selected EMEs are influenced by the distance between these economies. The study specifically focuses on economic distance and spatial distance. As stated earlier, this thesis aims at specifically studying EPU with respect to distance because, despite the vast study on the importance of distance (see, Makino & Tsang, 2011; Linder 1961; Tobler, 1970; Johanson & Wiedersheim-Paul, 1975; Szulanski, 1996; Tung & Verbeke 2010; and Dellestrand & Kappen, 2012), to the best of the author's knowledge, no study has investigated the relationship between distance and EPU (and more specifically in EMEs). For eample, studies conducted on distance show that, the differences between countries prevent or disturb the flows of information between the firm and the market (Johanson & Wiedersheim-Paul, 1975), introduces friction between countries (Shenkar et al. 2008), creates complexity (Vermeulen and Barkema 2002) to cross-border activities and increases the costs of coordination, integration and monitoring (Tan and Mahoney 2006).

The study on distance in relation to EPU has become the main focus of this chapter because i) evidence prove that geographical proximity plays a significant role in the dependence and similarities between EMEs (see for example, Tobler, 1970; Dell'Erba, Baldacci & Poghosyan, 2013; Ghemawat, 2011; Eun & Lee, 2010; Dunning, Kim, & Park, 2008; IMF 2011a, 2011b), but no analysis has been conducted to confirm this argument, ii) studies show that uncertainty increases when the economic characteristics (also termed as economic distance) between countries are different (Malhotra, Sivakumar & Zhu, 2009; Linder, 1961; Beck et al., 2006; Baker, 2017), iii) according to Krol (2018), there is a reduction (or increase) in EPU when countries have similar (or dissimilar) international economic and trade policies, and iv) in this era of globalisation and technological progress where trade and capital flows between countries are significantly determined by the economic distance between countries (Beck et al., 2006; Wilk, 2014), studies conducted has been minimal (Tung & Verbeke 2010) and no study has investigated the relationship between economic distance and EPU. Despite the fact that the globalisation processes has reduced the distance between economies and resulted in the convergence and standardisation of people's values and preferences (Levitt, 1984), countries in this era differ in economic, political, social, cultural, linguistic, and geographical aspects (Ghemawat, 2001). These differences continue to influence international business decisions (Ghemawat, 2001) as well as trade and capital flows because research findings show that higher EPU in EMEs increases exchange rate volatility, which can have a serious impact on trade flows (Krol 2014).

In answering the question of whether there exist a relationship between the differences and similarities of EPU among EMEs and distance between them, this study makes two important contributions. The first contribution of the study is to explore and measure the empirical relationship between economic distance and EPU in the selected EMEs. This implies that, can EPU and macroeconomic variables influence economic distance in EMEs? The findings will aid policymakers in identifying the differences and similarities that exist amongst EMEs as a result of their distinct and similar economic characteristics. Investors will also learn about the patterns of the relationship between economic distance and EPU in the EMEs. Another way to distinguish one emerging country from another is how they respond to uncertainty. Johanson and Vahlne's (1997, 2009) argument that "distance creates uncertainty" forms the theoretical framework of the study. According to Johanson and Vahlne's (1997, 2009) Uppsala model, greater psychic distance between paired countries increases uncertainty in global business expansion. As a result, the distance between economies has a significant impact on trade, investment, and an economy's economic activities. Their research sparked interest in the study of different dimensions of distance beyond psychic distance by observing other characteristics of inter-country connectivity. Administrative or political distance, economic distance, language distance, industrial development distance, financial distance, and socioeconomic distance were discovered in studies (see, for example, Ghemawat, 2001; Dow & Karunaratna, 2006; Berry, Guillen, & Zhou, 2010; Martin Martin & Drogendijk, 2014). Secondly, Beck, Gleditsch and Beardsley (2006) argue that distance does not only relate to geographical locations but rather the measure of distance is based on the connectivity between two locations, for example trade partnership. The economic distance in this study is defined as the extent of (or the distance that reflects) the similarities (or dissimilarities) of economic characteristics between units (or countries) (Dow & Karunaratna, 2006; Brewer, 2007; Johanson & Wiedersheim-Paul, 1975). The economic characteristics as classified by Ghemawat (2001) include economic wealth, quality and cost of natural, financial and human resources. According to Berry et al. (2010) the differences in economic distance can be reflected by economic indicators such as purchasing power, labour cost, macroeconomic stability, or the degree of openness of economies (Berry et al., 2010). Beck, Gleditsch and Beardsley (2006) also argued that distance does not only relate to geographical locations but rather the measure of distance is based on the connectivity between two locations, for example trade partnership. Lastly, according to Linder (1961), the economic distance between trade partners implies that the two countries have different demand structures when it comes to import and export. This difference in demand structures creates uncertainty for trade within countries and hinders intra-industry trade. Therefore, connected countries can generate uncertainty among each other. The EMEs in this research are members of the G20 and have strengthened trade, investment, policy and financial linkages (Schaechter, 2001; Luckhurst, 2016; Adler, 2008). The connectivity between these economies provides a strong argument for the likelihood that there exist an empirical relationship between economic distance and the EPU in EMEs. By adopting the dynamic linear regression method, the study explores and measures the empirical relationship between economic distance and EPU across the selected EMEs. We include other variables which are: import, export, SPX, CPI and broad money in the model.

The second contribution of this study is to adopt a non-parametric geospatial analysis to investigate the spatial dependence between EMEs (with respect to their EPU measures). The analysis of spatial autocorrelations between EMEs provides robust information for policy makes and investors for international portfolio management, policy decision processes and international trade since the study offers country-specific features and characteristics of EMEs based on their geographical proximity from each other. The foundation of the study on spatial analysis is based on Tobler's first law of geography that emphasised that the nearer things are to each other, the more related they are than to distant things (Tobler, 1970). Spatial autocorrelation measures the relationship variations between the values of a variable and its spatial lag (in this study, the variable selected is the EPU index) which are separated by some specific distance (in this study, we choose latitude-longitude coordinates). We then investigate bivariate spatial correlation where we extend the spatial association to EPU and the lag of each of the selected six macroeconomic variables in the study. This investigation has become necessary because recent findings in literature prove that there exist possible spatial cross-country linkages between EPU in EMEs. For example, according to Haining, 2001 one of the causes of spatial autocorrelation is spillovers effects. Dizioli, et al. (2016) and (Russel) 2016 studies has shown evidence of spillovers in EMEs which according to Haining's (2001) argument might be caused by the presence of spatial autocorrelation between economies. The interdependent relationship between EPU and economic activities in EMEs (IMF 2011a, 2011b) implies that EPU and key macroeconomic variables easily influence each other, thereby creating avenues for spillover transmission. Secondly, EMEs have global factors and economic linkages such as geographic proximity, bilateral trade and financial exposure (Jiang, Zhu, Tian & Nie , 2019; Ghemawat, 2001) that are key channels for spatial autocorrelation and spillover shock transmission in EMEs (Trung, 2019). These findings imply that, the concept of spatial (geographical) autocorrelation analysis is applicable to EPU and macroeconomic variables in EMEs. We therefore adopt this concept of spatial analysis to analyse the spatial cross-country linkages between EMEs to ascertain if the spatial correlation between the EPU index values and macroeconomic variables is as a result of the distance between EMEs. The study uses EPU indices as country-specific indicator for the spatial analysis. The spatial weights, neighbourhoods, and autocorrelations are created using the Local Indicators of Spatial Association (LISA) framework. Based on the spatial weights, the Local Moran's I (Moran 1948) statistic is used to access country dependence.

We discover that macroeconomic variables were largely statistically significant and have explanatory power to explain the economic distance between the EMEs. We also discover that changes in the values of import, CPI and broad money in most EMEs are statistically relevant and significantly impacts (or predicts) the values of the economic distance across the selected EMEs. The findings from this Chapter also show evidence of spatial autocorrelation among the EMEs with respect to EPU, GDP, CPI, broad money, share price and trade (export and import of goods and services). The varying results across EMEs and the variables reveal that EPU spatial autocorrelation is country specific and EPU correlates differently with each macroeconomic variable. The results of this spatial analysis is an empirical evidence to previous arguments that geographical proximity plays a significant role in the dependence and similarities between EMEs (see for example, Tobler, 1970; Dell'Erba, Baldacci & Poghosyan, 2013; Ghemawat, 2011; Eun & Lee, 2010; Dunning, Kim, & Park, 2008; IMF 2011a, 2011b).

4.2 Theoretical Models and Empirical Methodology

Although this study employs the dynamic linear regression and spatial econometric method, the objective is not to examine the best fitting model for the measure of EPU distance between developing countries especially because spatial analysis focuses on geographical distance while economic distance focuses on economic similarities and differences. Secondly, the two different models allows us to observe the findings as a result of their different distributional assumptions. Thus, the dynamic linear regression model deals with distributional assumptions of variables while the spatial economic model deals with non-parametric geospatial analysis.

4.2.1 Dynamic linear regression

In order to explore and measure the empirical relationship between economic distance and EPU in the selected EMEs, the study employs the dynamic linear regression method. Since the previous year's economic distance is likely to influence current year's economic distance as countries strive to bridge developmental gaps and the key macroeconomic variables are known to follow a dynamic process, the estimation is done within a dynamic framework. We adopt a dynamic linear regression method to estimate the relationship between economic distance and macroeconomic variables. Although the interface and internals of dynamic linear regression method are very similar to the static linear model, the dynamic linear regression method offers three advantages over the direct use of dynamic linear regression method. We include other variables which are: import, export, SPX, CPI and broad money in the model. We therefore investigate the impact of EPU and selected macroeconomic variables on the economic distance between EMEs.

Economic distance in this study refers to how similar the economic system and metrics are between the emerging countries. This could result from differences in terms of macro-economic indicators such as per capita GDP, economic growth rates, inflation, unemployment rate, rich–poor differences, and access to natural resources (Thai-Ha, 2017). Real GDP is used as proxy for economic distance. GDP was selected because, aside from the fact that GDP is a generally approved measure of economic distance (Malhotra, Sivakumar, & Zhu, 2009; Tsang & Yip 2007; Berry et al., 2010; Ghemawat, 2001), GDP is also a strong economic and trade policy indicator and a key quantifiable economic indicator for measuring and maximising economic policies in an economy (Lindstrom, 2008) as well as in an international context (OECD, 2002). Also, according to Wolverson (2013) economists have endorsed that GDP reflects the impacts of monetary policies, tax policies and spending policies in an economy and serves as a guide to policy making. GDP also reflects the overall growth, performance and economic activities of a country. This includes all goods and services in the countries. The real GDP is used instead of normal GDP because the real GDP (also referred to as inflation-corrected GDP) unlike nominal GDP is adjusted for inflation. Real GDP accounts for changes in price levels which help to differentiate an actual increase in production from an increase in per-unit price. This study measures the economic distance between emerging countries as the difference between the real GDP of two EMEs (this method was also been used by Thai-Ha, 2017 and Tsang, & Yip, 2007). The relationship between economic distance and EPU across pairs of the six developing countries under study are estimated. We select one EME at a time and pair the selected EME with each of (the rest of) the five (5) EMEs for the analysis. At each point in time the selected EME is identified as the host country (*h*) while the remaining five EMEs are identified as the partner economies (*i*). For each EME, five (5) regression analyses were conducted. Specifically, the economic distance between emerging countries is the host (*h*) economy's real GDP minus the real GDP of a partner (*i*) economy.

Following the above discussion, the dynamic linear regression model for the analysis is presented below:

$$ECONDIS_{hit} = \beta_{1,t} + \beta_{2,t}hEPU_t + \beta_{3,t}iEPU_t + \beta_{4,t}hEXP_t + \beta_{5,t}iEXP_t + \beta_{6,t}hIMP_t + \beta_{7,t}iIMP_t$$

$$+\beta_{8,t}hSPX_t + \beta_{9,t}iSPX_t + \beta_{10,t}hCPI_t + \beta_{11,t}iCPI_t + \beta_{12,t}hBRM_t + \beta_{13,t}iBRM_t$$

$$+\epsilon_{hit} \tag{4.1}$$

Where, h is host country, i is partner countries. It's important to note that country analysis are made for each of the six (6) EMEs. In which $ECONDIS_{hit}$ is the economic distance between the host country (h) and partner country (i) at year t, calculated by taking difference between the GDPs of host country and partner country. $hEPU_t$ and $iEPU_t$ is the value of EPU indicator from host country and partner country respectively at year t. $hEXP_t$ and $iEXP_t$ is the value of export indicator from host country and partner country respectively at year t. $hIMP_t$ and $iIMP_t$ is the value of import indicator from host country and partner country respectively at year t. $hSPX_t$ and $iSPX_t$ is the value of SPX indicator from host country and partner country respectively at year t. $hCPI_t$ and $iCPI_t$ is the value of CPI indicator from host country and partner country respectively at year t. $hBRM_t$ and $iBRM_t$ is the value of broad money indicator from host country and partner country respectively at year t. Where, $\beta_{1,t}$, $\beta_{2,t}$, $\beta_{3,t}$, $\beta_{4,t}$, $\beta_{5,t}$, $\beta_{6,t}$, $\beta_{7,t}$, $\beta_{8,t}$, $\beta_{9,t}$, $\beta_{10,t}$, $\beta_{11,t}$, $\beta_{12,t}$, $\beta_{13,t}$ are time varying regression parameters and ϵ_{hit} is the error term.

4.2.2 Spatial Autocorrelation

Using nonparametric geospatial analysis, this study derives the spatial weights for use in identifying developing economies' neighbours. To investigate if distance can influence the similarities or dissimilarities between EPU among developing countries, the study deploy the local Moran's I (Moran, 1984) as the measure of spatial autocorrelation. Spatial weights, neighbourhoods, and autocorrelations are non-parametrically generated using the GeoDa software. The Moran's I produces a scatter plot that categorises spatial autocorrelation into four classes shown by four quardrants that makes it easy to detect positive and negative autocorrelation. Finding the neighbours of each developing country is based on the distance weight function. The spatial weights, neighbourhoods, and autocorrelations are created using the Local Indicators of Spatial Association (LISA) framework. Based on spatial weights the Local Moran's I statistic is used to access country dependence.

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

$$L_i = f(y_i, yJ_i), \tag{4.2}$$

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. 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

$$I_i = z_i \sum_j w_{ij z_j}, \tag{4.3}$$

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}

$$w_{ij} = f\left(d_{ij}, \theta\right), \tag{4.4}$$

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 i 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, Sridharan, & Gholston, 2007).

4.3 Data, sample, and preliminary analysis

The available data for the economic distance and spatial correlation analysis ranges from 01/01/1999 to 31/12/2018. There are EPU indices and macroeconomic data for six (6) EMEs that are also members of the G20: Brazil, China, India, Korea, Mexico and Russia. The economic distance is calculated using a monthly time series. The study measures the economic distance between EMEs as the difference between the real GDP of two EMEs (this method was also been used by Thai-Ha, 2017 and Tsang, & Yip, 2007). The relationship between the economic distance and EPU of the selected EMEs are estimated by selecting one EME at a time and pairing it with the other EMEs. The spatial analysis focuses on the presence or absence of spatial autocorrelation among the EMEs. As a result, the study computes the aggregate of the monthly EPU index for each EME from 01/01/1999 to 31/12/2018 to represent the EPU value of each EME for the spatial analysis. The aggregates of the selected macroeconomic variables are also computed. The EPU indices were obtained from www.policyuncertainty.com. The macroeconomic variables data were obtained from the OECD database.

4.4 Empirical Results

4.4.1 Economic Distance

The study employs the dynamic linear regression method to investigate the empirical relationship between economic distance and EPU in the selected EMEs. The parameters of the explanatory variables (which are EPU, import, export, SPX, CPI and broad money) are tested using their t-value and p-values. The hypothesis for the test is stated below:

H_0: There is no relationship between economic distance and the explanatory variables.

H_1: There is a relationship between economic distance and the explanatory variables.

The study adopts to use 1%, 5% and 10% level of significance. Thus, if the p-value is less than 0.01, 0.05, and 0.1, we reject H_0 at 1%, 5% and 10% level of significance respectively. Otherwise we fail to reject H_0. If H_0 is rejected, it means that the variable is relevant to explain the economic distance between the economies. Table 4.1 displays the dynamic linear regression method solutions for the selected EMEs. For each cell the estimates are displayed with the equivalent standard errors in parenthesis. Asterisks are used to denote significant levels. Whhere ***, ** and * represents 1%, 5% and 10% significance levels respectively. It is clear that there are just a few evidence of a relationship between the pairs of economic distance and the explanatory variables across the selected EMEs even from the 10% significance level. We also observe that except in some few cases EPU does not have an explanatory power in the model is is not relevant to explain or drive the changes in the values of the economic distance between the selected EMEs. Lastly, we record that findings are specific to each pair of EMEs. It is important to note that a positive t-value sign indicates a positive relationship between economic distance and the explanatory variable while a negative sign indicates a negative relationship.

A focus on Brazil shows that changes in the values of economic distance are explained by some of the explanatory variables. Table 4.1 with the estimate values in parenthesis shows that Brazil-import (0.00376356), Brazil-CPI (-0.12873542), Brazil-broad money (0.06754254), China-import (0.00441998), China-CPI (0.03152483) and China- broad money (-0.10509860) have explanatory power in the model and are all relevant to explain the economic distance between Brazil and China at (5%, 1%, 1%, 1%, 5% and 1% significance levels respecyively). The findings implies that, for each extra Brazil-import, Brazil-broad money, China-import and China-CPI, the economic distance between Brazil and China increases. On the otherhand, for each extra rate of Brazil-CPI and China- broad money, economic distance between Brazil and China decreases. Second, with respect to Brazil and India, the variations in the economic distance between Brazil and India can be explained by Brazil-import (0.00542691), Brazil-CPI (-0.11028694) and India-broad money (-0.05662227). Their levels of significance are 5%, 1%, and 10% respecitively. Likewise, this implies that for each extra Brazil-import economic distance between Brazil and India increases and for each extra rate of Brazil-CPI and Brazil-broadmoney the economic distance between Brail and Indai decreases. Third, the economic distance between Brazil and Korea records that, Brazil-import (0.00436203), Brazil-CPI (-0.08372453), Korea-import (0.00570122), Korea-SPX (-0.00673976) and Korea-broad money (-0.06528969) as the explanatory variables that drive the changes in economic distance values. Their levels of significance are 5%, 1%, 10%, 5%, and 10% respecitively. This implies that the economic distance between Brazil and Korea is positively influenced by Brazil-import and Korea-import. On the otherhand we record a negative relationship for Brazil-CPI, Korea-SPX and Korea-broadmoney. Forth, the economic distance between Brazil and Mexico records Brazil-CPI (-0.11730136), Mexico-export (0.00888921) and Mexico-CPI (0.06281347) as the explanatory variables that are relevant to explain the economic distance between Brazil and Mexico. Their levels of significance are 1%, 10%, and 5% respecitively.The findings implies that, for each extra Mexico-export and Mexico-CPI, the economic distance between Brazil and Mexico increases. On the otherhand we record a negative relationship between economic distance and Brazil-CPI. Lastly, we identify that Brazil-CPI (-0.09634610) and Russia-export (0.00354890) has explanatory power to drive the changes in the values of the economic distance between Brazil and Russia. Their levels of significance are 1%, and 10% respecitively.

The findings on the economic distance between Brazil and the other EMEs show that the variables that affect economic distance between the EMEs are import, export, CPI and broadmoney. This implies that these macroeconomic variables significantly explain the economic distance between Brazil and the other EMEs. This confirms the theoritcal expectation that trade and institutional dstance (CPI and broad money) has an explanatory power in explaining economic distance between economies. This finding also suppots previous studies that argue that trade is significant channel of economic distance (IMF, 1997, Harrison, 1996; Novy & Taylor, 2014). Also, we ascertain that broad money which represents monetary policy activities as well as CPI which is an inflation indicator and a measure of economic policy activities (related to the purchasing power of domestic money) influence economic distance. This finding is supported by Malhotra, Lin and Farrell's (2016) and Ghemawat (2001) who argue that the institutional distance difference in policy measures and financial associations has a significant impact on the similarities and dissimilarities between economies. We discover that EPU has no explanatory power over economic distance in Brazil. Governemt and policy makers should therefore focus on strengthening the trade agreements between their trade partners since, these policies targeted at promoting foreign trade are important factors that significantly boost economic growth and convergence in EMEs (IMF, 1997; Harrison, 1996).

This next session focuses on the economic distance between China and the other selected EMEs. The economic distance between China and Brazil records a relationship with China-import (-

0.00441998), China-CPI (-0.03152483), China-broad money (0.10509860), Brazil-import (-0.00376356), Brazil-CPI (0.12873542) and Brazil-broad money (-0.06754254). Their levels of significance are 1%, 5%, 1%, 5%, 1% and 1% significance levels. These findings imply that an extra increase in China-broad money and Brazil-CPI leads to an increase in the economic distance between China and Brazil. On the otherhand, an extra increase in China-import, China-CPI, Brazil-import and Brazil-broad money leads to a decrease in the economic distance between China and Brazil. There was no evidence of a relationship between the explanatory variables and the economic differencies and similarities between China and India cannot be explained by the explanatory variables. Hence the economic activities between China and India do not influence their economic distance. Third, moving on to the economic distance between China and Korea we find evidence of a relationship between economic distance and Korea-SPX (-0.00626200) and Korea-broad money (-0.07695484). The level of signifance for both explanatory variables is 1% level of significance. Hence, stock market and monetary policy activities are significant in explaining the economic distance between China and Korea. Forth, the variations in the values of the economic distance between China and Mexico can be explained by China-SPX (0.00368205), China-broad money (0.07171705), Mexico-import (-0.01136225), Mexico SPX (-0.00439313) and Mexico-broad money (-0.02418565). Their levels of significance are 5%, 1%, 5%, 5%, and 5% respectively. Hence, China SPX, China-broad money, Mexico-import, Mexico-SPX and Mexico-broad money has explanatory and are therefore significant in explaining the economic distance between China and Mexico. The last output for China investigates the economic distance between China and Russia. It is evident that China-broad money (0.08161525), Russia-import (-0.00842975), Russia-SPX (-0.00231398), Russia-CPI (-0.03122287) and Russia-broad money (-0.01683817) drive changes in the economic distance between China and Russia. Their levels of significance are 1%, 1%, 10%, 10%, and 1% respectively. It is also clear from the findings in China that, import, CPI, broad money and SPX have an explanatory power to explain the economic distance between China and the other EMEs. As recorded in Brazil, EPU has no explanatory power in explaining the economic distance between China and the other EMEs. Hence, trade and capital flows significantly influence the economic distance between the economies. Investors are therefore advised to invest with economies with similar economic characteristics.

A study on India records only a few evidence of a relationship between economic distance and some of the explanatory variables. The economic distance between India and Brazil shows that India-broad money (0.05662227), Brazil-import (-0.00542691) and Brazil-CPI (0.11028694) have explanatory power in the model and are all relevant to explain the economic distance between India and Brazil. Their levels of significants are 10%, 5% and 1% respectively. Thus the economic distance between India and Brazil records a positive relationship with India-broad money and Brazil-CPI. This implies that an increase in broad money and inflation creates more distance between the economies. On the otherhand, an increase in Brazil-import leads to a decrease in the economic distance between India and Brazil. This finding implies that the similarities between the two economies are strengthened through trade. These findings apply to all the results pertaining to the economic distance between India and the other EMEs. We do not record any evidence of a relationship between the explanatory variables and the economic distance between India and China. The economic distance between India and Korea has a relationship with India-EPU (-0.00046954), India-broad money (0.04625919), Korea-import (-0.00526902) and Korea-broad money (-0.09271351). Their levels of significants are 10%, 10%, 5% and 1% respectively. The findings show that except for India-broad money, India-EPU, Korea-import and Korea-broad money have negative relationships with the economic distance between India and Korea. Hence an increase in these variables reduces the dissimilarities between the two economies. In other words, an increase in India-EPU, Korea-import and Korea-broad money reduces the economic distance between the economic. This findings also support studies that argue that the trade and economic policies between countries reduces the dictance between them, thereby increasing the investment level and business development between the two economies. We futher discover that, India-EPU influences the economic distance between India and Mexico. The negative relationship implies that an extra increase in India-EPU reduces the economic distance between the two economies. This finding support studies that argue that an increase in uncertainty significantly influences economic activities (see, Makino & Tsang, 2011; Linder 1961; Tobler, 1970; Johanson & Wiedersheim-Paul, 1975; Szulanski, 1996; and Tung & Verbeke 2010). Fourthly, the variations in the values of the economic distance between India and Mexico can be explained by Mexico-import (-0.0117152) and Mexico-broad money (-0.0238551). Their levels of significance are 5% for both explanatory variables. Again we record that import and broad money negatively influeneces the economic distance between India and Mexico. Last, for the economic distance between India and Russia, we record that, India-SPX (0.000450756) Russia-export (-0.00405423) and Russia-import (-0.00761453) have the explanatory power to explain the variations in the economic distance. Their levels of significance are 10%, 10% and 5% respectively. We can infere form the analysis of India that exp, import, broad money SPX, CPI, and EPU have an explanatory power in explaining the economic distance between India and the other EMEs. We futher record that, only one case where India-EPU causes the economic distance between the two EMEs. However, import and broad money have the largest records as explanatory variables in the analysis on India. This implies that trade and institutional factors inflences the economic distance between economies. The government and policy makers should therefore focus on strengthening the trade agreements between the economies as well as implement economic and monetary polices that can promote investment and stabilise uncertainty so as to increase the level of economic activites in these economies.

A focus on Korea also shows that changes in the values of economic distance are explained by some of the explanatory variables. Table 4 shows that Korea-import (-0.00570122), Korea-SPX (0.00673976), Brazil-import (-0.00436203) and Brazil- CPI (0.08372453) are the explanatory variables that have explanatory power in the model and are also relevant in explaining the economic distance between Korea and Brazil. The levels of signifance are 10%, 5%, 5% and 1% respectively. Likewise, the variations in the values of the economic distance between Korea and China can be explained by Korea-SPX (0.00626200) and Korea-broad money (0.07695484) as 1% significance level. The economic distance between Korea and India records that, Korea-import (0.00526902), Korea-broad money (0.09271351), India-EPU (0.00046954) and India-broad money (-0.04625919) as the explanatory variables that drive the changes in economic distance values at 5%, 1%, 10% and 5% significance level. The economic distance between Korea and Mexico records Korea-SPX (0.009911108), Korea-broad money (0.091830879), Mexico-SPX (0.005823339) and Mexico-CPI (0.055398806) as the explanatory variables that are relevant to explain the economic distance between Korea and Mexico. The significance levels are 1%, 1%, 5% and 10% respectively. Lastly, we identify that Korea-SPX (0.00647383) and Russia-import (0.00670225) have the explanatory power to drive the changes in the values of the economic distance between Korea and Russia. We can conclude from these findings that, import, broad money, SPX, and CPI have exploratory in explain the economic distance between Korea and the other EMEs. This finding is support by Malhotra, Lin and Farrell's (2016) and Ghemawat (2001) who argue that the institutional distance (difference) in policy measures and financial associations has a significant impact on the similarities and dissimilarities between economies. On the otherhand export, export has no explanatory power over the economic distance between the Korea and the other EMEs. Based on the argument that policies targeted at promoting foreign trade are important factors that significantly boost economic growth and convergence in EMEs (IMF, 1997, Harrison, 1996), the government and policy makers in Korea should make efforts to implement incentives to promote export-oriented investments such as simplying their administrative procedure, investing in export processing zones and creating policies that will attract foreign investment in export production. These measures will increase the economic similarities between economies that will promote Korea's export to the other EMEs.

This session focuses on the economic distance between Mexico and the other selected EMEs as displayed in Table 4.1. The economic distance between Mexico and Brazil records a relationship with Mexico-export (-0.00888921), Mexico-CPI (-0.06281347) and Brazil-CPI (0.11730136). Their levels of significance are 10%, 5% and 1% respectively. The negative sign depicts a negative relationship and a positive sign depicts a positive relationship. For the economic distance between Mexico and China, we record that Mexico-import (0.01136225), Mexico-SPX (0.00439313), Mexico-broad money (0.02418565), China-SPX (-0.00368205) and China-broad money (-0.07171705) have the explanatory power to drive the outcomes of economic distance between Mexico and China. Moving on to the economic distance between Mexica and India we find evidence of a positive relationship between economic distance and Mexico-import (0.0117152) and Mexico-broad money (0.0238551). Thence, Mexico-import and Mexico- broad money have the explanatory power to explain the economi distance between Mexico and India. The variations in the values of the economic distance between Mexico and Korea can be explained by Mexico-SPX (0.005823339), Mexico-CPI (-0.055398806), Korea-SPX (-0.009911108) and Korea-broad money (-0.091830879). The last output for Mexico investigates the economic distance between Mexico and Russia. It is evident that Mexico-CPI (-0.05851932), Mexico-broad money (-0.02254009), Russia-import (-0.00437229) and Russia-SPX (-0.00241334) drive changes in the economic distance between Mexico and Russia. In the case of Russia, the findings show a large record of negative relationships. EXP has a negative relationship with the economic distance between Mexico and Brazil. This implies that an extra increase in Mexico-EPU leads to a decrease in (or reduces) the economic distance between the two economies. This finding is similar to studies that argue that EPU influences economic distance (Novy & Taylor, 2014; Malhotra, Lin & Farrell, 2016). The positive relationship between economic distance and the explanatory variables (CPI, SPX, import and broad money) implies that an extra increase in any of this variables leads to an increase in (or increases) the economic distance between economies. On the otherhand, the negative relationship between economic distance and the explanatory variables (EPU, CPI, , SPX and broad money) means that an increase in these variable leads to a decrease in the economic distance between the two economies. The objectives of an economy is to create similar economic systems since this promotes foreign trade and convergence of economies (IMF, 1997, Harrison, 1996). Hence, policy makers must ensure that the economic and monteray polices should encourage trade and capital. Hence it’s important for policy makers to investigate the possible causes of the explanatory variables that cause an increase in the economic distance between economies as a result of an increase in import. Some possible reasons are that, an incearse in import maybe as a result of the changes in the monetary, government investments decisions and trade tariffs. These changes might create more differences between the economies, thereby increasing the esonomic distance between the two economies.

The study on Russia also records a few evidence of a relationship between economic distance and the explanatory variables. Table 4.1 shows that Brazil-export (-0.00354890) and Brazil-CPI (0.09634610) are the explanatory variables that is relevant to explain the economic distance between Russia and Brazil. The levels of signifance are 10% and 1% respectively. In this situation, an extra value in export, the economic distance between the two economies decreases. A change in the amount of export is largely attributed to a change in the terms of trade. The changes in the terms of trade of one economy can create economic differences between its parther countries. For the economic distance between Russia and China, we record a relationship between Russia-import (0.00842975), Russia-SPX (0.00231398), Russia-CPI (0.03122287), Russia-broad money (0.01683817) and China-broad money (-0.08161525). The economic distance between Russia and India has a relationship with Russia-export (0.00405423), Russia-import (0.00761453) and India-SPX (-0.00450756). Fourthly, the variations in the values of the economic distance between Russia and Korea can be explained by Russia-import (0.00670225) and Korea-SPX (0.00647383). And lastly, for the economic distance between Russia and Mexico, we record that, Russia-import (0.00437229), Russia-SPX (0.00241334), Mexico-CPI (0.05851932) and Mexico-broad money (0.02254009) have the explanatory powers to explain the variations in the economic distance.

Considering the fact that these EMEs are members of the G20 and have strengthened trade, investment and financial linkages (Schaechter, 2001), as well as economic interdependence (Luckhurst, 2016), it is clear that these EMEs are not independent of each other (Mazurek, 2012).

This trade, financial and economic linkages between the EMEs is reflected in this study through the explanatory power import, broad money, CPI and SPX have on the variations of the values of economic distance between the EMEs. Hence, it is evident that import, broad money, CPI and SPX form strong links between the EMEs which explains why these particular explanatory variables influence the economic distance between the EMEs. This finding is also supported by Beck, Gleditsch and Beardsley's (2006) argument that distance does not only relate to geographical locations but rather, the measure of distance is based on the connectivity between two locations. In other words, the trade and capital flows between the selected EMEs significantly influence the economic distance between the economies.

Table 4.1: Dynamic linear regression results for selected EMEs

BRAZIL					
ECONOMIC DISTANCE BETWEEN BRAZIL AND CHINA					
BRA.EPU	BRA.EXP	**BRA.IMP**	BRA.SPX	**BRA.CPI**	**BRA.BRM**
-0.00006595	0.00265115	**0.00376356**	0.00167433	**-0.12873542**	**0.06754254**
(0.00018667)	(0.00163081)	**(0.00161304)****	(0.00160597)	**(0.02654907)*****	**(0.01771600)*****
CHI.EPU	CHI.EXP	**CHI.IMP**	CHI.SPX	**CHI.CPI**	**CHI.BRM**
-0.00026329	0.00036989	**0.00441998**	-0.00262579	**0.03152483**	**-0.10509860**
(0.00026022)	(0.00158714)	**(0.00160279)*****	(0.00163930)	**(0.0168813)****	**(0.01978777)*****
ECONOMIC DISTANCE BETWEEN BRAZIL AND INDIA					
BRA.EPU	BRA.EXP	**BRA.IMP**	BRA.SPX	**BRA.CPI**	BRA.BRM
0.00006934	0.00047288	**0.00542691**	0.00117471	**-0.11028694**	0.02370386
(0.00026625)	(0.00230033)	**(0.00229746)****	(0.00277911)	**(0.03779069)*****	(0.02509114)
IND.EPU	IND.EXP	IND.IMP	IND.SPX	IND.CPI	**IND.BRM**
0.00041917	0.00194799	0.00234318	-0.00235509	0.00235925	**-0.05662227**
(0.00038846)	(0.00222838)	(0.00206226)	(0.00316430)	(0.01877438)	**(0.03054649)***
ECONOMIC DISTANCE BETWEEN BRAZIL AND KOREA					
BRA.EPU	BRA.EXP	**BRA.IMP**	BRA.SPX	**BRA.CPI**	BRA.BRM
-0.00002018	0.00073935	**0.00436203**	0.00188663	**-0.08372453**	0.01028798
(0.00021374)	(0.00184784)	**(0.00183963)****	(0.00217365)	**(0.03026340)*****	(0.02016213)
KOR.EPU	KOR.EXP	**KOR.IMP**	**KOR.SPX**	KOR.CPI	**KOR.BRM**
-0.00001705	0.00022069	**0.00570122**	**-0.00673976**	0.03731028	**-0.06528969**
(0.00033081)	(0.00248735)	**(0.00308337)***	**(0.00260891)****	(0.03118525)	**(0.03582828)***
ECONOMIC DISTANCE BETWEEN BRAZIL AND MEXICO					
BRA.EPU	BRA.EXP	BRA.IMP	BRA.SPX	**BRA.CPI**	BRA.BRM
-0.00005880	0.00003545	0.00253659	0.00085404	**-0.11730136**	-0.00164390
(0.00020843)	(0.00181671)	(0.00181076)	(0.00241787)	**(0.02934968)*****	(0.01984574)

MEX.EPU	**MEX.EXP**	MEX.IMP	MEX.SPX	**MEX.CPI**	MEX.BRM
-0.00026593	**0.00888921**	-0.00280635	-0.00054826	**0.06281347**	-0.00656389
(0.00024632)	**(0.00533319)***	(0.00545805)	(0.00318908)	**(0.03134162)****	(0.01259634)

ECONOMIC DISTANCE BETWEEN BRAZIL AND RUSSIA

BRA.EPU	BRA.EXP	BRA.IMP	BRA.SPX	**BRA.CPI**	BRA.BRM
0.00009716	-0.00022652	0.00306542	-0.00085437	**-0.09634610**	0.00230074
(0.00022721)	(0.00198778)	(0.00195055)	(0.00229095)	**(0.03422723)*****	(0.02229849)
RUS.EPU	**RUS.EXP**	RUS.IMP	RUS.SPX	RUS.CPI	RUS.BRM
-0.00009805	**0.00354890**	-0.00175890	-0.00088717	-0.01248484	-0.00851073
(0.00018486)	**(0.00205826)***	(0.00264310)	(0.00182726)	(0.02086276)	(0.00704812)

CHINA

ECONOMIC DISTANCE BETWEEN CHINA AND BRAZIL

CHI.EPU	CHI.EXP	**CHI.IMP**	CHI.SPX	**CHI.CPI**	**CHI.BRM**
0.00026329	-0.00036989	**-0.00441998**	0.00262579	**-0.03152483**	**0.10509860**
(0.00026022)	(0.00158714)	**(0.00160279)*****	(0.00163930)	**(0.01596240)****	**(0.01978777)*****
BRA.EPU	BRA.EXP	**BRA.IMP**	BRA.SPX	**BRA.CPI**	**BRA.BRM**
0.00006595	-0.00265115	**-0.00376356**	-0.00167433	**0.12873542**	**-0.06754254**
(0.00018667)	(0.00163081)	**(0.00161304)****	(0.00160597)	**(0.02654907)*****	**(0.01771600)*****

ECONOMIC DISTANCE BETWEEN CHINA AND INDIA

CHI.EPU	CHI.EXP	CHI.IMP	CHI.SPX	CHI.CPI	CHI.BRM
0.0001689433	-0.0000001538	0.0010649225	0.0004202291	0.0115745851	0.0005762179
(0.0002397687)	(0.0015065714)	(0.0014907079)	(0.0015304755)	(0.0150208778)	0.0182428156)
IND.EPU	IND.EXP	IND.IMP	IND.SPX	IND.CPI	IND.BRM
0.0001904573	0.0013695856	0.0000114836	-0.0020314045	0.0077006580	-0.0152880718
(0.0002557888)	(0.0014925724)	(0.0013515913)	(0.0017684059)	(0.0124101069)	(0.0197980011)

ECONOMIC DISTANCE BETWEEN CHINA AND KOREA

CHI.EPU	CHI.EXP	CHI.IMP	CHI.SPX	CHI.CPI	CHI.BRM
0.00010756	-0.00095672	0.00077432	0.00192284	0.01624548	0.02054796
(0.00025321	(0.00148338)	(0.00177351)	(0.00151702)	(0.01593173)	(0.01838087)
KOR.EPU	KOR.EXP	KOR.IMP	**KOR.SPX**	KOR.CPI	**KOR.BRM**
-0.00012573	-0.00243053	-0.00105590	**-0.00626200**	0.00802497	**-0.07695484**
(0.00027994)	(0.00214387)	(0.00262210)	**(0.00183367)*****	(0.02679290)	**(0.02948619)*****

ECONOMIC DISTANCE BETWEEN CHINA AND MEXICO

CHI.EPU	CHI.EXP	CHI.IMP	**CHI.SPX**	CHI.CPI	**CHI.BRM**
0.00008953	0.00228102	-0.00069781 (-	**0.00368205**	-0.00123744	**0.07171705**
(0.00023369)	(0.00141481)	0.00069781)	**(0.00144335)****	(0.01454579)	**(0.01774142)*****
MEX.EPU	MEX.EXP	**MEX.IMP**	**MEX.SPX**	MEX.CPI	**MEX.BRM**
-0.00016067	-0.00142772	**-0.01136225**	**-0.00439313**	0.00746207	**-0.02418565**
(0.00019705)	(0.00426358)	**(0.00438960)****	**(0.00187544)****	(0.02543013)	**(0.01013059)****

ECONOMIC DISTANCE BETWEEN CHINA AND RUSSIA

CHI.EPU	CHI.EXP	CHI.IMP	CHI.SPX	CHI.CPI	**CHI.BRM**
-0.00021094	-0.00003919	0.00138239	0.00161764	0.00280471	**0.08161525**
(0.00027886)	(0.00175823)	(0.00178853)	(0.00174856)	(0.01752908)	**(0.02104572)*****

RUS.EPU	RUS.EXP	**RUS.IMP**	**RUS.SPX**	**RUS.CPI**	**RUS.BRM**
0.00007769	-0.00190551	**-0.00842975**	**-0.00231398**	**-0.03122287**	**-0.01683817**
(0.00016714)	(0.00180309)	**(0.00241732)*** **	**(0.00139929)***	**0.01728094)***	**(0.00630061)*****

INDIA

ECONOMIC DISTANCE BETWEEN INDIA AND BRAZIL

IND.EPU	IND.EXP	IND.IMP	IND.SPX	IND.CPI	**IND.BRM**
-0.00041917	-0.00194799	-0.00234318	0.00235509	-0.00235925	**0.05662227**
(0.00038846)	(0.00222838)	(0.00206226)	(0.00316430)	(0.01877438)	**(0.03054649)***
BRA.EPU	BRA.EXP	**BRA.IMP**	BRA.SPX	**BRA.CPI**	BRA.BRM
-0.00006934	-0.00047288	**-0.00542691**	-0.00117471	**0.11028694**	-0.02370386
(0.00026625)	(0.00230033)	**(0.00229746)****	(0.00277911)	**(0.03779069)*****	(0.02509114)

ECONOMIC DISTANCE BETWEEN INDIA AND CHINA

IND.EPU	IND.EXP	IND.IMP	IND.SPX	IND.CPI	IND.BRM
-0.0001904573	-0.0013695856	-0.0000114836	0.0020314045	-0.0077006580	0.0152880718
(0.0002557888)	(0.0014925724)	(0.0013515913)	(0.0017684059)	(0.0124101069)	(0.0197980011)
CHI.EPU	CHI.EXP	CHI.IMP	CHI.SPX	CHI.CPI	CHI.BRM
-0.0001689433	0.0000001538	-0.0010649225	-0.0004202291	-0.0115745851	-0.0005762179
(0.0002397687)	(0.0015065714)	(0.0014907079)	(0.0015304755)	(0.0150208778)	(0.0182428156)

ECONOMIC DISTANCE BETWEEN INDIA AND KOREA

IND.EPU	IND.EXP	IND.IMP	IND.SP	IND.CPI	**IND.BRM**
-0.00046954	0.00022147	-0.00007221	0.00131658	-0.00299085	**0.04625919**
(0.00026086)*	(0.00149179)	(0.00135499)	(0.00209574)	(0.01236771)	**(0.01968468)****
KOR.EPU	KOR.EXP	**KOR.IMP**	KOR.SPX	KOR.CPI	**KOR.BRM**
-0.00004046	-0.00018535	**-0.00526902**	-0.00352410	0.00902471	**-0.09271351**
(0.00027431)	(0.00203672)	**(0.00254959)****	(0.00217120)	(0.02522969)	**(0.02941525)*****

ECONOMIC DISTANCE BETWEEN INDIA AND MEXICO

IND.EPU	IND.EXP	IND.IMP	IND.SPX	IND.CPI	IND.BRM
-0.0003074	-0.0014388	-0.0022685	0.0023825	-0.0188880	0.0120868
(0.0002849)	(0.0016371)	(0.0015750)	(0.0022465)	(0.0142029)	(0.0221269)
MEX.EPU	MEX.EXP	**MEX.IMP**	MEX.SPX	MEX.CPI	**MEX.BRM**
0.0001080	-0.0013715	**-0.0117152**	0.0014067	- 0.0225348	**- 0.0238551**
(0.0002310)	(0.0049735)	**(0.0051803)****	(0.0026249)	(0.0301705	**(0.0118029)****

ECONOMIC DISTANCE BETWEEN INDIA AND RUSSIA

IND.EPU	IND.EXP	IND.IMP	IND.SPX	IND.CPI	IND.BRM
-0.00027500	-0.00113966	-0.00072192	0.00450756	0.00796839	0.01091105
(0.00033852)	(0.00192885)	(0.00180227)	(0.00249939)*	(0.01657319)	(0.02606365)
RUS.EPU	**RUS.EXP**	**RUS.IMP**	RUS.SPX	RUS.CPI	RUS.BRM
0.00005457	**-0.00405423**	**-0.00761453**	-0.00152044	-0.01448873	-0.00930838
0.00019060)	**(0.00205848)***	**(0.00266244)****	(0.00173673)	(0.02032630)	(0.00706659)

KOREA

ECONOMIC DISTANCE BETWEEN KOREA AND BRAZIL

KOREA.EPU	KOR.EXP	**KOR.IMP**	**KOR.SPX**	KOR.CPI	KOR.BRM
0.00001705	-0.00022069	**-0.00570122**	**0.00673976**	-0.03731028	0.06528969
(0.00033081)	(0.00248735)	**(0.00308337)***	**(0.00260891)****	(0.03118525)	(0.03582828)
BRA.EPU	BRA.EXP	**BRA.IMP**	BRA.SPX	BRA.CPI	BRA.BRM
0.00002018	-0.00073935	**-0.00436203**			

(0.00021374)	(0.00184784)	**(0.00183963)****	-0.00188663	0.08372453	-0.01028798
			(0.00217365)	(0.03026340)***	(0.02016213)

ECONOMIC DISTANCE BETWEEN KOREA AND CHINA

KOREA.EPU	KOR.EXP	KOR.IMP	**KOR.SPX**	KOR.CPI	**KOR.BRM**
0.00012573	0.00243053	0.00105590	**0.00626200**	-0.00802497	**0.07695484**
(0.00027994)	(0.00214387)	(0.00262210)	**0.00183367)*****	(0.02679290)	**(0.02948619)*****
CHI.EPU	CHI.EXP	CHI.IMP - -	CHI.SP X	CHI.CP	CHI.BRM
-0.00010756	0.00095672	0.00077432	-0.00192284	-0.01624548	-0.02054796
(0.00025321)	(0.00148338)	(0.00177351)	(0.00151702)	(0.01593173)	(0.01838087)

ECONOMIC DISTANCE BETWEEN KOREA AND INDIA

KOREA.EPU	KOR.EXP	**KOR.IMP**	KOR.SPX	KOR.CPI	**KOR.BRM**
0.00004046	0.00018535	**0.00526902**	0.00352410	-0.00902471	**0.09271351**
(0.00027431)	(0.00203672)	**(0.00254959)****	(0.00217120)	(0.02522969)	**(0.02941525)*****
IND.EPU	IND.EXP	IND.IMP	IND.SPX	IND.CP	**IND.BRM**
0.00046954	-0.00022147	0.00007221	-0.00131658	0.00299085	**-0.04625919**
(0.00026086)*	(0.00149179)	(0.00135499)	(0.00209574)	(0.01236771)	**(0.01968468)****

ECONOMIC DISTANCE BETWEEN KOREA AND MEXICO

KOREA.EPU	KOR.EXP	KOR.IMP	**KOR.SPX**	KOR.CPI	**KOR.BRM**
-0.000301270	0.002293980	-0.003889818	**0.009911108**	0.010439177	**0.091830879**
(0.000301221)	(0.002200588)	(0.002824645)	**(0.009911108)*****	(0.027887911)	**(0.032165609)*****
MEX.EPU	MEX.EXP	MEX.IMP	**MEX.SPX**	**MEX.CPI**	MEX.BRM
-0.000009376	0.001569885	-0.008100388	**-0.005823339**	**0.055398806**	0.001040575
(0.000231283)	(0.004893355)	(0.005142049)	**(0.002854321)****	**(0.028500829)***	(0.011502665)

ECONOMIC DISTANCE BETWEEN KOREA AND RUSSIA

KOREA.EPU	KOR.EXP	KOR.IMP	**KOR.SPX**	KOR.CPI	KOR.BRM
-0.00021109	0.00311648	-0.00264394	**0.00647383**	-0.00313822	0.01773821
(0.00029466)	(0.00215181)	(0.00272615)	**(0.00220090)*****	(0.02719020)	(0.03162124)
RUS.EPU	RUS.EXP	**RUS.IMP**	RUS.SPX	RUS.CPI	RUS.BRM
0.00002057	-0.00271993	**-0.00670225**	-0.00110287	0.01759763	-0.00661966
(0.00015236)	(0.00169911)	**(0.00220774)*****	(0.00141600)	(0.01604052)	(0.00571284)

MEXICO

ECONOMIC DISTANCE BETWEEN MEXICO AND BRAZIL

MEX.EPU	**MEX.EXP**	MEX.IMP	MEX.SPX	**MEX.CPI**	MEX.BRM
0.00026593	**-0.00888921**	0.00280635	0.00054826	**-0.06281347**	0.00656389
(0.00024632)	**(0.00533319)***	(0.00545805)	(0.00318908)	**(0.03134162)****	(0.01259634)
BRA.EPU	BRA.EXP	BRA.IMP	BRA.SPX	**BRA.CPI**	BRA.BRM
0.00005880	-0.00003545	-0.00253659	-0.00085404	**0.11730136**	0.00164390
(0.00020843)	(0.00181671)	(0.00181076)	(0.00241787)	**(0.02934968)*****	(0.01984574)

ECONOMIC DISTANCE BETWEEN MEXICO AND CHINA

MEX.EPU	MEX.EXP	**MEX.IMP**	**MEX.SPX**	MEX.CPI	**MEX.BRM**
0.00016067	0.00142772	**0.01136225**	**0.00439313**	-0.00746207	**0.02418565**
(0.00019705)	(0.00426358)	**(0.00438960)****	**(0.00187544)****	(0.02543013)	**(0.01013059)****
CHI.EPU	CHI.EXP	CHI.IMP	**CHI.SPX**	CHI.CPI	**CHI.BRM**
-0.00008953	0.00228102	0.00069781	**-0.00368205**	0.00123744	**-0.07171705**
(0.00023369)	(0.00141481)	(0.00145874)	**(0.00144335)****	(0.01454579)	**(0.01774142)*****

ECONOMIC DISTANCE BETWEEN MEXICO AND INDIA

MEX.EPU	MEX.EXP	**MEX.IMP**	MEX.SPX	MEX.CPI	**MEX.BRM**
-0.0001080	0.0013715	**0.0117152**	-0.0014067	0.0225348	**0.0238551**
(0.0002310)	(0.0049735)	**(0.0051803)****	(0.0026249)	(0.0301705)	**(0.0118029)****
IND.EPU	IND.EXP	IND.IMP	IND.SPX	IND.CPI	IND.BRM
0.0003074	0.0014388	0.0022685	-0.0023825	0.0188880	-0.0120868
(0.0002849)	(0.0016371)	(0.0015750)	(0.0022465)	(0.0142029)	(0.0221269)

ECONOMIC DISTANCE BETWEEN MEXICO AND KOREA

MEX.EPU	MEX.EXP	MEX.IMP	MEX.SPX	**MEX.CPI**	MEX.BRM
0.000009376	-0.001569885	0.008100388	0.005823339	**-0.055398806**	-0.001040575
(0.000231283)	(0.004893355)	(0.005142049)	(0.002854321)**	**(0.028500829)***	(0.011502665)
KOR.EPU	KOR.EXP	KOR.IMP	**KOR.SPX**	KOR.CPI	**KOR.BRM**
0.000301270	-0.002293980	0.003889818	**-0.009911108**	-0.010439177	**-0.091830879**
(0.000301221)	(0.002200588)	(0.002824645)	**(0.002647589)*****	(0.027887911)	**(0.032165609)*****

ECONOMIC DISTANCE BETWEEN MEXICO AND RUSSIA

MEX.EPU	MEX.EXP	MEX.IMP	MEX.SPX	**MEX.CPI**	**MEX.BRM**
0.00011651	-0.00312684	0.00538357	0.00177050	**-0.05851932**	**-0.02254009**
(0.00020676)	(0.00452999)	(0.00466882)	(0.00232448)	**(0.02671964)****	**(0.01056936)****
RUS.EPU	RUS.EXP	**RUS.IMP**	RUS.SPX	RUS.CPI	RUS.BRM
0.00010906	0.00080929	**-0.00437229**	-0.00241334	-0.02313025	-0.00638324
(0.00014277)	(0.00158384)	**(0.00207164)****	(0.00141842)*	(0.01578794)	(0.00539430)

RUSSIA

ECONOMIC DISTANCE BETWEEN RUSSIA AND BRAZIL

RUS.EPU	RUS.EXP	RUS.IMP	RUS.SPX	RUS.CPI	RUS.BRM
0.00009805	-0.00354890	0.00175890	0.00088717	0.01248484	0.00851073
(0.00018486)	(0.00205826)*	(0.00264310)	(0.00182726)	(0.02086276)	(0.00704812)
BRA.EPU	BRA.EXP	BRA.IMP	BRA.SPX	**BRA.CPI**	BRA.BRM
-0.00009716	0.00022652	-0.00306542	0.00085437	**0.09634610**	-0.00230074
(0.00022721)	(0.00198778)	(0.00195055)	(0.00229095)	**(0.03422723)*****	(0.02229849)

ECONOMIC DISTANCE BETWEEN RUSSIA AND CHINA

RUS.EPU	RUS.EXP	**RUS.IMP**	RUS.SPX	RUS.CPI	**RUS.BRM**
-0.00007769	0.00190551	**0.00842975**	0.00231398	0.03122287	**0.01683817**
(0.00016714)	(0.00180309)	**(0.00241732)*****	(0.00139929)*	(0.01728094)*	**(0.00630061)*****
CHI.EPU	CHI.EXP	CHI.IMP	CHI.SPX	CHI.CPI	**CHI.BRM**
0.00021094	0.00003919	-0.00138239	-0.00161764	-0.00280471	**-0.08161525**
(0.00027886)	(0.00175823)	(0.00178853)	(0.00174856)	(0.01752908)	**(0.02104572)*****

ECONOMIC DISTANCE BETWEEN RUSSIA AND INDIA

RUS.EPU	**RUS.EXP**	**RUS.IMP**	RUS.SPX	RUS.CPI	RUS.BRM
-0.00005457	**0.00405423**	**0.00761453**	0.00152044	0.01448873	0.00930838
(0.00019060)	**(0.00205848)***	**(0.00266244)****	(0.00173673)	(0.02032630)	(0.00706659)
IND.EPU	IND.EXP	IND.IMP	IND.SPX	IND.CPI	IND.BRM
0.00027500	0.00113966	0.00072192	-0.00450756	-0.00796839	-0.01091105
(0.00033852)	(0.00192885)	(0.00180227)	(0.00249939)*	(0.01657319)	(0.02606365)

ECONOMIC DISTANCE BETWEEN RUSSIA AND KOREA

RUS.EPU	RUS.EXP	**RUS.IMP**	RUS.SPX	RUS.CPI	RUS.BRM
-0.00002057	0.00271993	**0.00670225**	0.00110287	0.01759763	0.00661966
(0.00015236)	(0.00169911)	**(0.00220774)*** **	(0.00141600)	(0.01604052)	(0.00571284)
KOR.EPU	KOR.EXP	KOR.IMP	**KOR.SPX**	KOR.CPI	KOR.BRM
0.00021109	-0.00311648	0.00264394	**0.00647383**	0.00313822	-0.01773821
(0.00029466)	(0.00215181)	(0.00272615)	**(0.00220090)*** **	(0.02719020)	(0.03162124)
ECONOMIC DISTANCE BETWEEN RUSSIA AND MEXICO					
RUS.EPU	RUS.EXP	**RUS.IMP**	RUS.SPX	RUS.CPI	RUS.BRM
-0.00010906	-0.00080929	**0.00437229**	0.00241334	0.02313025	0.00638324
(0.00014277)	(0.00158384)	**(0.00207164)** **	(0.00141842)*	(0.01578794)	(0.00539430)
MEX.EPU	MEX.EXP	MEX.IMP	MEX.SPX	**MEX.CPI**	**MEX.BRM**
-0.00011651	0.00312684	-0.00538357	-0.00177050	**0.05851932**	**0.02254009**
(0.00020676)	(0.00452999)	(0.00466882)	(0.00232448)	**(0.02671964)** **	**(0.01056936)** **

*Note: BRA: Brazil, CHI: China, IND: India, KOR: Korea, MEX: Mexico, RUS: Russia, EPU: Economic Policy Uncertainty, EXP: export, IMP: import, SPX: share price index, CPI: consumer price index, BRM: broad money The p-values of the causality test are classified as follows: ***, **, and * reflect statistical significance at 0.01, 0.05 and 0.10 levels, respectively.*

4.4.2 Spatial Correlation

Spatial correlation in this study is investigated through LISA. LISA indicates the presence or absence of significant spatial clusters (thus evidence of spatial autocorrelation) for each location under observation. The Local Moran Statistic implemented in GeoDa is a special case of a LISA. In this study, we compute LISA through the Local Moran statistic in GeoDa. The findings of the statistic (thus the type and strength of spatial autocorrelation) are visualised with the aid of the Moran's I scatter plot in the GeoDa software. The Moran's I scatter plot provides a statistic that compares a location's value with its neighbouring values by regressing the original standadised value of each country's location on the x-axis and the spatial lag of the (average of) neighbouring countries values of each country on the y-axis. In the GeoDa software, the average of the neighbours of a particular location is calculated by multiplying the values of each of the neighbours of that location with the "spatial weight" of the function and then all the product of each of the neighbours are summed up. The visual scatter plots show a slope which corresponds to the overall values of the Moran's I. A positive Moran's I value indicates the presence of a positive spatial autocorrelation (where low values correlate with low neighbouring values and high values correlates with high neighbouring values) and a negative Moran's I value indicates the presence of a negative spatial autocorrelation (where low values correlate with high neighbouring values and high values correlates with low neighbouring values). Spatial autocorrelation or spatial dependence is therefore the observed relationship between the spatial closeness among observed units or variables and the numerical similarities and dissimilarities among the values of those observed units.

To proceed with our analysis we first find the geographical location of each EME by linking each EME to its point latitude - longitude coordinates because the geographical location of each country has an impact on the results. The geographical locations of the EMEs are presented in Figure 4.1. Neighbours are then defined using the binary row- standised spatial weights matrix in the GeoDa software. The neighbours are calculated based on each country's geographical locations (latitude –longitude coordinates) and thus, are independent of each country's EPU index aggregate. Table 4.2 presents the neighbours of each EME. A centroid represents the EME serving as the point of reference to calculate the distance weight and neighbours represents the countries closest to the selected EME. Since this analysis primarily focuses on the presence or absence of spatial autocorrelation among developing countries (rather than measures associated with each monthly EPU data of each developing country), the aggregate of the monthly EPU index for each EME from 01/01/1999 to 31/12/2018 is calculated to represent each EME in the analysis.

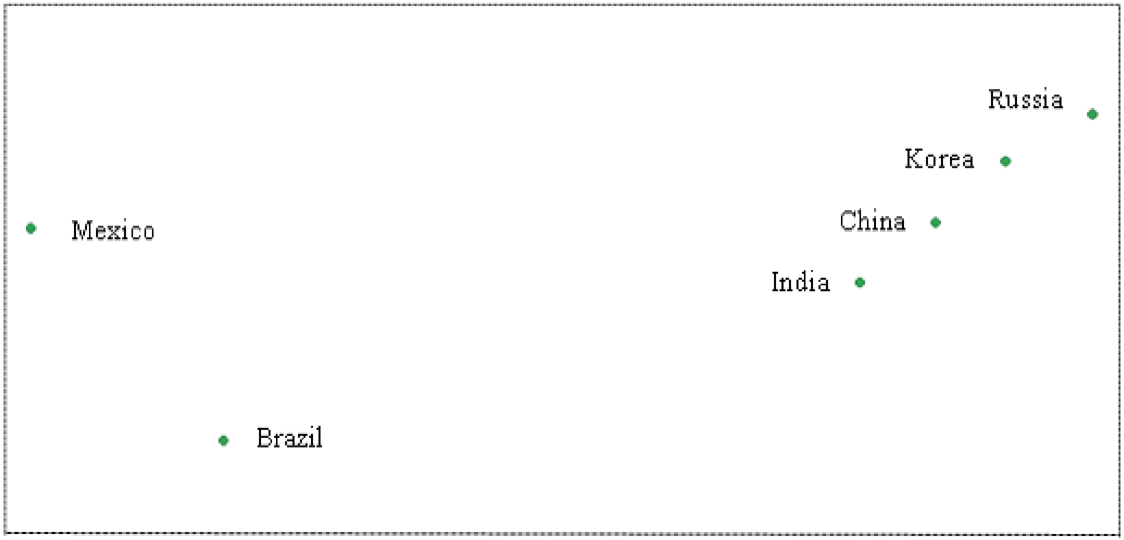


Figure 4.1: Spatial location map of the 6 EMEs
Note: The figure shows the GeoDa output of the actual locations of the EMEs on a regular map.

Table 4.2: Developing countries and their neighbours

Centroid	Neighbours	Centroid	Neighbours
Brazil	Mexico	Korea	Russia, India, China
China	Russia, Korea, India	Mexico	Brazil
India	Russia, Korea, China	Russia	Korea, India, China

Note: Neighbours are determined by distance- based weight matrices. The distance- based weight matrix is generated from the GeoDa software using the distance band. Specifically, arc distance metric and the distance variance coordinate.

4.4.2.1Spatial autocorrelation (EPU across EMEs)

The visualisation of the type and strength of the spatial autocorrelation between all the six countries and their neighbours is displayed in the Moran scatter plot represented in Figure 4.2. The Moran scatter plot regresses spatially lagged EPU index (y- axis) on standardised EPU index (x- axis). The positively sloping straight line (also known as linear smoother) fitted to the scatter plot corresponds to the Moran's I value for the overall dataset which is shown in Figure 4.2 as 0.244377. The value 0.244377 indicates a positive spatial autocorrelation for the overall (total of six countries) dataset. This implies that EPU values are similar in the selected EMEs. This is risky for investors who may want to invest or diversify their portfolio all at once in the six economies because, in the case of heightened (or lessened) EPU values, all the six economies will be affected simultaneously. Investors prefer to use negatively-correlated assets or securities to hedge their portfolio and reduce market risk as a result of simultaneous volatility occurrences in multiple economies. The nonlinear fit for the regression (also known as LOWESS smoother) can be identified as the curved lined fitted to the scatter plot. The LOWESS smother's movement reveals the structural breaks that exist on the scatter plot. Out of the four structural breaks, the first session from the left of Figure 4.2 showed a step and positive curve suggesting evidence of positive spatial autocorrelation. The second structural break showed a very steep and negative curve that shows evidence of negative spatial autocorrelation. Pattern three however shows a larger scope of positive autocorrelation as compares to pattern four. Regionalised Moran's I is used to further investigate the alternating positive and negative spatial autocorrelation in subsets of the overall observation. Evidence from Figure 4.2 also reveals that the observations' values on the scatter plot have been categorised into four quadrants. The standardised x-axis values are centered on a mean of 0 where values greater than 0 for both the x- axis and y- axis are termed as high and values lower than 0 are termed as low. To interpret the quadrants, reading of a point on the scatter plot starts from the x- axis (standardised observation value) then, followed by reading on the y- axis (lagged values of observation's surrounding values).

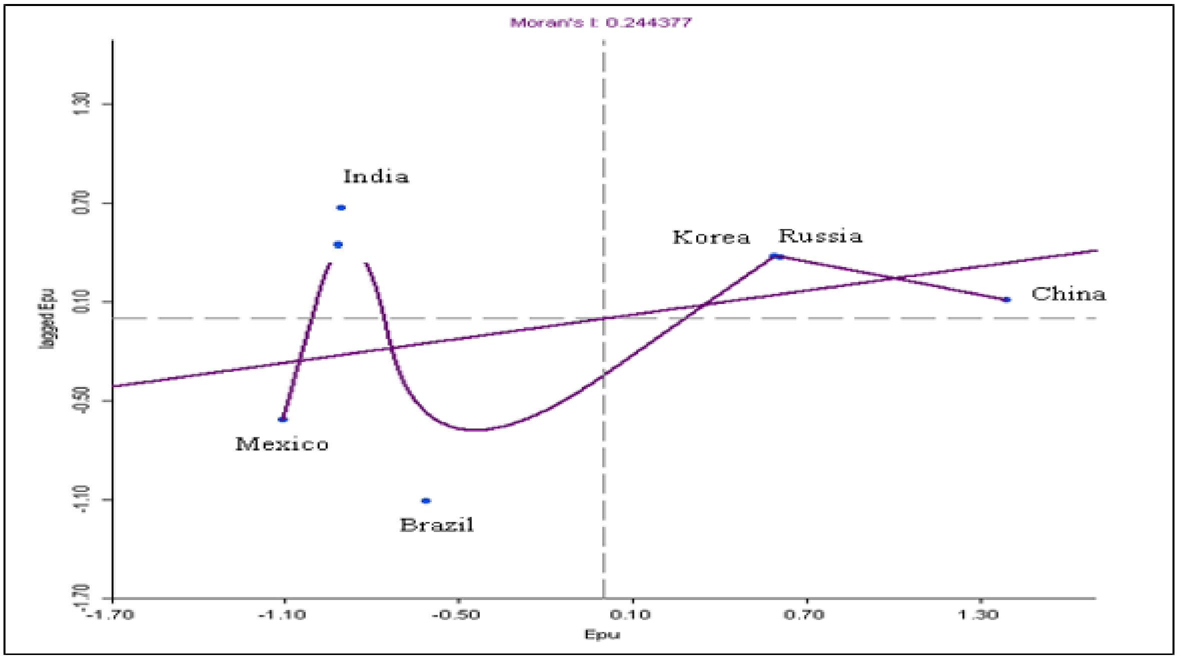


Figure 4.2: Moran's I (EPU across EMEs).
Note: The Moran's I autocorrelation value is 0.244377.

Therefore, starting from the lower left on a clockwise rotation, the lower-left quadrant is termed as low-low, the upper-left quadrant is termed low-high, upper-right quadrant is termed as high-high and lastly, lower-right quadrant is termed as high-low. The low-low and high-high signifies positive spatial autocorrelations which indicates that neighbouring locations have similar values. On the other hand, low-high and high-low signify negative spatial autocorrelations indicating dissimilar values at neighbouring locations. As evident from Figure 4.2 the EMEs are distributed within the low-low, low-high and high-high quardrants. Specifically, economies with low EPU index values that are surrounded by neighbours with low EPU index values are Mexico and Brazil. Also, countries with high EPU index values that are surrounded by neighbours with high EPU index values are Korea, Russia and China. These economies therefore have similar EPU values which imply that their vulnerability to uncertainty in their respective economies might be similar.

However, India is the only economy with low EPU index values that are surrounded by neighbours with high EPU index values. This implies that low EPU values in India spatially correlate with high EPU values from its neighbours.

Although the slope of the linear fit provides an estimate of the Moran's I, it does not reveal any information about the significance of the Moran' I statistic. Is the Moran's I value 0.244377 statistically significant? To test for significance, 999 permutations (a significant level for reliable inference) is run to compute a pseudo p-value to determine the significance of the results. It is important to note that the pseudo p-value in Geoda (and spatial autocorrelation in general) should not be interpreted as an analytical p-value generated from a normal distribution curve because the pseudo p-value from spatial autocorrelation is only a summary of the results from permutations (also known as random reference distribution) and as such the significance of the pseudo p-value is relatively determined by the number of permutations (Anselin, (2005). The pseudo p-value is computed as $P = \frac{M+1}{R+1}$, where M is the number of simulated Moran's I values that are equal to or more extreme than the actual Moran's I value and R is the number of permutations (which is 999). The 999 permutations (that assigns randomly shuffled numbers to each location) results in 999 sets of reference distribution. The computed Moran's I for each of the 999 sets of reference distribution is then compared to the Moran's I statistic (0.244377) to determine the probability that the actual spatial distribution is derived from a random distribution. The pseudo p-value shows the probability that the actual spatial pattern was created by some random process. The null hypothesis for this test states that, the actual values of each developing country are randomly distributed across the spatial location (meaning that, the observed spatial pattern results from random spatial arrangement). In such a situation a high probability of the spatial arrangement is found to be the same as or similar to the actual data distribution. This situation is also termed as "many versions of complete spatial randomness". The null hypothesis also states that, the actual data is more spatially distributed than one would expect by chance alone. In such a situation, once in a while, a random distribution produces the same outcome of the actual distribution of the data set, but the probability of this outcome is small.

Since the pseudo p-value is as a result of randomly shuffled numbers, multiple permutations run results in new pseudo p-values. To conduct a sensitivity analysis as a result of the possible outcomes of the pseudo p-values, multiple 999 permutations were run on GeoDa for the same Moran's I scatter plot. It was observed that the different pseudo p-values under the 999 permutations were quite stable with the lowest value been 0.159000 (as evident in Figure 4.3) and the highest been 0.218000 (as evident in Figure 4.4). The most extreme pseudo p-value is 0.218000 resulting from the fact that, 21.8% out of 999 permuted Moran's I values were equal to or more extreme than the actual Moran's I value 0.244377 (shown by the green line in Figure 4.3 and Figure 4.4). The pseudo p-value also implies that 21.8% probability of the spatial arrangement is found to be the same as or similar to the actual data distribution. This 21.8% probability is an acceptable size which suggests the rejection of the null hypothesis and an acceptance of the alternative hypothesis that the actual data is more spatially distributed than one would expect by chance alone. The positive sign of the z-value 1.0583 indicates that the clustered spatial pattern is positively correlated and statistically significant rather than a random dispersion. Based on the above findings, it can be established that the Moran's I value (0.244377) is statistically significant and signifies an overall positive spatial autocorrelation among all the six EMEs. Therefore, practical implications of the analysis are very useful.

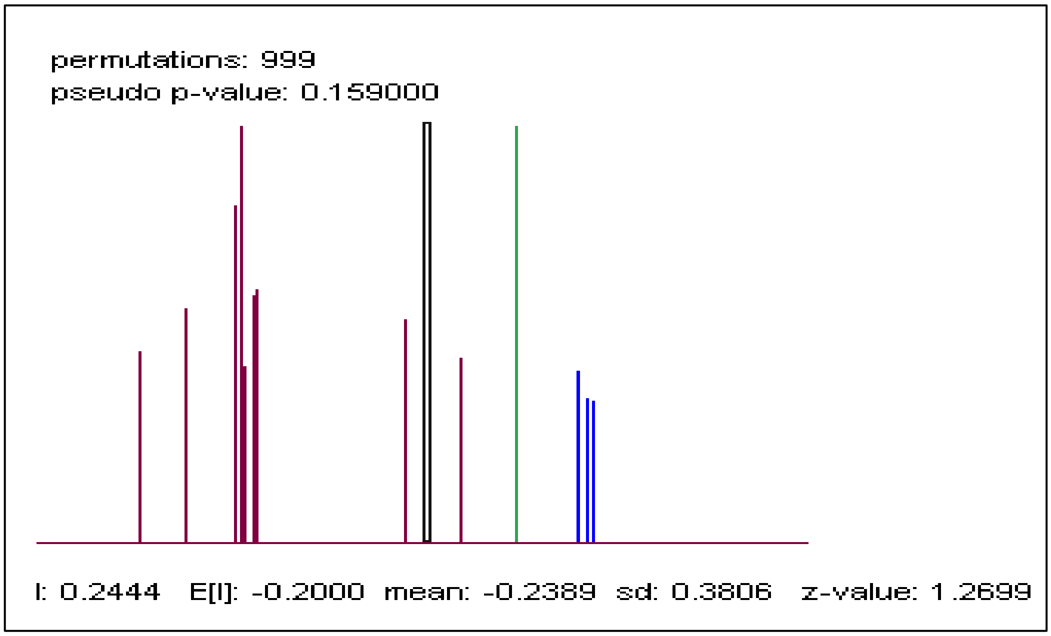


Figure 4.3: Lowest permutation for the randomisation test of the significance of Moran's I for EPU across EMEs.
Note: The Moran's I pseudo p-value is 0.159000. The Moran's I value of 0.244377 is represented by the green line.

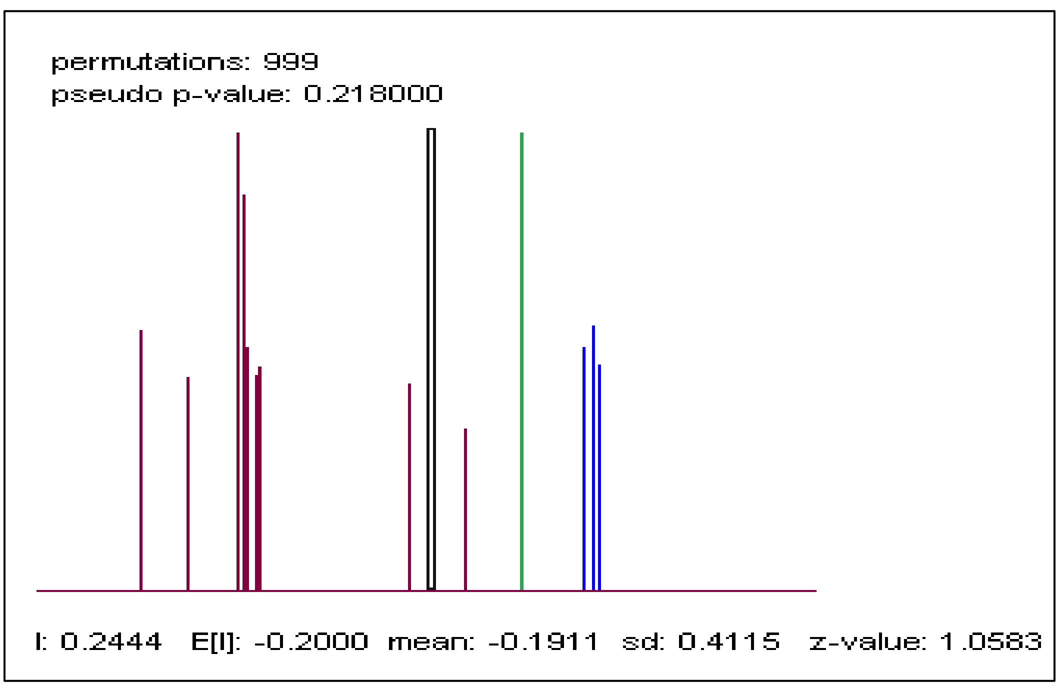


Figure 4.4: Highest permutation for the randomisation test of the significance of Moran's I for EPU across EMEs.
Note: The Moran's I pseudo p-value is 0.218000. The Moran's I value of 0.244377 is represented by the green line.

The evidence of positive spatial autocorrelation indicates the presence of interdependence among the EMEs and this implies that a certain amount of information (or a common incident) is shared and duplicated among neighbouring EMEs. This implies that, "each sample point carries information not only about its own sample site but also some information about neighbouring site values" (Haining, 2001). This finding is in sync with Tobler's (1970) first law of geography that "everything is related to everything else, but nearer things are more related than distant things". The question that arises now is that what might be the different potential factors that influence the spatial distribution of EPU index values among the developing countries. According to Haining (2001) one of the situations that lead to spatial autocorrelation is spillover processes. One key channel that transmits spillover shocks is the trade openness a country shares with other countries (Trung, 2019). In a situation where a country has higher trade with a particular country, the negative impact of shock is suffered more intensely by that country than other countries. The negative impact of the shocks affects outputs of that country, which leads to a strong rise in the EPU index values of the affected country (Ludvigson, Ma and Ng, 2015; Boom, 2009). Trung's (2019) study on US EPU spillover effects on the global economy revealed that although US EPU spillover has a significant spillover effect on most economies by causing a rise in output in the first month (e.g., Brazil, Canada, Korea, Malaysia, Norway and United Kingdom), China and Mexico's output declined drastically because they are large trading partners of US. Chile as noted by Trung (2019) is also a high trade partner of US and was negatively affected having the same negative impact as China.

Likewise, Trung's (2019) finding is found to be applicable in this study in the sense that, the neighbours of each centroid EME (see Table 4.1, for neighbours of each EME) form members of their top trade partners (see Workman, 2020). The trade openness and the proximity between these economies creates a link whereby the EMEs and their trade partners have strong collaborations of common practices in some policy areas for effective policy coordination (Adler, 2008) making them dependent on each other (Mazurek, 2012). Therefore, in a situation where an EME experiences a rise in EPU as a result of changes or speculated changes in international economic and trade policies, the negative impact of the shock is suffered more intensely by the neighbouring economies. The negative impact of the shocks affects the trade outputs of the recipient economies, as well as their EPU outcomes (Ludvigson, Ma and Ng, 2015; Boom, 2009). This scenario for example explains why Brazil's high EPU values correlates with high EPU values form its neighbours. Consequently, Brazil heighted EPU values is shared and duplicated among its neighbouring economies. This scenario is also likewise for Mexico, Russia, Korea and China. The heterogeneous spillover effects across EMEs (for example India and its neighbouring economies) can be due to the different structures of EPU (for example monetary policy uncertainty and fiscal policy uncertainty) as well as the receiving economies' distinct characteristics (such as, the level of development, financial openness, and quality of institutions) (Trung, 2019). The relationship between the neighbouring EMEs could also be dependent on their demographics, political institutions, and natural endowments across the spatial area.

As explained earlier, Figure 4.2 shows evidence of overall positive autocorrelation between all six economies which depicts a risky investment for investors who wish to diversify their portfolio across all the six countries. However, the LOWESS smother displays interchanging positive and negative spatial autocorrelation which creates the possibility of different autocorrelation results when the selected EMEs are divided into sub-regions. This sub-division is referred to as regionalised Moran's I test of autocorrelation (Anselin, 2010). The study therefore divides the six EMEs into regions based on the map rendition. Figure 4.5 displays the two regions. Region A on the left represents Mexico and Brazil, and Region B on the right represents China, India, Korea and Russia. To investigate the regionalised autocorrelation, Region A is selected (in rectangle on the far left of Figure 4.6) and the spatial autocorrelation is displayed on the left of the original Moran's I output and is labeled as "selected". The remaining region (Region B) is on the far right is labeled as "unselected".

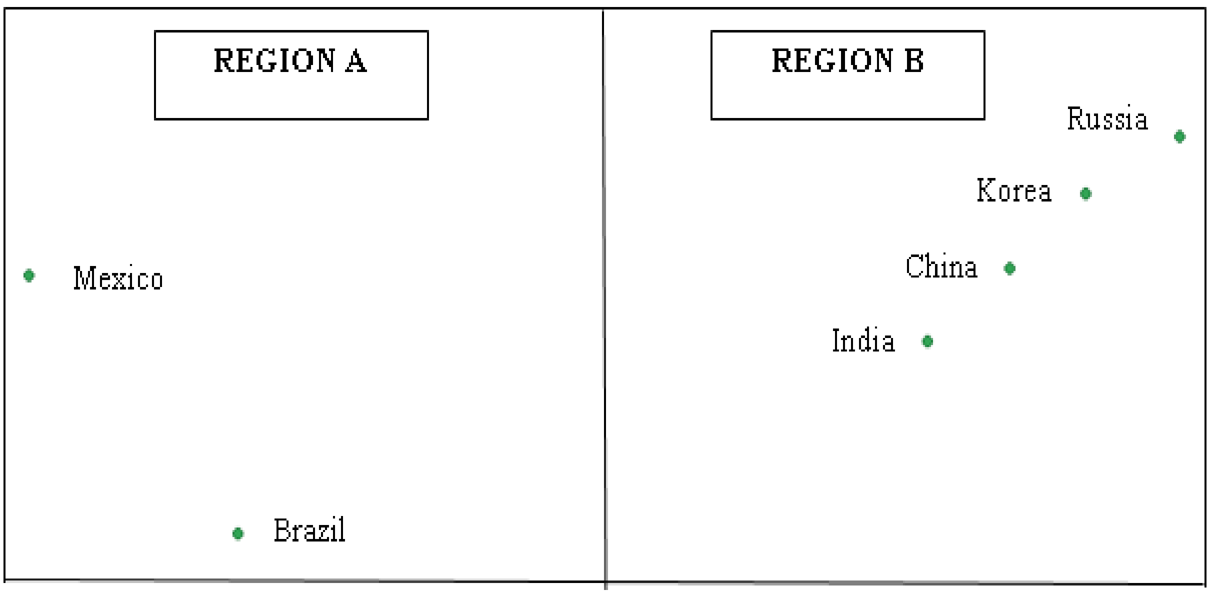


Figure 4.5: Regionalised spatial location map of the six EMEs.
Note: Region A: Mexico and Brazil, and Region B: China, India, Korea and Russia

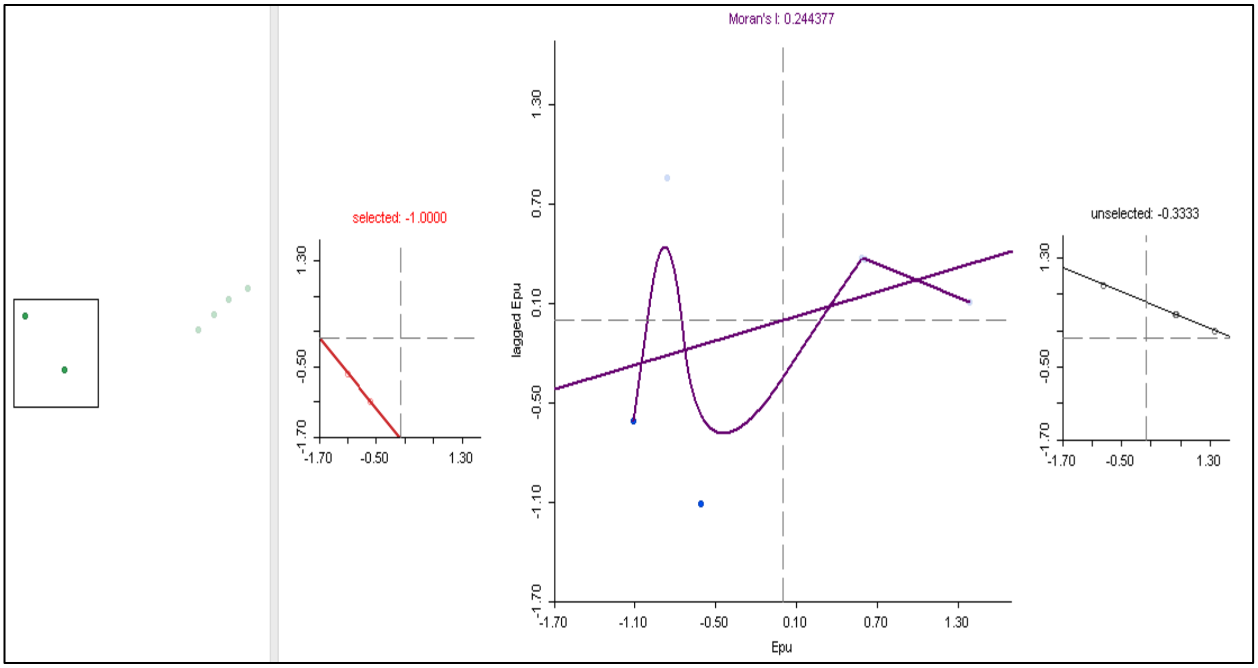


Figure 4.6: Regionalised Moran's I test (EPU across EMEs).
Note: Left pane selected regions are Brazil and Mexico. Unselected regions (on the far right) are China, India, Korea and Russia.

There is evidence of negative spatial autocorrelation for both Region A (-1.0000) and Region B (-0.3333). This implies that it is safer for investors to invest in Region A and Region B separately since they can avoid the risk of losing all their investment in the case of heightened EPU that might lead to a fall in output and investment. The negative spatial autocorrelation also implies dissimilarities in the EPU values across neighbouring economies. This implies that, heightened EPU in one EME does not spatially correlate with heightened EPU in the neighbouring economies indicating a safe zone for trade, investment and portfolio diversification.

4.4.2.2 Bivariate Spatial correlation (EPU verses GDP across EMEs)

The rest of the empirical results in this session focused on bivariate spatial dependence. It is therefore important to repatriate that unlike the univariate (one variable analysis) where the

Moran’s I scatter plot regresses the standardised EPU index (x- axis) and spatially lagged EPU index (y- axis), the bivariate Moran’s I scatter plot regresses the standardised first variable (EPU) on the x-axis and the spatially lagged of the second variable (each of the macroeconomic variables) on the y-axis. We are therefore going to pair EPU (x-axis) with each of the macroeconomic variable (y-axis) and conduct a bivariate Moran’s I analysis. The spatially lagged of the second variable on the y-axis is the average of observations of the second variable at neighbouring locations of each centroid economy. The Moran’s I statistic value of the scatter plot (which also indicates the slope of the linear best fit) represents the regression coefficient of the bivariate regression.

This sub-session investigates if EPU spatially correlates with GDP in the selected EMEs. Figure 4.7 shows that, there exist a spatial relationship between the EPU and GDP of neighbouring economies. The Moran’s I scatter plot regresses spatial lag of the (average of) neighbouring countries’s GDP values of each country on the y-axis and standardised EPU index on the x- axis. The overall Moran’s I value of 0.23251 displayed by the upward sloping curve depict a positive relationship between the six selected economies. It also implies that the EPU of an economy and the GDP values (which represents the economic activities and growth) of its neighbouring economies have similar values which is a risky platform for portfolio diversification as explained earlier. Policy makers can also regulate EPU fluctuations knowing very well how their neighbouring economies will respond due to the possible impact of spillover in the neighbouring economies. Investors who also monitor GDP as well as EPU for decision making purposes (such as investment in commodity, firms, equity and real estate) now have insight into how EPU and GDP correlate across the selected EMEs.

We now select each point in the quadrants and identify their locations on the map to investigate how each EME associates with its neighbouring economies. As evident from Figure 4.7 the EMEs are distributed within all the four quadrants. Specifically, economies with low EPU index values that are surrounded by neighbours with low GDP values are Mexico and India. Also, the economy with high EPU index values that are surrounded by neighbours with high GDP values is China. These economies therefore have similar values which imply that their vulnerability to uncertainty in their respective economies might be similar. Another possible reason for the positive spatial autocorrelation between EPU values and neighbouring GDP values is the “growth option” theory. This theory states that uncertainty can increase economic activities (for more details see, Bar-Ilan & Strange, 1996; Pastor & Veronesi, 2006; Segal, Shaliastovich, & Yaron, 2015; Kraft, Schwartz, & Weiss, 2018).

On the other hand, Brazil’s low EPU index values are surrounded by neighbours with high GDP values and economies with high EPU index values that are surrounded by neighbours with low GDP values are Russia and Korea. This implies that these three economies (Brazil, Russia and Korea) have dissimilar values with their neighbouring economies. This incident can be explained by the “classic theories” view that, there is a fall in real activity (or output) and a decline in economic growth when market frictions and financial markets interrelate with real economic uncertainty (see, Gilchrist, Sim, & Zakrajsek, 2010; Bloom 2009). Likewise, a fall in uncertainty increases economic growth. This finding is in sync with Nakamura, Sergeyev, and Steinsson’s (2017) argument that economic activity (measured as growth rate) negatively correlates with volatility shocks and this interdependence between EMEs is through spillover effects. Thus, the presence of spatial autocorrelation implies that GDP values carries information about EPU variations in the selected EMEs where high EPU values correlate with low neighbouring GDP values and low EPU values correlate with high neighbouring GDP values.

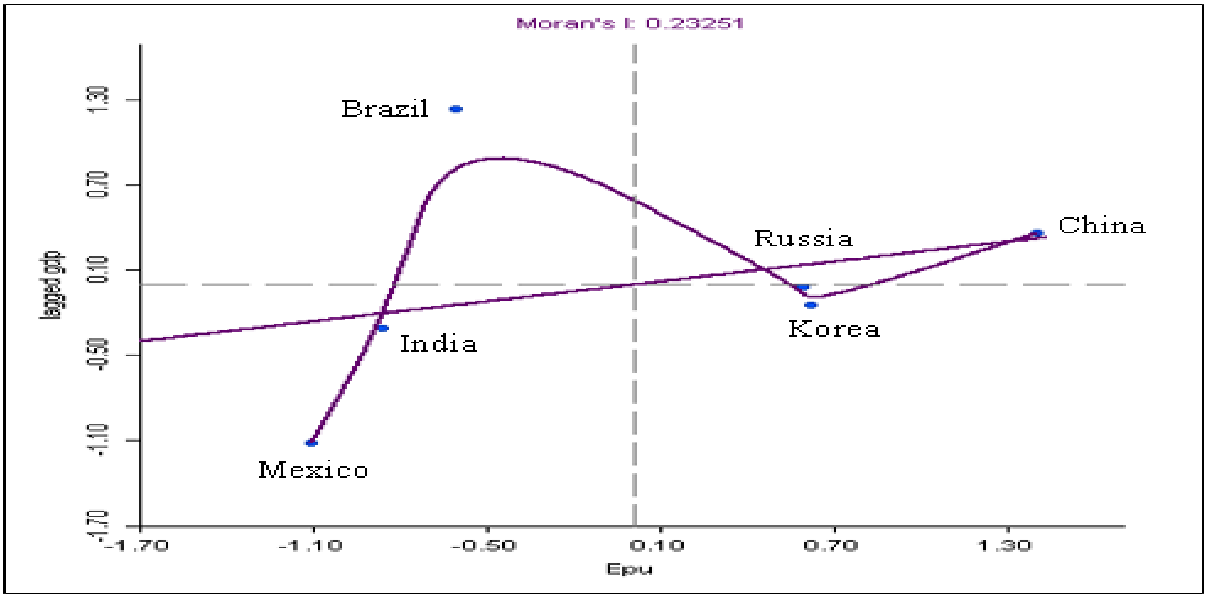


Figure 4.7: Moran's I (EPU verses GDP across EMEs).
Note: The Moran's I autocorrelation value is 0.23251.

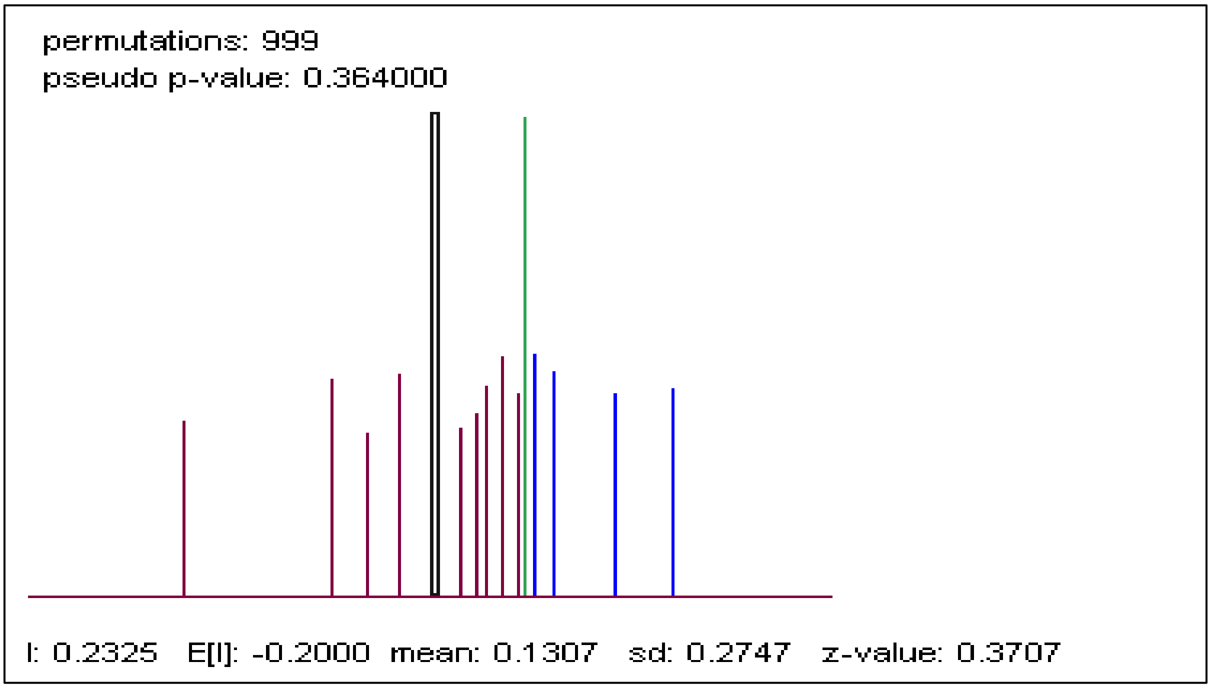


Figure 4.8: Extreme permutation for the randomisation test of the significance of Moran's I (EPU verses GDP across EMEs).
Note: The Moran's I pseudo p-value is 0.364000. The Moran's I value of 0.23251 is represented by the green line.

The most extreme pseudo p-value is 0.364000 resulting from the fact that, 36.4% out of 999 permuted Moran's I values were equal to or more extreme than the actual Moran's I value 0.23251 (shown by the green line in Figure 4.8). The 36.4% probability is an acceptable size which suggests the rejection of the null hypothesis and an acceptance of the alternative hypothesis that the actual data is more spatially distributed than one would expect by chance alone. The positive sign of the z-value 0.3707 indicates that the clustered spatial pattern is statistically significant rather than a random dispersion.

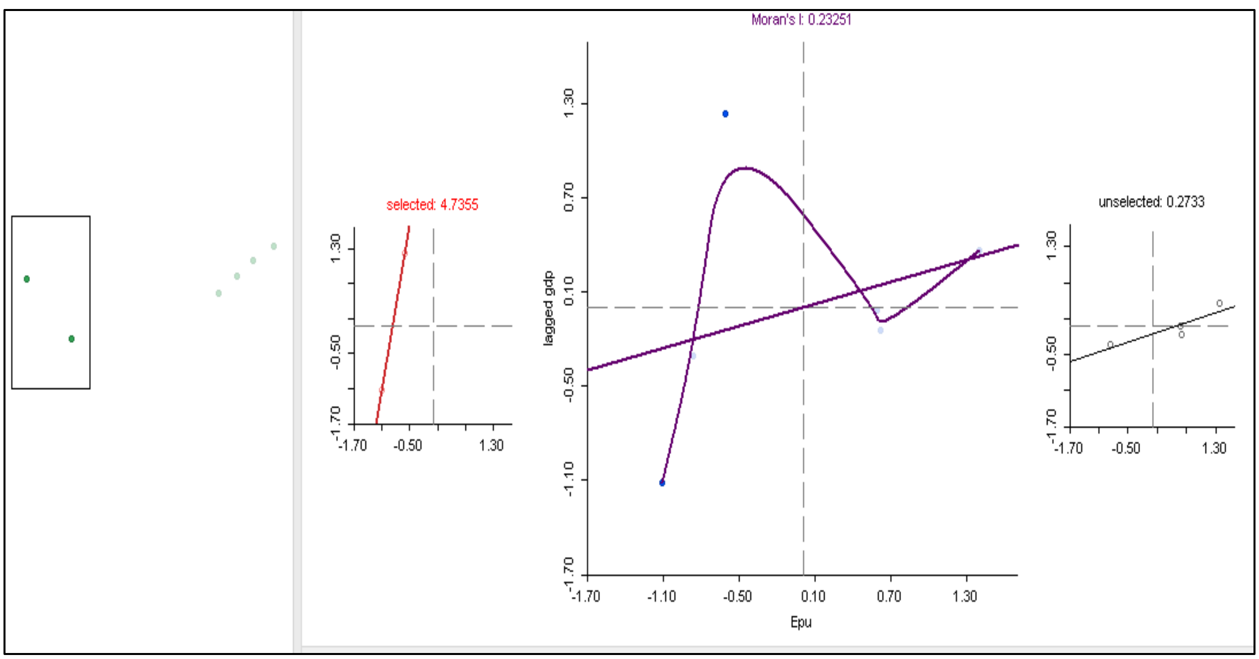


Figure 4.9: Regionalised Moran's I test (EPU verses GDP across EMEs).
Note: Left pane selected regions are Brazil and Mexico. Unselected regions (on the far right) are China, India, Korea and Russia.

Proceeding to the regionlaised Moran's I test in Figure 4.9, both Region A and Region B display positive spatial autocorrelation with values of 4.7355 and 0.2733 respectively. Region A ("selected" region in Figure 4.9) displays autocorrelation analysis for Region A and Region B ("unselected" region in Figure 4.9) displays auto correlation analysis for Region B. There is no evidence of heterogeneity since the selected subsets shows a similar degree of dependence when compared to the data set as a whole. For investors and policy makers who highpoint economic activities in their investment decisions and policy implementations (respectively), this finding informs them that, for both region A and Region B, EPU and GDP are spatially independent and have similar values where high EPU values tend to have high GDP (productivity) neighbours and low EPU values correlate with low GDP values in neighbouring economies. This will be a good zone for investment and portfolio diversification. This makes the prediction of GDP outcomes in an economy as a result of EPU variations in its neighbouring EMEs possible and useful for decision making.

4.4.2.3 Bivariate Spatial Correlation (EPU verses SPX across EMEs)

This session investigates if EPU spatially correlates with SPX in the selected EMEs. The Moran's I scatter plot regresses spatial lag of the (average of) neighbouring countries SPX values of each country on the y-axis and standardised EPU index on the x- axis. Effective and stable financial markets provide firms the opportunity to sell equities and/or borrow funds to finance their businesses and investment activities, which tends to promote growth in an economy (Bayraktar, 2014). Therefore, the ability to measure the development level of financial markets across countries is very important since it helps in policy formulation and influences investors' decisions to invest in a country. In this study a SPX (price of the stock) is used as the measure of the development level of the financial markets since the price of the stock is what determines the index of the stock and also has the ability to reflect the stock market performance of an economy. Also, movement (as a result of the changes) in share prices reflects whether the market conditions are active or lethargic (Suharsono, Aziza, & Pramesti, 2017). As evident in literature, the SPX (also termed as stock price index) negatively correlates with uncertainty (see for example, Donadelli, 2015; Brogaard & Detzel, 2012; Brogaard, & Detzel, 2015; Sum, 2012; Arouri & Roubaud, 2016; Yoon, Al Mamun, Uddin, and Kang, 2019). The spatial autocorrelation analysis conducted also shows evidence of negative spatial autocorrelation at both the composite level and regionalised level. This strongly buttresses the empirical evidence that uncertainty has a negative relationship with SPX.

Figure 4.10 shows that, there exist a negative spatial autocorrelation between EPU and SPX of the six selected economies. The overall Moran's I value of -0.457886 displayed a steep downward sloping curve. It also implies that the EPU of an economy and the SPX values of its neighbouring economies have dissimilar values which create a safe platform for portfolio diversification. This is because, when EPU and SPX respond in opposing ways to market influences, investors will be able to prevent the occurrence of a total loss in investment in an event of heightened EPU or SPX values since the positive performances will neutralise the negative and accumulate long-term returns. For country specific relationship with its neighbours, we identify that, economies with low EPU that are surrounded by high SPX values are India and Mexico. These two countries and their neighbouring economies will be a good place to invest in shares when their EPU is stable (or low) since the stable EPU correlates with high SPX in neighbouring economies. On one hand EPU is stable and on the other there is good returns for share prices. Economies with high EPU index values that are surrounded by neighbours with low SPX values are Russia, China and Korea. These economies are risky zones for investment in the stock market since low SPX is a poor avenue for investment and high EPU is an indication of uncertainty. Also, investors and policy makers can easily predict happenings in their neighbouring economies as a result of happenings in their economies. Interestingly, all the economies except Brazil, exhibit similar values with their neighbours. Brazil's low EPU values spatially correlates with low SPX values of its neighbour Mexico making it a non-profitable place for stock market investments. Lastly, there was no country selection in the high-high quadrant.

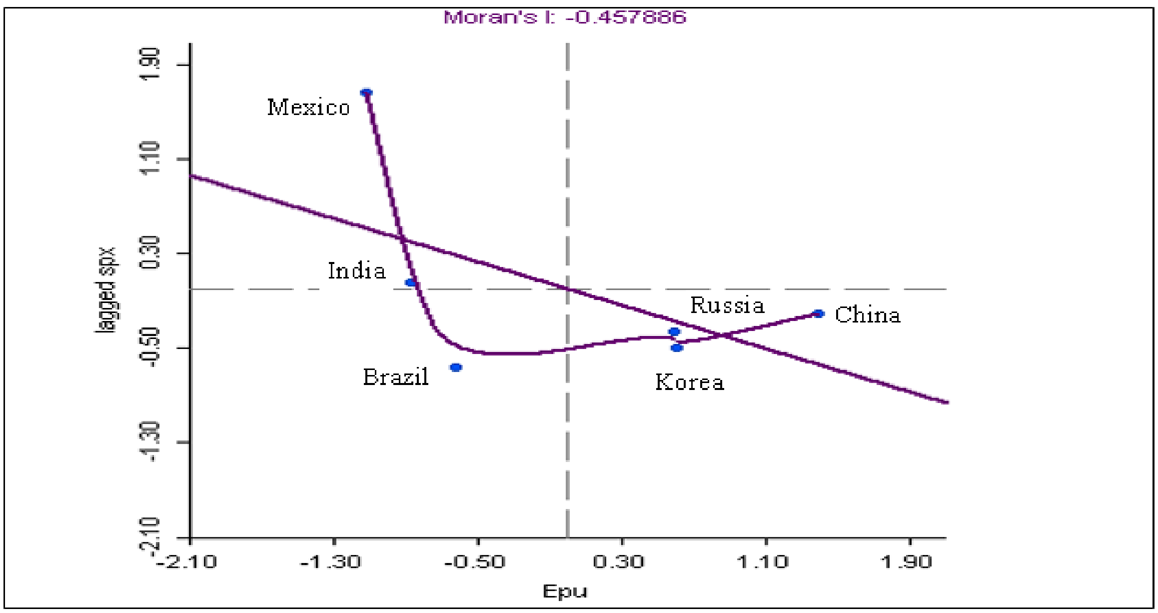


Figure 4.10: Moran's I (EPU verses SPX across EMEs).
Note: The Moran's I autocorrelation value is -0.457886.

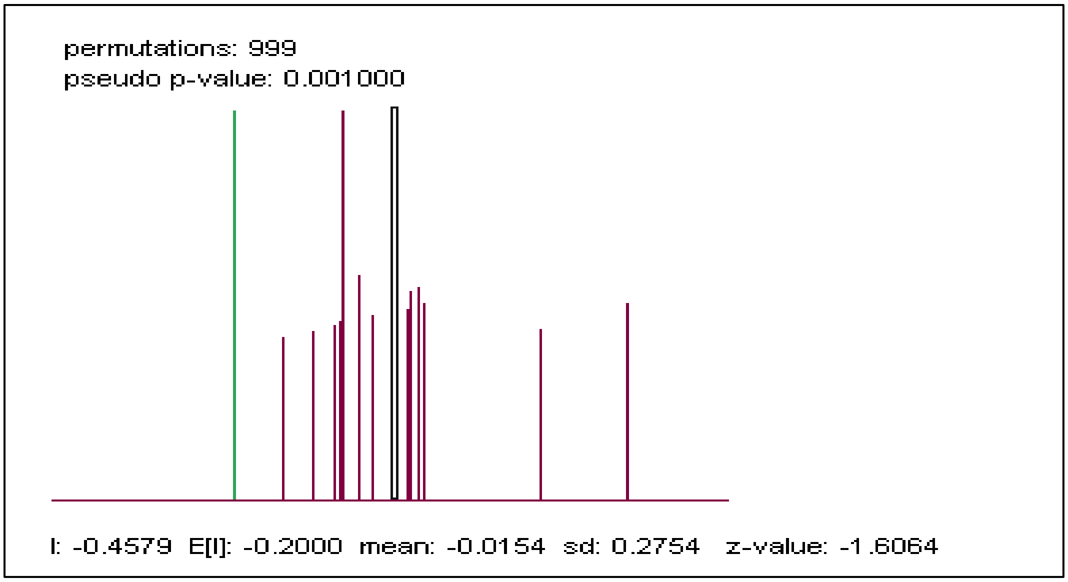


Figure 4.11: Extreme permutation for the randomisation test of the significance of Moran's I (EPU verses SPX across EMEs).

Note: The Moran's I pseudo p-value is 0.001000. The Moran's I value of -0.457886 is represented by the green line.

In the case of EPU versus SPX, the most extreme pseudo p-value is 0.001000 resulting from the fact that, 0.1% out of 999 permuted Moran's I values were equal to or more extreme than the actual Moran's I value -0.457886 (shown by the green line in Figure 4.11). The 0.1% probability leads to the rejection of the null hypothesis and an acceptance of the alternative hypothesis that the actual data is more spatially distributed than one would expect by chance alone. Once again, the negative z-value -1.6064 indicates that the dispersed (dissimilar but dependent) spatial pattern is statistically significant rather than a random dispersion.

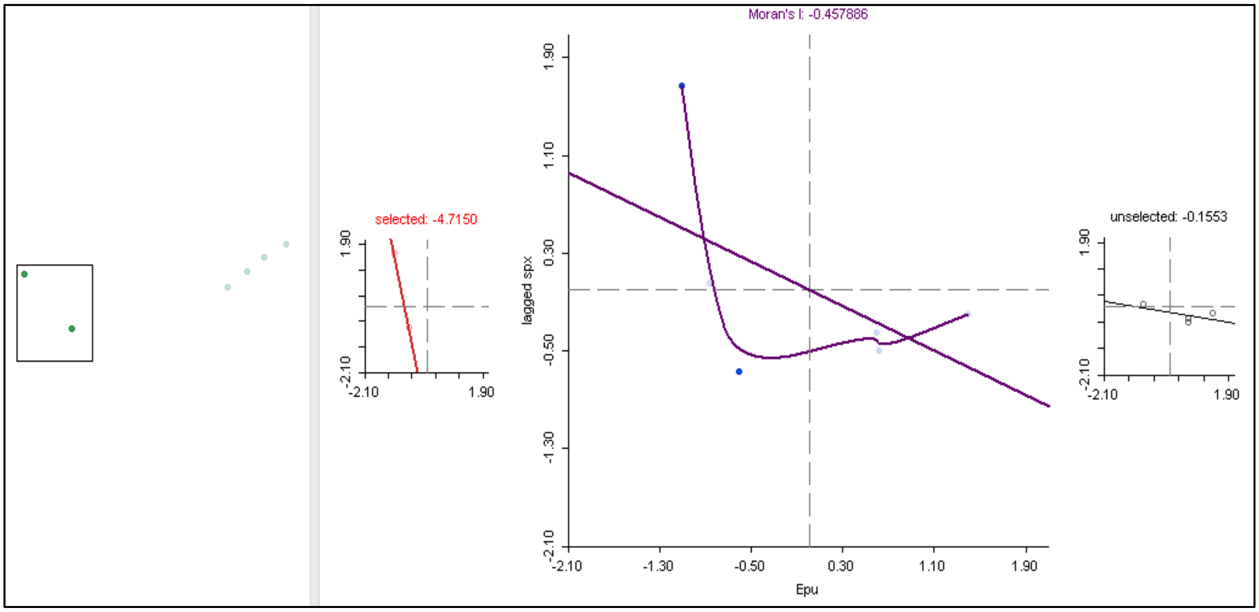


Figure 4.12: Regionalised Moran's I test (EPU verses SPX across EMEs).
Note: Left pane selected regions are Brazil and Mexico. Unselected regions (on the far right) are China, India, Korea and Russia.

Likewise, Figure 4.12 displays a negative spatial autocorrelation in the regionlaised Moran's I test for both Region A (- 4.7150) and Region B (-0.1553) respectively. In this case, there is evidence of less heterogeneity since the selected subsets shows similar degree of dependence when compared to the data set as a whole. The spatial properties that are likely to cause this dependence is the trade and investment partnership between neighbours. Also high EPU values in a country can spillover to neighouring partner economies causing a drop in share price due to uncertainty and "wait –and- see" practices in the stock market. This implies that even in the regionalised test, the findings strongly buttresses the empirical evidence that uncertainty negatively correlates with SPX (see for example, Donadelli, 2015; Brogaard & Detzel, 2012; Brogaard, & Detzel, 2015; Sum, 2012; Arouri & Roubaud, 2016; Yoon, Al Mamun, Uddin, and Kang, 2019). For investors who invest in the stock market and policy makers who highpoint SPX in their decisions and policy implementations, this finding informs them that, EPU plays a significant role in the outcome of

SPX among neighbouring economies and as such the spatial relationship between the EME with respect to EPU and SPX is very valuable to investors and policy makers. We conclude that, distance influences the values of SPX and EPU in EMEs.

4.4.2.4 Bivariate Spatial Correlation (EPU verses CPI across EMEs)

The CPI is a general indicator of the inflation in an economy. In this study CPI is also justified as a variable for monetary policy analysis because CPI is directly influenced by monetary and fiscal policy decisions by governments (Baker, et al., 2016; Pesce, 2010). This therefor makes CPI a good proxy of the effectiveness of the government's economic policy. This session therefore investigates if EPU spatially correlates with CPI. The Moran's I scatter plot regresses spatial lag of the (average of) neighbouring countries CPI values of each country on the y-axis and standardised EPU index on the x- axis. Figure 4.13 shows an overall negative spatial autocorrelation between EPU and CPI of the six selected economies. The negative overall Moran's I value of -0.118163 is evident in the downward sloping curve. The presence of negative spatial autocorrelation indicates that, the EPU of an economy and the CPI values of its neighbouring economies have dissimilar values. Once again this finding is a safe platform for portfolio diversification because, dissimilar values across the EMEs minimises risk. The next step is to investigate how each EME's EPU correlates with its neighbouring economies' CPI values. We identify that Mexico's low EPU values is surrounded by neighbours with low CPI values. Mexico and its neighbouring economies form a safe zone for investment since EPU and CPI's low values are good indicators for investorment. Economies with low EPU that are surrounded by high CPI values are India and Brazil. Thirdly, economies with high EPU index values that are surrounded by neighbours with low CPI values are China and Korea. This implies that China and Korea's high EPU values correlates with low neighbouring CPI values. Lastly, Russia's high EPU values correlates with high CPI values. As a result of the economic and trade linkages between Russia and its neighbours (Korea, China and India), it is likely that the high CPI values in the neighbouring economies has spillover effects on Russia. This happening might cause the EPU in Russia to rise since it might affect trade, monetary and fiscal policies across the economies. The last three quadrants are high risk zone for investors who invest in commodities.

These findings are particularly important for policy makers since they now have insight into the spatial relationship between EPU and CPI (serving as proxy for government economic policy implementation) across EMEs which is very useful for decision making, regulating CPI and predicting happenings in their neighbouring economies as a result of happenings in their economies. It is also very relevant to investors and companies who invest in commodities and equities since they are now able to understand how EPU spatially correlates with CPI across EMEs which helps them to make well informed decisions.

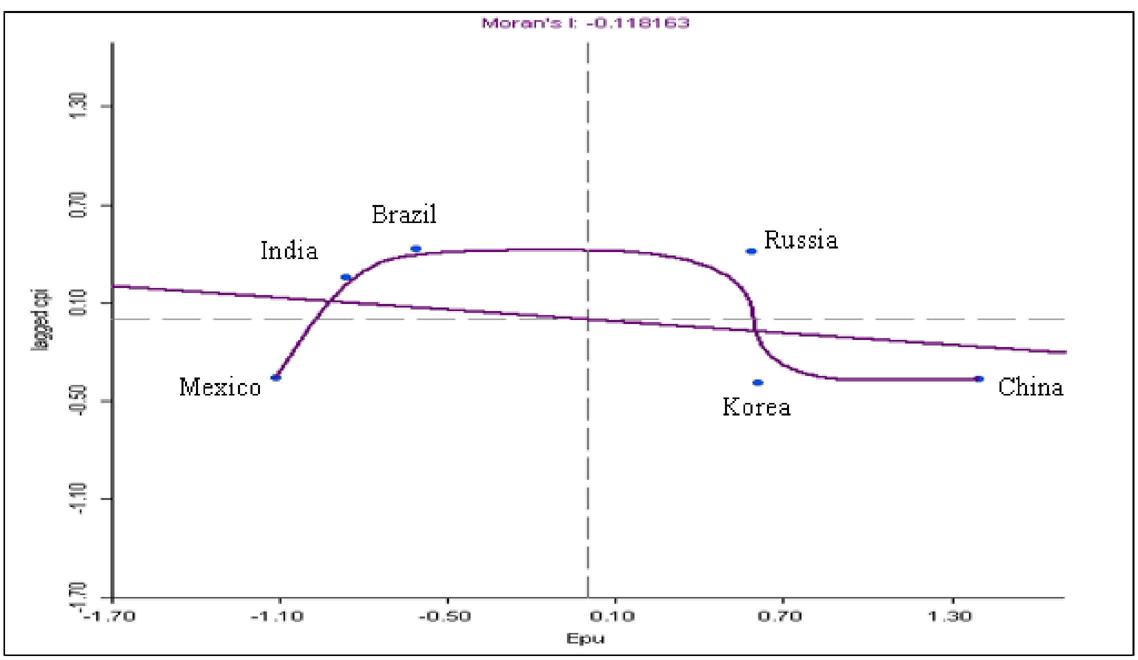


Figure 4.13: Moran's I (EPU verses CPI across EMEs).
Note: The Moran's I autocorrelation value is -0.118163.

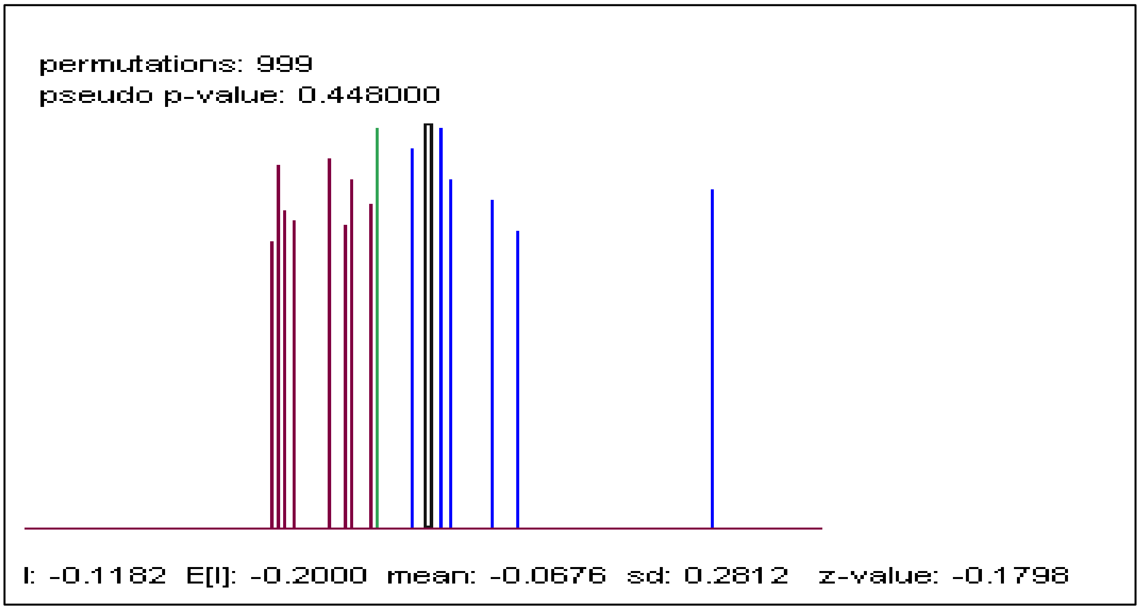


Figure 4.14: Extreme permutation for the randomisation test of the significance of Moran's I (EPU verses CPI across EMEs).
Note: The Moran's I pseudo p-value is 0.448000. The Moran's I value of -0.118163 is represented by the green line.

To test for significance we compute the most extreme pseudo p-value for 999 permutations. Figure 4.14 shows the most extreme pseudo p-value to be 0.448000. This implies that, 44.8% out of 999 permuted Moran's I values were equal to or more extreme than the actual Moran's I value -0.118163 (shown by the green line in Figure 4.14). The 44.8% probability leads to the rejection of the null hypothesis and an acceptance of the alternative hypothesis that the actual data is more spatially distributed than one would expect by chance alone. The negative z-value -0.1798 indicates that the dispersed spatial pattern is statistically significant rather than a random dispersion. Focusing on Regionalised Moran's I test, Region A (which represents Brazil and Mexico) can be identified as the "selected" pot on the left of the composite Moran's I plot in Figure 4.15. Likewise, Region B (represented by India, China, Korea and Russia) is displayed as the "unselected" plot on the far right of Figure 4.15. The two different outcomes from the Region A and Region B confirms the structural break patterns that exist in the LOWESS smother. Region A shows evidence of positive spatial autocorrelation between EPU and CPI with a Mora's I value of 1.5981. This implies that in Region A, nearby EMEs have similar values (high- high and low-low). This implies a high risk region for portfolio investment in commodities and stock markets since the burst of high CPI across all EMEs can result in the collapse of all investments and commodities all at once. Although there are opportunities and risk as a result of the numeric similarities in values, the risk outweighs the opportunities. Thus, investors must take caution of the trend of EPU fluctuations before investing in Region A. Region B has a Moran's I value of -0.2600 showing evidence of a negative spatial autocorrelation in Region B. This implies that the spatial proximity between the EMEs in Region B results in numeric dissimilarities between the EPU values and CPI values of neighbours. Although this is a good region for investment and portfolio diversification, investors must take caution to avoid investment when EPU is low in a centroid economy since it correlates high CPI values from neighbouring economies in this portfolio which will eventually lead to a drop in the investor's profit. Once again, there is a certain amount of information that is shared among the neighbouring EMEs. This findings clearly inform us that, each EME's EPU is dependent on (and is influenced by) its neighbouring economies' implemented economic policies. Investors and policy makers must pay attention to economic policies implemented in EMEs since it significantly influences or is influenced by the EPU outcomes in other neighbouring economies.

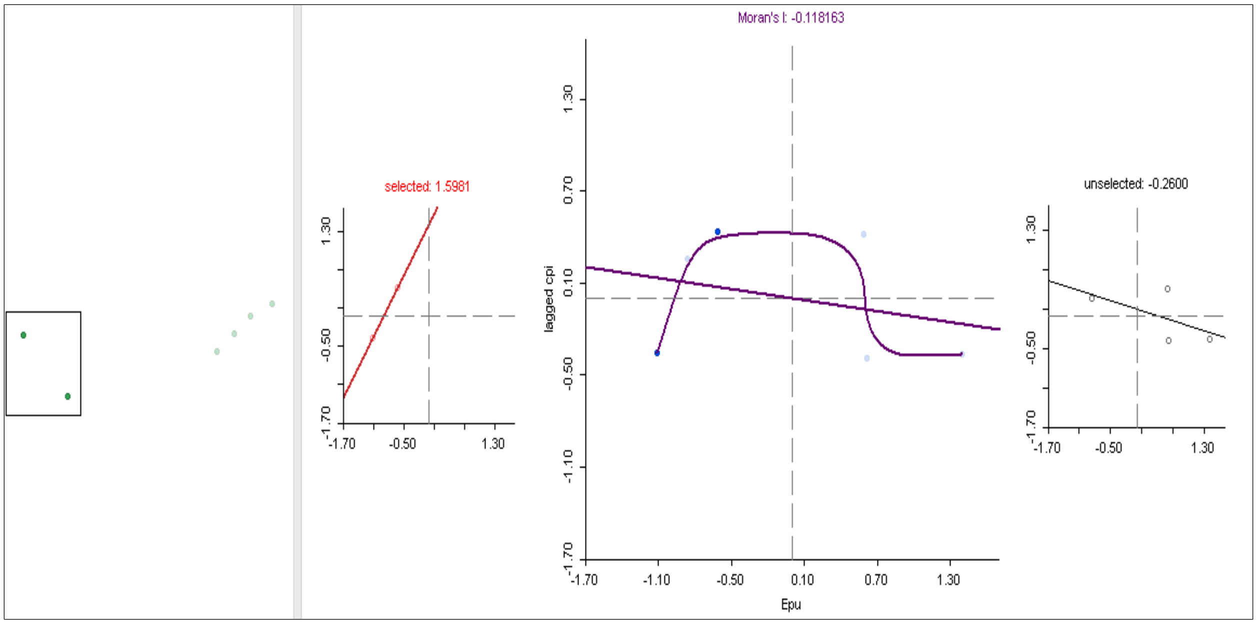


Figure 4.15: Regionalised Moran's I test (EPU verses CPI across EMEs).
Note: Left pane selected regions are Brazil and Mexico. Unselected regions (on the far right) are China, India, Korea and Russia.

4.4.2.5 Bivariate Spatial Correlation (EPU verses BRM across EMEs)

Broad money (BRM) represents the measures of monetary policy stance in an economy. It is the amount of money available to the money-holding sectors in the economy used for the purchasing of goods, services, financial and nonfinancial assets in an economy. Although BRM measures the level of money supply and CPI reflects price levels of goods and services, they both reflect the outcomes of implemented monetary policy decision in an economy. It is not surprising that both CPI and BRM have negative sloping straight lines and very close LOWESS smother patterns. Therefore, similar analogies drawn for CPI apply to BRM. The Moran's I value of BRM (-0.377516) as seen in Figure 4.16 is however stronger than the CPI value (-0.118163). For the spatial correlation between EMEs and their respective neighbours, points on the scatter plots are only displayed in the low-high and high-low quadrants. Specifically, the low EPU values of

Mexico, India and Brazil spatially correlate with their neighbouring economies' high BRM values. On the other hand, Korea, Russia and China have high EPU values and they are surrounded by neighbours with low BRM values. Some key events that can simultaneously influence the EPU values and BRM values of neighbouring economies is the spillover effects of trade, monetary and fiscal policy uncertainties. It is safe for investors to invest in Mexico, India and Brazil and their neighbouring economies respectively since low EPU in these economies spatially correlate with their neighbours' high BRM values.

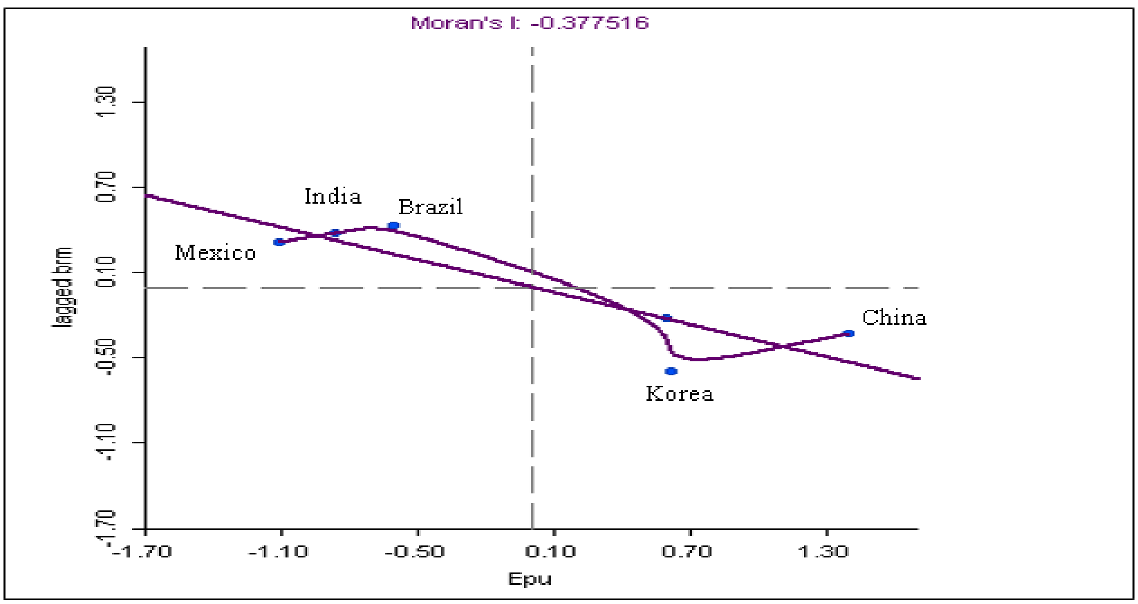


Figure 4.16: Moran's I (EPU verses BRM across EMEs).
Note: The Moran's I autocorrelation value is -0.377516.

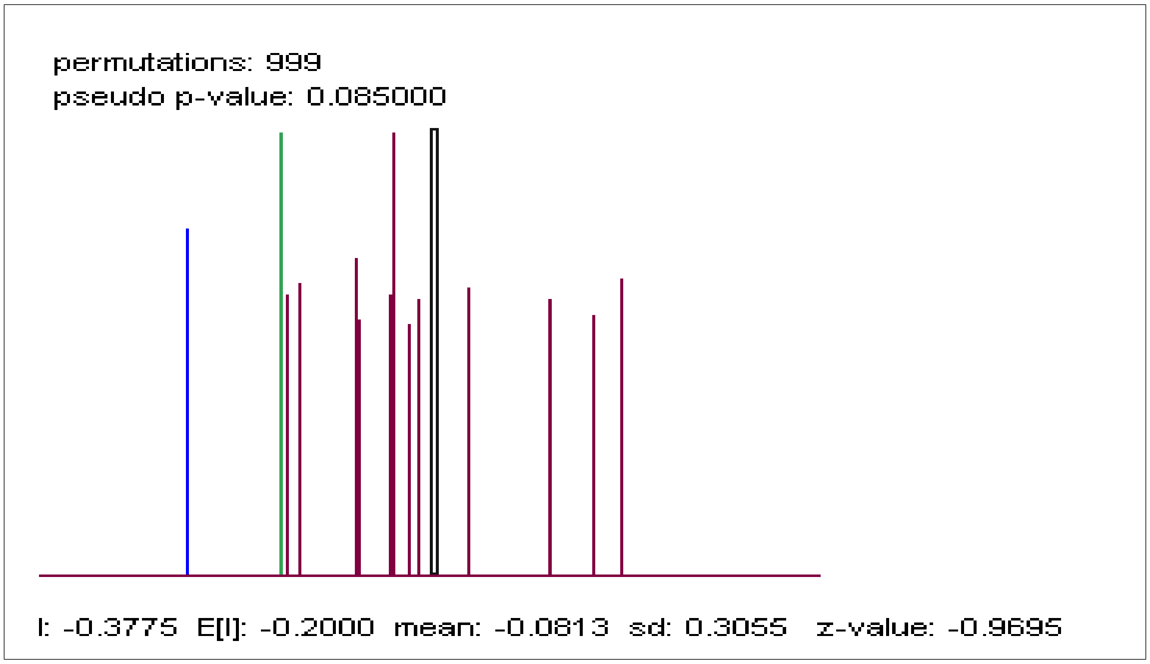


Figure 4.17: Extreme permutation for the randomisation test of the significance of Moran's I (EPU verses BRM across EMEs).
Note: The Moran's I pseudo p-value is 0.085000. The Moran's I value of -0.377516.is represented by the green line.

To test for significance, 999 permutations (a significant level for reliable inference) is run to compute a pseudo p-value. The most extreme pseudo p-value following the 999 permutations is 0.085000. This can be seen in Figure 4.17. The pseudo p–value of 0.085000 implies that 8.5% out of 999 permuted Moran's I values were equal to or more extreme than the actual Moran's I value -0.377516 (shown by the green line in Figure 4.17). The 8.5% probability leads to the rejection of the null hypothesis and an acceptance of the alternative hypothesis that the actual data is more spatially distributed than one would expect by chance. The negative z-value -0.9695 indicates that the dispersed (dissimilar but dependent) spatial pattern is statistically significant rather than a random dispersion.

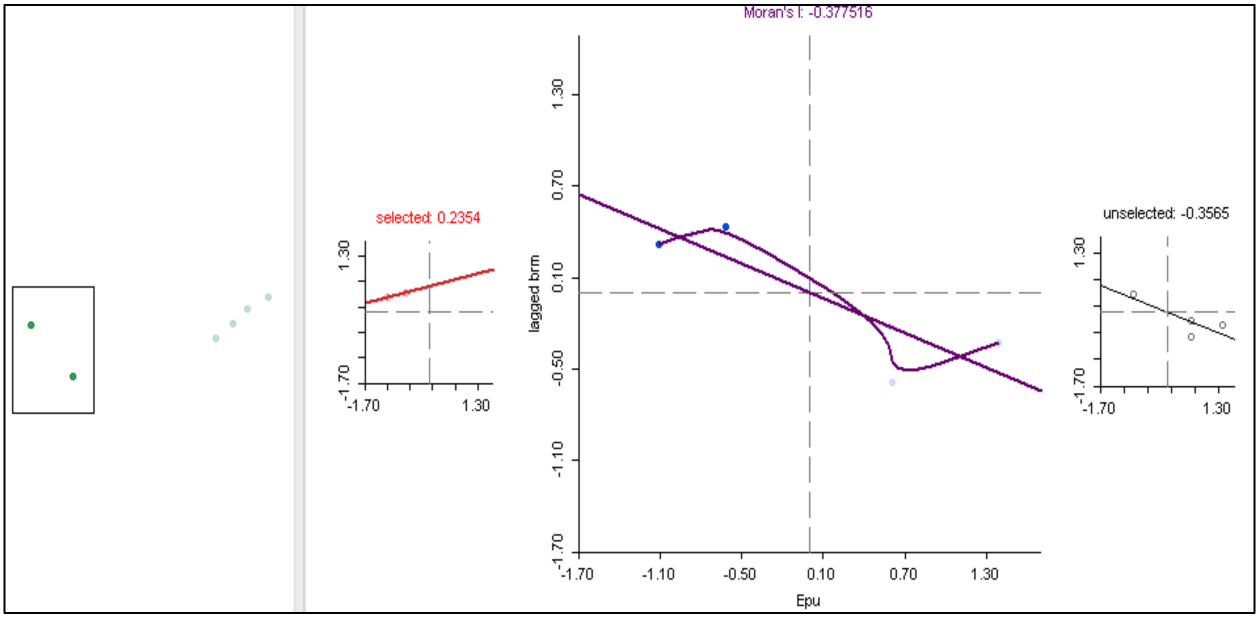


Figure 4.18: Regionalised Moran's I test (EPU verses BRM across EMEs).
Note: Left pane selected regions are Brazil and Mexico. Unselected regions (on the far right) are China, India, Korea and Russia.

The LOWESS smother displays interchanging positive and negative spatial autocorrelation which creates the possibility for different autocorrelation results when the selected EMEs are divided into sub-regions. In Figure 4.18, Region A (left to the composite Moran's I scatter plot) with a p-value 0.2354 shows evidence of positive spatial autocorrelation and Region B (right to the composite Moran's I scatter plot) with p-value -0.3565 indicates negative spatial autocorrelation. This implies that, there is evidence of heterogeneity. In terms of implications for business and investment the negative spatial autocorrelation (Region B) is preferred. The dissimilarity in the EPU and BRM means that EMEs are unlikely to suffer significant loss from heightened uncertainty and decline in the amount of BRM in one market or a number of them. In terms of application, policy makers also now have insight into the patterns of the spatial autocorrelation between EPU and BRM in EMEs for prediction purposes as well as better policy implementations.

4.4.2.6 Bivariate Spatial Correlation (EPU verses Trade across EMEs)

Findings of a study conducted by Novy and Taylor (2014) shows that, international trade strongly responses to large uncertainty shocks. The evidence of spatial autocorrelation between EPU and import (IMP) as well as EPU and Export (EXP) reinforces Novy and Taylor's (2014) findings. This also implies that, in a spatial dimension there exist a relationship between uncertainty and trade. Dingel, Meng, and Hsiang (2019) also argued that global economic activities (especially trade) are strongly spatially correlated because neighbouring economies often have similar demographics, political institutions (such as political stability, corruption and rule of law), and natural endowments (such as temperature, access to water and suitable soil for agriculture) and human capital. The Moran's I value for EPU and IMP (0.128927) in Figure 4.19 and the Moran's I value for EPU and EXP (0.0980655) in Figure 4.20 are very similar. As evident in the LOWESS smother movement, both variables' structural breaks move in the exact same pattern. For both IMP (Figure 4.19) and EXP (Figure 4.20), the first structural break from the left shows a positive sloping curve suggesting evidence of positive spatial autocorrelation. The second structural break show a steep negative sloping curve that shows evidence of negative spatial autocorrelation. Pattern three shows a larger scope of a positive slope and pattern four shows evidence of a negative slope. The scope of the positive slope is larger than the negative slope which confirms the overall positive spatial autocorrelation between the EMEs. It implies that there is a similar amount of information that is spatially shared between EPU and trade (EXP and IMP respectively) in the selected EMEs. The neoclassical trade models argue that the "terms of trade" of an economy determines its gains and the terms of trade are not determined by local economic conditions (Dingel, Meng, & Hsiang, 2019). It can be argued that terms of trade between partner economies plays a significant role in the positive spatial autocorrelation recorded for the six EMEs. Baley, Veldkamp, and Waugh's (2019) study on the relationship between uncertainty and trade argued that "*Higher uncertainty leads to increases in trade because agents receive improved terms of trade, particularly in states of nature where consumption is most valuable. Trade creates value, in part, by offering a mechanism to share risk and risk sharing is most effective when both parties are uninformed*". This argument to an extent explains why high EPU values tend to be spatially correlated with high IMP and EXP values (respectively) at neighbouring locations.

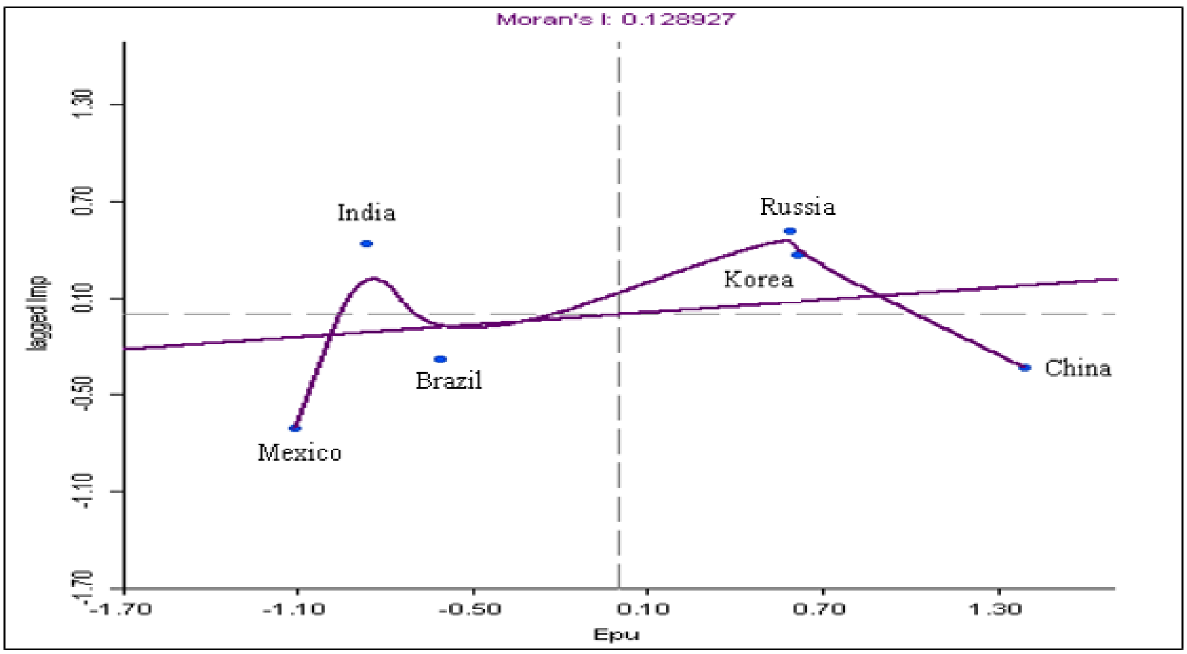


Figure 4.19: Moran's I (EPU verses IMP across EMEs).
Note: The Moran's I autocorrelation value is 0.128927.

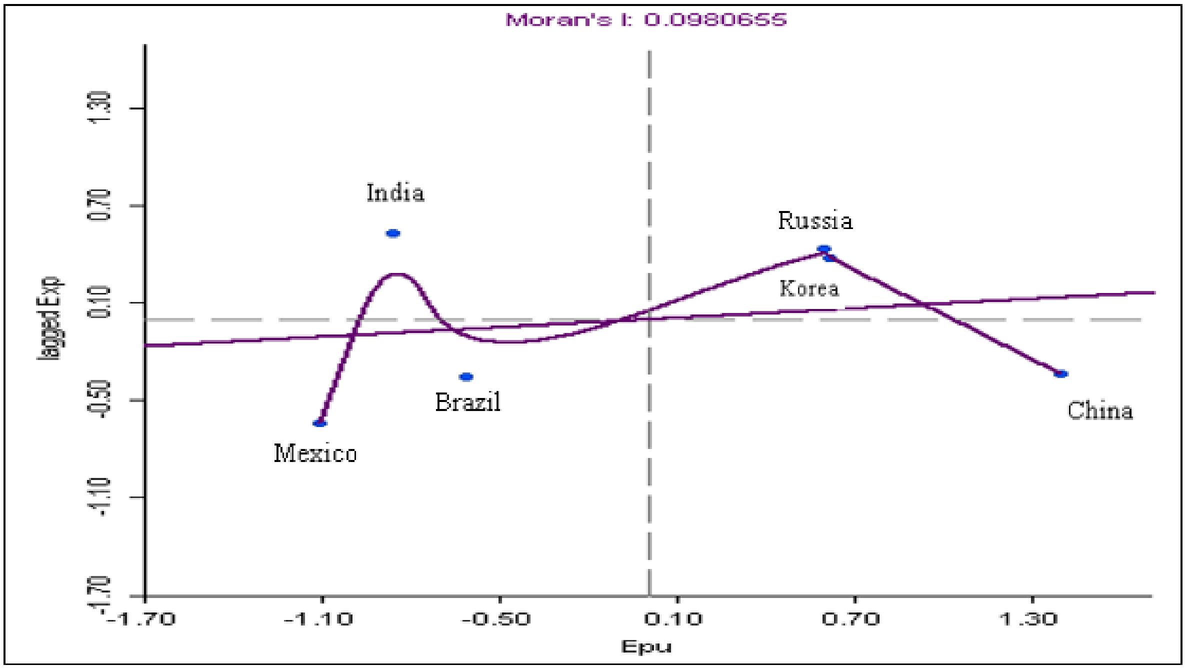


Figure 4.20: Moran's I (EPU verses EXP across EMEs).
Note: The Moran's I autocorrelation value is 0.0980655.

For the spatial correlation between EMEs and their respective neighbours, the location of EMEs on the scatter plots for both the spatial correlations between EPU and IMP and spatial correlations between EPU and EXP are exactly the same. Specifically, the low EPU values of Mexico and Brazil spatially correlate with their neighbouring economies' low IMP and EXP values. On the other hand India has low EPU values and they are surrounded by neighbours with high IMP and EXP values. China's high EPU values are surrounded by low IMP and EXP values. Russia and Korea are located in the high- high quadrant. Figure 4.21 displays the most extreme pseudo p-value 0.169000 for the spatial autocorrelation between EPU and IMP. Findings imply that, 16.9% out of 999 permuted Moran's I values were equal to or more extreme than the actual Moran's I value 0.128927. The 16.9% probability is an acceptable size which suggests the rejection of the null hypothesis and an acceptance of the alternative hypothesis that the actual data is more spatially distributed than one would expect by chance alone. The positive sign of the z-value 1.0467 indicates that the clustered spatial pattern is statistically significant rather than a random dispersion. Likewise, the most extreme p-value out of 999 permutation for the spatial autocorrelation between EPU and EXP is 0.283000 (see Figure 4.22). The 28.3% probability suggests an acceptance of the alternative hypothesis. The actual data is more spatially distributed than a random distribution. The z-value of 0.8989 shows evidence of the significance of the positive correlation.

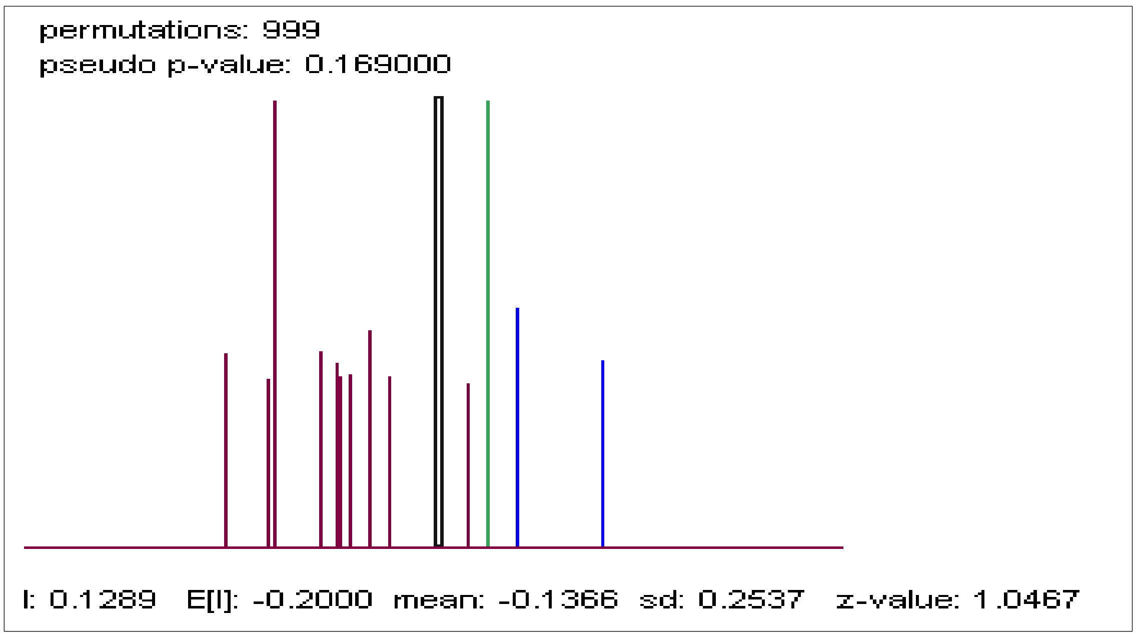


Figure 4.21: Extreme permutation for the randomisation test of the significance of Moran's I (EPU verses IMP across EMEs).

Note: The Moran's I pseudo p-value is 0.169000. The Moran's I value of 0.128927.is represented by the green line.

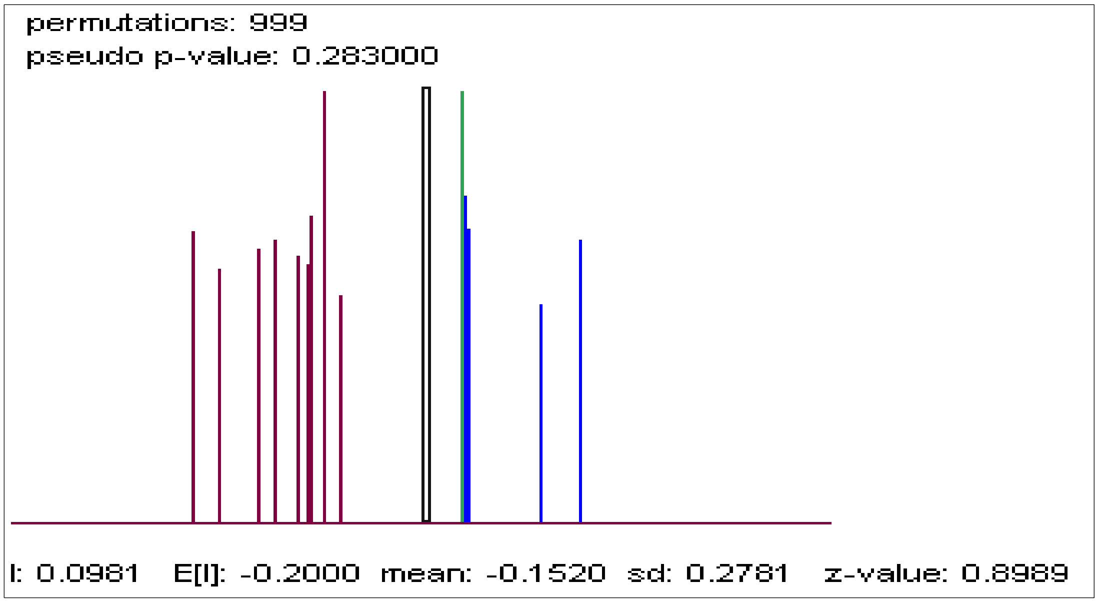


Figure 4.22: Extreme permutation for the randomisation test of the significance of Moran's I (EPU verses EXP across EMEs).

Note: The Moran's I pseudo p-value is 0.283000. The Moran's I value of 0.0980655.is represented by the green line.

Regionalised Moran's I is used to further investigate the alternating positive and negative spatial autocorrelation in the subsets of the overall observation. Figure 4.23 display the regionalised Moran's I for EPU and IMP. Region A (0.8606) is positively spatially correlated and Region B (-0.2809) is negatively spatially correlated. Similarly, Figure 4.24 display the regionalised Moran's I for EPU and EXP. Region A (0.5589) is positively spatially correlated and Region B (-0.3281) is negatively spatially correlated. Both cases show evidence of heterogeneity since the selected subsets shows dissimilar degree of dependence when compared to the data set as a whole. The analogies drawn for the composite positive spatial autocorrelation is still applicable to Region A. Region B implies dissimilar values at neighbouring locations. The evidence of negative spatial autocorrelation in Region B is likely caused by the negative impact of EPU spillover on neighbouring economies terms of trade and level of production. The dissimilar values make Region B an efficient platform for portfolio diversification. The presence of heterogeneity implies that the degree of openness between economies largely influences the spillover effects of EPU transmitted.

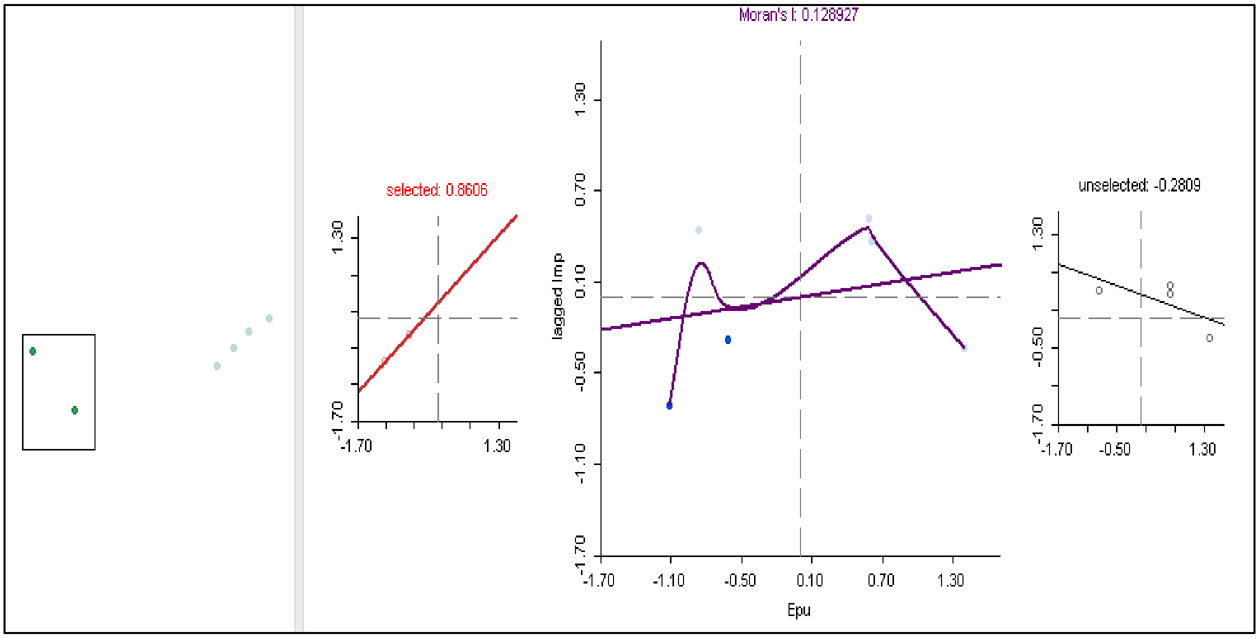


Figure 4.23: Regionalised Moran's I test (EPU verses IMP across EMEs).
Note: Left pane selected regions are Brazil and Mexico. Unselected regions (on the far right) are China, India, Korea and Russia.

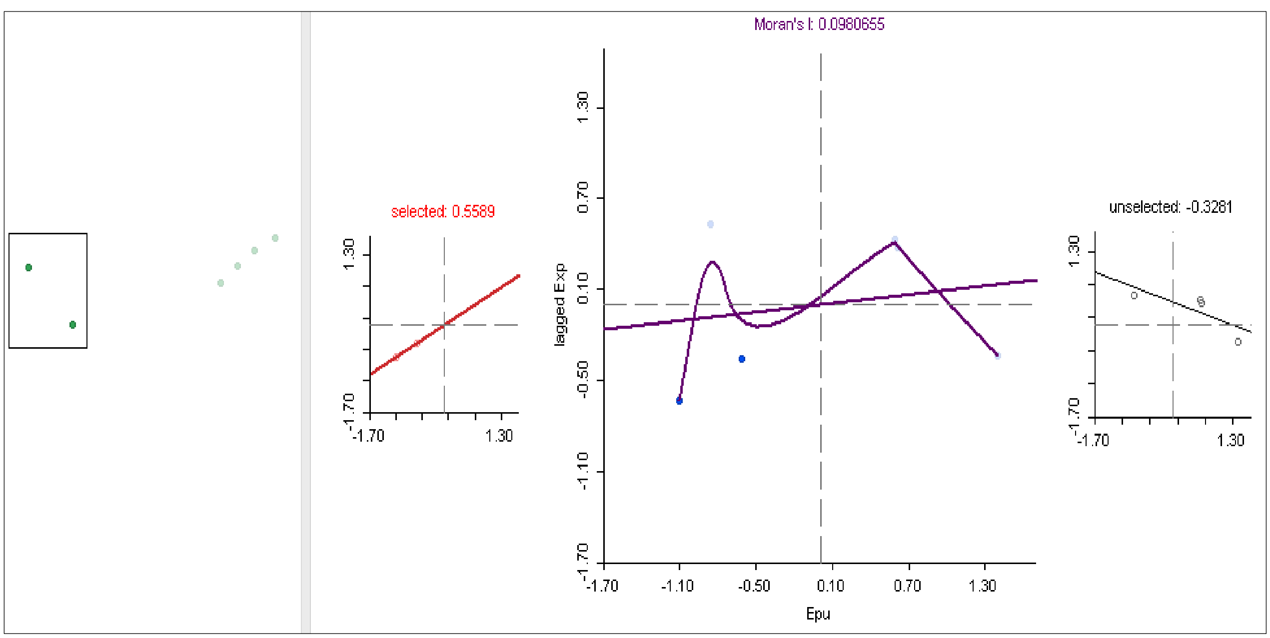


Figure 4.24: Regionalised Moran's I test (EPU verses EXP across EMEs).
Note: Left pane selected regions are Brazil and Mexico. Unselected regions (on the far right) are China, India, Korea and Russia.

4.5 Conclusion

Understanding of the trends and impact of EPU and its relationship with macroeconomic variables has become essential because of its significant negative impact on economic activities. The first session of this Chapter focus on the "economic dimension" of distance and specifically investigate whether EPU and macroeconomic variables influence the economic distance between EMEs. The variables selected for this investigation are EPU, GDP, CPI, trade (export and import of goods and services), broad money and SPX. We discover that macroeconomic variables were largely statistically significant and have explanatory power to explain the economic distance between the EMEs as compared to the role EPU plays in explaining the economic distance between EMEs. Thus, we find limited evidence of EPU effects on the economic distance between EMEs. We also discover that changes in the values of import, CPI and broad money in most EMEs are statistically relevant and significantly drive the changes in the values of economic distance between the selected EMEs. We therefore argue that the trade and capital flows between the selected EMEs significantly influence the economic distance between the economies.

The second session of this Chapter investigated the dependence between EMEs as a result of the spatial distance between them. The results showed evidence of spatial autocorrelation across all the EMEs which support Tobler's first law of geography. The similarities and dissimilarities between the selected EMEs are significantly influenced by the distance between them. It was observed that for each of the Moran's I scatter plots the six EMEs were independently positioned within the quardrants. This implies that, country and geographical specific features (or characteristics) affect the outcome of the results. Secondly, heterogeneity was recorded when the six EMEs were divided into sub regions. The different outputs generated when the EMEs were regionalised indicate that acquiring knowledge on the specific characteristics of each economy and how it integrates with other economies is very necessary. Thirdly, the study discovered that international policies (for example trade policies), terms of trade, spillover effects, monetary and fiscal policies are some of the factors that influence EPU spatial autocorrelation in EMEs. However, a more robust study should be conducted to investigate the factors leading to spatial autocorrelation in EMEs since this will help curtail incidences of heightened EPU. Finally, the study identified safe zones for portfolio diversification and risk minimisation. Economies that were negatively spatially correlated were seen as safe zones since investors can avoid the risk of losing all their investment in a case of heightened EPU, fall in economic growth, depreciation of share prices, reduction in export and import and drop in money supply (respectively). This study provides information for investors who intend to invest in stock markets, financial institutions, international trade and sales of commodities. Investors are advised to invest and trade with economies with which they have economic similarities since this lowers the barriers to cross-border trade and investment. Policy makers and regulators also have access to findings on a broad field of macroeconomic variables and their relationship with EPU. The relationship between macroeconomic variables and the economic distance between economies will assist policymakers and investors in identifying economies with similar economic characteristics with the objective of promoting economic partnerships between these economies. Policymakers and regulators can implement policies and trade agreements to reduce the economic distance between these EMEs with dissimilar characteristics.

CHAPTER FIVE

SPILLOVER BETWEEN ECONOMIC POLICY UNCERTAINTY AND MACROECONOMIC INDICATORS IN EMERGING MARKET ECONOMIES

5.1 Introduction

This chapter focuses on the directional spillover effects of EPU in emerging market economies. This investigation is significant because previous studies on the spillover of uncertainty shocks within and beyond an economy have not been able to show the direction of these spillovers (see, Colombo, 2013; Zhu & Yan, 2015; Luk, Cheng, Ng, &Wong, 2020; Trung, 2019a; Diebold & Yilmaz, 2009). This research is important to EMEs for five reasons. First, Carrière-Swallow and Céspedes (2013) discovered that uncertainty spillover shocks affect emerging economies much more than developed economies. Their findings show that exogenous uncertainty shocks transmitted to developing countries reduce investment and private consumption. Second, studies have shown that the Great Recession of 2007-2009 increased uncertainty in most EMEs due to the transmission of US shocks (Fernandez-Villaverde, Guerrón-Quintana, Rubio-Ramírez, & Uribe, 2011; Bloom, 2014). Third, research has shown that monetary and fiscal policy actions (rather than general uncertainty) have a greater impact on increasing and decreasing uncertainty shocks in EMEs (Krol, 2014). Fourth, EMEs have recently influenced the rise in EPU by transmitting negative shocks to other countries (Dizioli, Guajardo, Klyuev, Mano, & Raissi, 2016; and Russel, 2016). Last, studies on the effect of EPU in EMEs are meagre because the majority of EPU research has focused on developed countries (Redl, 2018). Kang and Yoon (2019), for example, included China as the only developing country in their studies; Istiak and Alam (2020) concentrate on Gulf Cooperation Council countries (Saudi Arabia, United Arab Emirates (UAE), Qatar, Kuwait, Bahrain, and Oman); and Luk, Cheng, Ng, and Wong (2020) investigate EPU spillover from the United States, Europe, Mainland China, and Japan to Hong Kong (see also Trung, 2019b; and Thiem, 2018). The interdependence of EPU and economic activities in EMEs (IMF 2011a, 2011b) implies that EPU and key macroeconomic variables correlate. Their interdependence therefore opens up channels for spillover transmission.

These implications of uncertainty on EMEs have made it very relevant to focus on the role uncertainty plays in developing countries. This study therefore investigates these arguments by finding evidence of the severity of the amount and direction of the EPU spillover received or contributed by one economy to other economies, confirming arguments on volatilities of uncertainty in most EMEs during the Great Recession that occurred during 2007-2009, investigate whether EPU or key macroeconomic variables are the main transmitter of spillover shocks in EMEs and finally investigate the effects of EPU spillover in developing countries. We adopt Baruník and Křehlík's (2018) methodology for the analysis since it's able to capture frequency domain as well as time-frequency dynamics spillover connectedness. Investors are more concerned about the net transmitters, net recipients and the amount of EPU spillover across economies because this information will help investors to understand the network connectedness across developing countries and the degrees of spillover shocks which will aid them in undertaking precise investment decisions and intelligently planning their portfolio diversification strategies. This research also helps investors guard against heightened EPU caused by spillover shocks in developing countries.

The findings from this study shows evidence of spillover and causal spillover between EPU and macroeconomic variables within each EME. However, the degree of spillover shock transmission is generally low. We also discover that EPU does not dominate in the transition or receiving of spillover shocks in all the selected EMEs. The results therefore suggest that investors should rather be alert about GDP and SPX because they are the main transmitters of spillover shocks to the other variables across all the selected EMEs. The time-varying total spillover index confirms arguments of volatilities of uncertainty in EMEs during the Great Recession that occurred during 2007-2009. We also observed a decline in spillover effects in the long-term. This suggests that investors can diversify their portfolio in the long-term. Inter-country spillover analysis shows that Korea- EPU is the main transmitter of spillover shocks to the selected EMEs across all frequency bands. On the other hand, the main transmitter of spillover shocks to Korea-EPU is China-EPU and Mexico-SPX across all the frequency bands.

5.2 Theoretical Models and Empirical Methodology

To investigate the network spillover effect and directional connectedness between EPU and related macroeconomic variables in EMEs and explore their time-frequency dynamics, this investigation used Baruník and Křehlík's (2018) methodology. Baruník and Křehlík (2018) is able to captures frequency domain as well as time-frequency dynamics. The time-frequency dynamics is measured by time domain variance decomposition while the frequency dynamics measures the decomposition into frequency bands. One of the important features of spillover analysis that Baruník and Křehlík (2018) have been able to address is its ability to capture time-varying instability, non- linearity and non-stationaity within a set of variables (see for example Bampinas & Panagiotidis, 2017). Thirdly, unlike other methodologies that focus on either time domain or frequency domain, Baruník and Křehlík (2018) has the ability to account for both composite and pairwise spillover and captures the information at various frequencies and varying times simultaneously. This methodology is also able to measure the net spillover by finding the difference between “from” spillover and “to” spillover. This framework estimates EPU spillovers among EME’s in the short-, medium-, and long- term.

Baruník and Křehlík’s (2018) measure of spillover was inspired by Diebold and Yilmaz’s (2012) methodology. When compared to Diebold and Yilmaz (2012), Baruník and Křehlík (2018) is able to imply causality in spillover using the “within” connectedness. Second, although Diebold and Yilmaz (2012) require a global stationarity for all variables, the Baruník and Křehlík (2018) relies on local stationarity framework. The local stationarity in the Vector autoregression (VAR) system creates a convenient approximation of nonstationary data through stationary models. Finally, when compared to Diebold and Yilmaz (2012), Barunk and Kehlk's (2018) technique is more robust in a rolling window analysis. This is because there is no evidence of serial correlation when a rolling window approach is applied to Baruník and Křehlík’s (2018) methodology. The study undertook a full sample analysis focusing on the composite and pairwise connectedness of variables, while a rolling-sample analysis assists researchers to understand the dynamics (nature) of connectedness and how trends vary over time and across frequencies. A country specific analysis of all variables and variable specific dynamics across EMEs were conducted.

Inspired by Diebold and Yilmaz (2012), Baruník and Křehlík (2018) measure connectedness using generalised forecast error variance decompositions. 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

$$Y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \epsilon_{t,} \tag{5.1}$$

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 $MA(\infty)$

$$Y_t = \psi(L)\epsilon_t, \tag{5.2}$$

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

$$(\Theta_H)_{j,k} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H} ((\psi_h \Pi)_{j,k})^2}{\sum_{h=0}^{H} (\psi_h \Pi_{h'})_{j,k}}, \tag{5.3}$$

where $h = 1, \dots, H$ 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

$$(\widetilde{\Theta}_H)_{j,k} = \frac{(\Theta_H)_{j,k}}{\sum_{k=1}^{N} (\Theta_H)_{j,k}}. \tag{5.4}$$

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

$$C_H = 100 * \frac{\sum_{j \neq k} (\widetilde{\Theta}_H)_{j,k}}{\sum \widetilde{\Theta}_H} = 100 * \left(1 - \frac{Tr\{\widetilde{\Theta}_H\}}{\sum \widetilde{\Theta}_H}\right), \qquad (5.5)$$

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. 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

$$S_{y(\omega)} = \sum_{h=-\infty}^{\infty} E\,(Y'Y_{t-h})e^{-i\omega h} = \psi(e^{-i\omega})\Pi\psi'(e^{+i\omega}). \qquad (5.6)$$

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

$$(\mathcal{F}(\omega))_{j,k} = \frac{\sigma_{kk}^{-1}|\psi(e^{-i\omega})\Pi_{j,k}|^2}{(\psi(e^{-i\omega})\Pi\psi'(e^{+i\omega}))_{j,j}} \qquad (5.7)$$

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.

D to frequencies. The weighting function can be defined as

$$\Gamma_j = \frac{(\psi(e^{-i\omega})\Pi\psi'(e^{+i\omega}))_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\psi(e^{-i\lambda})\Pi\psi'(e^{+i\lambda}))_{j,j}\,d\lambda} \tag{5.8}$$

summing up real-valued 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. It is appropriate to quantify connectedness over frequency bands rather than at single frequencies. In formal terms, for a frequency band $d = (a, b): a, b \in (-\pi, \pi), a < b$, the GFEVD can be defined as

$$(\Theta_d)_{j,k} = \frac{1}{2\pi}\int_a^b \Gamma_j(\omega)\big(\mathcal{F}(\omega)\big)_{j,k}\,d\omega. \tag{5.9}$$

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

$$(\widetilde{\Theta}_d)_{j,k} = (\Theta_d)_{j,k}/\sum\nolimits_k(\Theta_\infty)_{j,k}. \tag{5.10}$$

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

$$C_d^W = 100.\left(1 - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum\widetilde{\Theta}_d}\right) \tag{5.11}$$

$$C_d^F = 100.\left(\frac{\sum\widetilde{\Theta}_d}{\sum\widetilde{\Theta}_\infty} - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum\widetilde{\Theta}_\infty}\right) = C_d^W.\left(\frac{\sum\widetilde{\Theta}_d}{\sum\widetilde{\Theta}_\infty}\right) \tag{5.12}$$

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).

5.3 Data, sample, and preliminary analysis

The series used as input in the analysis are monthly data from 1st January 1999to 31st December 2018. The macroeconomic variables were gleaned from the Organisation for Economic Co-operation and Development database. The variables selected in this study are EPU, CPI, broad money, trade (export of goods and import of goods), GDP, and SPX. The six EMEs selected for analysis are Brazil, China, India, Korea, Mexico and Russia. To account for both time and frequency domain spillover connectedness, the study selects three (3) frequency bands (thus, 3.14 ~ 0.79, 0.79 ~ 0.26, 0.26 ~ 0.00) to highlight short-, medium-, and long-term dynamics respectively. The frequency bands are shown in Table 5.1. For time-frequency domain analysis, we use a 12-months (equivalent to 1 year) ahead forecast horizon (*H*) and a rolling window size of 36 months (equivalent to 3 years). This time frame is enough to account for a time-varying phenomenon. Instead of independently selecting the start and end of a crisis, the rolling window by itself accounts for any major changes in the spillover indices as the data is rolled across the full sample period (Yilmaz, 2010).

Table 5.1: Interpretation of time-scales & frequencies

WAVELET MULTIPLE CORRELATION AND WAVELET MULTIPLE CROSS-CORRELATION SCALES			
Frequency	**Band**	**Months**	**Interpretation**
d_1	3.14 ~ 0.79	1 ~ 4	Monthly to quarterly
d_2	0.79 ~ 0.26	4 ~ 12	Quarterly to annual
d_3	0.26 ~ 0.00	12 ~ ∞	Annual and beyond

5.4 Empirical Results

The objective of this analysis is to investigate the spillover between economic policy uncertainty and macroeconomic indicators in emerging market economies. The first session focused on static spillover connectedness while the second sessions addressed spillover in the time-frequency domain. The static spillover connectedness presents findings on the total and net bi-directional spillovers in the frequency-domain (thus, static environment) within three (3) frequency bands. It first focused on total and net spillover among EPU and macroeconomic variables within each EME, then it investigated an inter-country analysis to examine spillover transmission across the selected EMEs. The time-varying spillover index with rolling window analysis showed strong evidence of spillover connectedness within each EMEs with strong exhibits of country specific features. We also identified that sharp spillover connectedness over lapped with global and country specific economic and financial incidents.

5.4.1 Intra-country Static spillover connectedness within selected EMEs.

This session selects each EME and uses Baruník and Křehlík's (2018) methodology to investigate the network spillover effect and directional connectedness between EPU and related macroeconomic variables (representing economic activities) in each of the selected EMEs. The $ijth$ entry is the estimated contribution to the forecast-error variance of variable i coming from innovations to market$j$. The Diagonal entries ($i = j$) (Tables 5.2-5.16) are the own variance shares estimates which indicate the fraction of the forecast error variance of market i that is coming from its own shocks. The column labeled "FROM_ABS" represents the total spillover received by a variable from all the other variables while its row equivalence "TO_ABS" represents the spillover transmitted from by one variable to all the other variables. The last column and row

"FROM_WITH" and "TO_ABS" respectively serves an additional purpose of showing causality in the system. This implies that, there is a corresponding "within" connectedness value that indicates the causality for every "absolute" connectedness value.

5.4.1.1 Static spillover connectedness between EPU and Macroeconomic variables in Brazil

Proceeding with Brazil, Table 5.2 shows the total and net spillover of the variables in the Brazil. Clearly there exist spillover effects from EPU to macroeconomic variables, and vice versa in Brazil except for EPU to GDP (frequency band 1), export to EPU, GDP to EPU, broad money to EPU, EPU to SPX and export to SPX (all in frequency band 3). It is evident from Table 5.2 that the average absolute (from) spillover among EPU, GDP, broad money, import, export, CPI and SPX decreased across the frequencies increases. Thus, we can infer that spillover in Brazil dominates in the short-term having average absolute (from) spillover values of 9.97, 5.00 and 6.38 on frequency bands 1, 2 and 3 respectively. The directional spillover transmitted 'To' shows that the highest contributor to the other variables is import contributing 3.60%, followed by export (2.69%) and broad money (1.14%). Interestingly, EPU is the fifth contributor (0.71%) in the first (1^{st}) frequency band. In the medium-term, the highest contributor to the other variables is GDP contributing 1.26%, with SPX contributing 2.44% to the other variables in the long-term. The variable that receives the highest spillover from the rest of the six (6) variables in the short-term is export receiving 3.23% and followed by import (2.97%). In frequency band 1, EPU receives a total 0.83% spillover shocks from the macroeconomic variables with import making the highest contribution of 2.15%. In the medium-term, EPU receives a total of 0.05% with GDP making the highest contribution of 0.14%. The long-term records the least value of 0.01%. Clearly, export, GDP and broad money had no records of spillover to EPU in the long-term. EPU transmits its highest spillover shocks to import (1.75%), import (0.46%) and GDP (0.53) in frequency bands 1, 2 and 3 respectively. It was observed that export (18.61%), SPX (4.16%), and GDP (8.61%) are the variables that received the highest spillover shocks in frequency bans 1, 2 and 3 respectively. The results therefore suggest that investors should rather be alert about import, GDP and SPX because they are the main transmitters of spillover shocks to the other variables in frequency bands 1, 2 and 3 respectively. Second, it is clear that EPU does not dominate in the transition or receiving of spillover shocks in Brazil. Third, diversification benefits are effective in the long-term since we recorded a drop in spillover effects in the long-term. Fourth, there is also evidence of causal spillover for each variable across the three (3) frequency bands.

The last row recorded the net spillover for each variable. The net spillover calculates the difference between “FROM” and “TO” spillovers per each variable and indicates the net transmitter and net recipient variable. A positive net spillover value of a variable denotes that the variable is a net transmitter while negative net spillover denotes a net recipient. It is therefore evident from Table 5.2 that in the short-term EPU, export, SPX and CPI are net recipients while import, GDP, and broad money are net transmitters. In frequency band 2, EPU and export are now net transmitter while GDP maintains its position as a net transmitter. On the other hand, import, SPX, CPI and broad money are net recipients. In frequency band 3, EPU, export, import and SPX are net transmitters while, GDP, CPI and broad money are net recipients. It is clear that all the variables’ net transmission vary across frequency bands except for CPI that is identified as a net recipient across all frequency bands.

For a more detailed investigation of connectedness we now focus on net pairwise spillover which shows the detailed amount of transmission between two variables under investigation. The net pairwise spillover between two variables i and j is the difference between the gross shocks transmitted from market i to market j and those transmitted from j to i. Findings on net pairwise connectedness is very helpful for two-variable (within each EME) and two-country (across EMEs) portfolio construction and analysis. Table 5.3 shows the net pairwise connected between the seven variables. It is evident that the amounts of pairwise net directional connectedness recorded across the three frequencies (specifically for each pair) differs and generally shows alternating signs (positive/negative) in the system. Thus, Table 5.3 shows that the pairwise net directional connectedness from CPI to broad money and import to GDP record positive signs across all frequencies. On the otherhand, GDP to broad money, import to broad money and export to broad money record negative signs across all frequencies. Except for these few cases, we find no pattern of transmission in the whole system. Therefore, policy makers and investors are adviced to analyse outputs on a pair-specific and frequency-dependent bases.

Table 5.2: Total spillover and Net spillover indices between EPU and Macroeconomic variables in Brazil

				BRAZIL					
	EPU	**EXP**	**IMP**	**GDP**	**SPX**	**CPI**	**BRM**	**FROM_ABS**	**FROM_WTH**
Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)									
EPU	89.140	1.920	2.150	0.040	0.330	0.490	0.890	0.830	1.410
EXP	1.370	66.790	18.610	0.890	0.360	0.620	0.740	3.230	5.490
IMP	1.750	14.430	65.320	0.400	1.850	1.300	1.060	2.970	5.060
GDP	0	0.020	0.100	0.330	0.160	0.180	0.020	0.070	0.120
SPX	0.780	0.730	1.780	0.590	58.570	0.850	2.910	1.090	1.860
CPI	0.850	0.610	1.280	0.320	2.390	27.240	2.380	1.120	1.900
BRM	0.210	1.130	1.270	0.050	1.210	0.770	34.120	0.660	1.130
TO_ABS	0.710	2.690	3.60	0.330	0.900	0.600	1.140	9.970	
TO_WTH	1.210	4.580	6.120	0.560	1.530	1.020	1.950		16.970
NET	-0.12108	-0.53626	0.627705	0.259093	-0.19231	0.51663	0.479486		
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)									
EPU	3.390	0.060	0.020	0.140	0.080	0.010	0.040	0.050	0.290
EXP	0.280	5.280	0.870	1.010	0.150	0.240	0.270	0.40	2.340
IMP	0.460	1.400	3.620	1.770	0.090	0.380	0.290	0.630	3.620
GDP	0.270	1.700	0.730	21.340	2.440	1.920	0.420	1.070	6.180
SPX	0.110	0.880	0.170	4.160	14.220	0.900	1.810	1.150	6.640
CPI	0.130	0.190	2.110	0.680	2.640	18.620	1.380	1.020	5.900
BRM	0.240	2.170	0.390	1.070	0.810	0.070	19.610	0.680	3.930
TO_ABS	0.210	0.920	0.610	1.260	0.890	0.500	0.600	5.000	
TO_WTH	1.230	5.290	3.560	7.300	5.120	2.910	3.480		28.900
NET	0.162699	0.511403	-0.01152	0.193579	-0.2629	-0.5158	-0.07746		
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months									
EPU	1.250	0	0.010	0	0.020	0.010	0	0.010	0.030
EXP	0.020	0.980	0.180	1.030	0.280	0.010	0.010	0.220	0.920
IMP	0.040	0.030	1.500	2.860	1.170	0.190	0.090	0.630	2.610
GDP	0.530	2.890	0.340	50.840	8.610	7.020	0.130	2.790	11.650

	BRAZIL								
	EPU	**EXP**	**IMP**	**GDP**	**SPX**	**CPI**	**BRM**	**FROM_ABS**	**FROM_WTH**
SPX	0	0	0.090	1.460	9.840	0.030	0.110	0.240	1.010
CPI	0.040	0.190	4.560	0.800	2.380	30.310	0.910	1.270	5.290
BRM	0.190	1.710	0.770	1.280	4.590	0.040	28.310	1.220	5.110
TO_ABS	0.120	0.690	0.850	1.060	2.440	1.040	0.180	6.380	
TO_WTH	0.490	2.870	3.550	4.430	10.180	4.360	0.740		26.620
NET	0.109892	0.468741	0.225388	-1.72968	2.195512	-0.2229	-1.04695		

Note: Absolute to measures spillovers from country j to other countries. Absolute from measures spillovers from other countries to country j. Within to measures spillovers from country j to other countries, including from own innovations to country k. Within from measures spillovers from other countries to country j, including from own innovations to country k (see Tiwari et al., 2018, 2019). Positive ***Net*** *denotes that the variable is a* ***net transmitter*** *while negative* ***Net*** *denote* ***net recipient.*** *EPU-economic policy uncertainty, EXP- export, IMP-import, GDP- gross domestic product, SPX- share price index, CPI- consumer price index, BRM- broad money.*

Table 5.3: Pairwise net directional spillover between EPU and macroeconomic variables in Brazil

Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
0.078	0.056	-0.005	-0.064	-0.051	0.097	0.597
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.124	-0.052	0.002	-0.056	0.043	0.010	0.003
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
-0.029	-0.063	-0.020	0.005	-0.220	0.243	0.230
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
-0.032	-0.063	-0.019	-0.004	-0.016	-0.028	-0.075
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
-0.098	-0.105	0.006	-0.271	0.148	-0.012	-0.248
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
-0.015	-0.246	0.177	-0.093	-0.249	0.143	0.187
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
-0.003	-0.004	-0.076	0.003	-0.004	-0.027	0.022
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
-0.266	0.040	-0.025	-0.243	0.359	0.155	-0.624
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
-0.097	-1.021	-0.889	-0.164	-0.335	-0.641	0.124

Note: epu-economic policy uncertainty, exp- export, imp-import, gdp- gross domestic product, spx- share price index, cpi- consumer price index, brm- broad money.

5.4.1.2 Static spillover connectedness between EPU and Macroeconomic variables in China

This session addresses the total and net spillover of EPU and macroeconomic variables in China. The average absolute (from) spillover of 8.19, 2, 3.37 on frequency bands 1, 2 and 3 in Table 5.4 shows that spillover among the seven variables dominates in the short-term (frequency band 1). It is clear from the average absolute (from) spillover values that the frequency bands 2 and 3 are quite low when compared to frequency band 1. We observe that import (10.77) received the highest spillover in frequency band 1, followed by GDP (1.63) in the medium- term frequency band and SPX (5.31) in the long-term frequency band. The directional spillover transmitted ‘Absolute to’ shows that the highest **contributor** to the other variables in frequency band 1 is export contributing 2.11%, while GDP and SPX contribute the highest spillover shocks (0.53%) in the medium-term frequency band. In the frequency band 3 we identify GDP as the highest contributor (1.21%). The results therefore suggest that investors should rather be alert about export, import, GDP and SPX because they are the main transmitters of spillover shocks to the other variables in China. With respect to EPU, EPU is not a major contributor of spillover shocks in China it records a "TO_ABS" spillover values of 0.62, 0.07 and 0.10 to the other variables in frequency band 1, frequency band 2 and frequency band 3 respectively. More specifically, the variables that receive the highest portion of EPU shocks are SPX (1.97%), GDP (0.20%) and GDP (0.39%) in frequency bands 1, 2 and 3 respectively. Clearly, investors must keep an eye on SPX and GDP since they are the main recipients of EPU shocks in China.

The variable that **receives** the highest spillover from the rest of the six (6) variables (see "FROM_ABS" row) in the short-term is export receiving 2.35% and followed by SPX (0.47%) in the medium frequency band and lastly with GDP receiving the highest spillover value of 1.39% in frequency band 3. In frequency band 1, EPU receives a total 0.92% spillover shocks from the macroeconomic variables with import making the highest contribution of 1.79%. In the medium-term, EPU receives a total of 0.06% with SPX making the highest contribution of 0.32%. The long-term records the least value of 0.04% with SPX again making the highest contribution of 0.22%. It is evident that, import, GDP and CPI makes no spillover contributions to EPU in the long-term. We can therefore conclude that EPU does not dominate in the transmission or receiving of spillover shocks in China. Just as was recorded for Brazil, diversification benefits in China are also effective in the long-term since we recorded a drop in spillover effects in the long-term. Thirdly, there is also evidence of causal spillover for each variable across the three (3) frequency bands. We also find evidence of spillover effects from EPU to macroeconomic variables, and vice versa in China except for GDP to EPU, GDP to broad money (frequency band 1), broad money to export, GDP to EPU, GDP to broad money (all in frequency band 2), import to EPU, GDP to EPU, CPI to EPU, EPU to export, EPU to import, export to broad money, SPX to CPI and CPI (all in frequency band 3). Table 5.4 records the net spillover for each variable in China on the last row. In the short-term EPU, export and import are net recipients while GDP, SPX, CPI and broad money are net transmitters. In frequency band 2, EPU and export are now net transmitter (just as recorded in Brazil) while GDP, SPX and broad money maintains their positions as a net transmitter. Import also maintains its position as net recipient while CPI joins the net recipient group in the medium-term frequency band. In frequency band 3, EPU, export, SPX and broad money are net transmitters with import, GDP and CPI serving as the net recipient. Although the roles the variables play as net transmitters/ recipients vary across each frequency bands for most of the variables, we observe that SPX and broad money are net transmitters, and import is a net recipient across all the three (3) frequency bands. For the net pairwise connected Table 5.3 records positive signs across all frequencies for the pairwise net directional connectedness from GDP to broad money, import to broad money, import to GDP and export to GDP only. On the other hand, negative values are recorded from GDP to consumer to CPI and from EPU to GDP across all frequencies. Analysis must be pair-specific since there is no pattern of transmission in the whole system.

Table 5.4: Total spillover and Net spillover indices between EPU and Macroeconomic variables in China

	CHINA								
	EPU	EXP	IMP	GDP	SPX	CPI	BRM	FROM_ABS	FROM_WTH
	Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)								
EPU	83.380	1.050	1.790	0.030	1.770	0.740	1.030	0.920	1.440
EXP	0.570	74.870	8.330	0.250	5.620	1.510	0.200	2.350	3.720
IMP	0.130	10.770	71.700	0.420	0.220	4.510	0.300	2.330	3.690
GDP	0.430	0.090	0.030	16.060	0.420	0.080	0.450	0.210	0.340
SPX	1.970	1.760	0.830	0.690	45.980	0.450	0.710	0.920	1.450
CPI	0.960	0.940	1.830	1.440	0.700	55.680	1.580	1.060	1.680
BRM	0.290	0.150	0.080	0.050	0.490	1.660	38.540	0.390	0.610
TO_ABS	0.620	2.110	1.840	0.410	1.320	1.280	0.610	8.190	
TO_WTH	0.980	3.330	2.900	0.650	2.080	2.020	0.970		12.920
NET	-0.29366	-0.24728	0.49528	0.196407	0.401532	0.213981	0.224306		
	Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)								
EPU	6.440	0.020	0.010	0	0.320	0.010	0.050	0.060	0.340
EXP	0.030	4.230	0.900	0.260	0.140	0.070	0	0.200	1.130
IMP	0.010	0.780	4.740	0.680	0.100	0.020	0.280	0.270	1.500
GDP	0.200	0.040	0.060	21.550	1.610	0.080	1.100	0.440	2.470
SPX	0.190	1.030	0.010	1.630	21.770	0.330	0.060	0.470	2.620
CPI	0.010	0.170	0.480	1.140	0.450	20.840	0.120	0.340	1.900
BRM	0.080	0.020	0.050	0	1.070	0.340	31.090	0.220	1.250
TO_ABS	0.070	0.300	0.220	0.530	0.530	0.120	0.230	2.000	
TO_WTH	0.420	1.660	1.210	2.980	2.960	0.690	1.300		11.210
NET	0.013593	0.095001	0.05264	0.090862	0.060393	-0.21551	0.008295		
	Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months								
EPU	3.090	0.010	0	0	0.220	0	0.010	0.040	0.190
EXP	0	1.850	0.480	0.600	0.030	0.020	0.060	0.170	0.890
IMP	0	0.280	2.470	1.580	0.350	0.020	0.630	0.410	2.170
GDP	0.390	0.120	0.160	48.050	5.310	0.410	3.370	1.390	7.400

					CHINA				
	EPU	**EXP**	**IMP**	**GDP**	**SPX**	**CPI**	**BRM**	**FROM_ABS**	**FROM_WTH**
SPX	0.230	0.770	0.010	4.150	16.930	0.340	0.150	0.810	4.280
CPI	0.010	0.040	0.180	2.060	0	10.890	0.480	0.400	2.100
BRM	0.060	0	0.040	0.080	0.920	0	25.000	0.160	0.840
TO_ABS	0.100	0.180	0.130	1.210	0.980	0.110	0.670	3.370	
TO_WTH	0.530	0.930	0.660	6.420	5.180	0.590	3.570		17.890
NET	0.062294	0.007379	0.28383	-0.18469	0.169444	-0.28428	0.513685		

Note: Absolute to measures spillovers from country j to other countries. Absolute from measures spillovers from other countries to country j. Within to measures spillovers from country j to other countries, including from own innovations to country k. Within from measures spillovers from other countries to country j, including from own innovations to country k (see Tiwari et al., 2018, 2019). Positive ***Net*** *denotes that the variable is a* ***net transmitter*** *while negative* ***Net*** *denote* ***net recipient.*** *EPU-economic policy uncertainty, EXP- export, IMP-import, GDP- gross domestic product, SPX- share price index, CPI- consumer price index, BRM- broad money.*

Table 5.5: Pairwise net directional spillover between EPU and macroeconomic variables in China

Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
0.068	0.237	-0.058	-0.029	-0.032	0.106	-0.349
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.023	0.553	0.081	0.008	0.055	-0.087	0.382
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
0.033	-0.040	-0.194	0.058	-0.036	0.032	-0.012
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
-0.0006	-0.0001	-0.027	0.018	0.00009	-0.004	0.017
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.031	-0.127	-0.014	-0.002	0.089	0.013	-0.065
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
0.033	-0.003	-0.151	0.157	-0.016	-0.144	-0.031
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
0.002	0.0003	-0.055	-0.002	-0.001	-0.007	0.028
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
-0.067	-0.106	-0.004	0.008	0.008	0.050	-0.024
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
0.084	-0.166	-0.235	0.470	0.048	-0.109	0.068

Note: epu-economic policy uncertainty, exp- export, imp-import, gdp- gross domestic product, spx- share price index, cpi- consumer price index, brm- broad money.

5.4.1.3 Static spillover connectedness between EPU and Macroeconomic variables in India

India's evidence of total and net spillover are displayed in Table 5.6.The average absolute (from) spillover results show output values of 7.91, 1.94 and 2.77 in frequency bands 1, 2 and 3 respectively. It is also evident that the spillover among the seven variables in India dominates in the short-term (frequency band 1). It is also clear that the frequency bands 2 and 3 are quite low when compared to frequency band 1.The highest amount of spillover received by each variable from the other variables in the analysis in the short-term frequency are 1.06 for EPU, 2.05 for export, 2.42 for import, 0.09 for GDP, 1.05 for SPX, 0.42 for CPI, and 0.81 for broad money. In frequency band 2, the total spillover received by each variable is 0.13 for EPU, 0.22 for export, 0.28 for import, 0.09 for GDP, 0.53 for SPX, 0.13 for CPI, and 0.56 for broad money. In the long-term frequency band, we record EXP (0.08), export (0.2), import (0.24), GDP (0.55), SPX (1.23), CPI (0.04) and broad money (0.42). Clearly, import (2.42) received the highest spillover in frequency band 1, followed by broad money (0.56) in the medium- term frequency band and SPX (1.23) in the long-term frequency band.

In frequency band 1, EPU receives a total 0.16% spillover shocks from the macroeconomic variables with SPX making the highest contribution of 3.22%. In the medium-term, EPU receives a total of 0.13% with SPX making the highest contribution of 0.48%. In the long-term, EPU receives a total spillover record of 0.08% with SPX again making the highest contribution of 0.29%. It is evident that, export and broad money do not make any spillover contributions to EPU in the long-term. We can therefore conclude that EPU does not dominate in the transmission or receiving of spillover shocks in India. However, SPX is the variable that transmits the highest amount of spillover shocks to EPU in India across all the three frequency bands. Just as was recorded for Brazil and China, diversification benefits in India are also effective in the medium and long-term since we recorded a drop in spillover effects in the long-term and medium-term. We also find evidence of causal spillover for each variable across the three (3) frequency bands.

The directional spillover transmitted ‘TO_ABS’ in the row session shows the spillover for j variable to other variables. The variable that **contributors** the highest to the other variables in frequency band 1 is import contributing 2.54%, while import contribute the highest spillover shocks (0.42%) in the medium-term frequency band. In the frequency band 3 we identify GDP as the highest contributor (1.33%). Investors should be alert about import and GDP because they are the main transmitters of spillover shocks to the other variables in India. Focusing on EPU, we discover that EPU is not a major contributor of spillover shocks in India since it transmits a total spillover values of only 0.75 (4th transmitter of shocks across the 7 variables), 0.26 (6th transmitter) and 0.32 (3rd transmitter) in frequency band 1, frequency band 2 and frequency band 3 respectively. More specifically, the variables that receive the highest portion of EPU shocks are import (1.53%), SPX (1.32%) and SPX (1.18%) in frequency bands 1, 2 and 3 respectively. Clearly, the main recipients of EPU spillover shocks in India are import and SPX and investors must observe the trends of these variables. Clearly there exist spillover effects from EPU to macroeconomic variables, and vice versa in India except for EPU to export, EPU to import (frequency band 2), export to EPU, broad money to EPU, broad money to export, broad money to import and SPX to CPI (all in frequency band 3).

Table 5.4 also records the net spillover for each variable in India on the last row. In the short-term EPU, export, SPX and CPI are net recipients while import, GDP and broad money are net transmitters. In frequency band 2, EPU and export are now net transmitter (just as recorded in Brazil and India) while import and GDP maintains their positions as a net transmitters in addition to CPI. On the hand, SPX and broad money are the net recipients in the frequency band 2. In frequency band 3, EPU, GDP and CPI are net transmitters with export, import, SPX and broad money serving as the net recipient. Despite the varying outputs at the frequency bands, it is observed that GDP maintained the role of a net transmitter across all the frequency bands and SPX maintained its position as a net recipient across all the frequency bands.

Table 5.7 shows the net pairwise connected between the seven selected variables in India. The amounts of pairwise net directional connectedness recorded across the three frequencies all differ in magnitude with only a few recording the same signal (positive/negative) across all frequencies. Table 5.3 shows that the pairwise net directional connectedness from export to GDP and from import to GDP are positive across all frequencies. While pairwise net directional connectedness from EPU to CPI, export to import, import to GDP, import to CPI, GDP to SPX, GDP to broad money and from CPI to broad money record negative signs across all frequencies. We find no pattern of transmission in the whole system and therefore conclude that outputs must be analysed on a pair-specific and frequency-dependent bases.

Table 5.6: Total spillover and Net spillover indices between EPU and Macroeconomic variables in India

	INDIA								
	EPU	**EXP**	**IMP**	**GDP**	**SPX**	**CPI**	**BRM**	**FROM_ABS**	**FROM_WTH**
	Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)								
EPU	79.770	0.130	1.410	1.280	3.220	0.280	1.080	1.060	1.630
EXP	0.120	74.510	11.390	0.910	0.430	0.050	1.430	2.050	3.170
IMP	1.530	11.440	69.180	0.130	1.760	0.070	2.040	2.420	3.750
GDP	0.200	0.040	0.050	8.020	0.120	0.160	0.060	0.090	0.140
SPX	2.650	0.590	2.090	0.540	53.020	0.460	1.040	1.050	1.630
CPI	0.300	0.490	0.800	0.870	0.130	61.060	0.340	0.420	0.650
BRM	0.430	0.670	2.030	0.130	0.900	1.530	51.680	0.810	1.260
TO_ABS	0.750	1.910	2.540	0.550	0.940	0.360	0.860	7.910	
TO_WTH	1.160	2.950	3.930	0.850	1.450	0.560	1.320		12.230
NET	-0.30757	0.13848	0.117345	0.45987	0.11734	-0.0565	0.042679		
	Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)								
EPU	7.640	0.010	0.130	0.150	0.480	0.080	0.040	0.130	0.830
EXP	0	5.730	1.100	0.170	0.220	0.020	0.020	0.220	1.440
IMP	0	1.270	7.000	0.110	0.540	0.020	0.030	0.280	1.860
GDP	0.110	0.070	0.040	11.600	0.330	0.040	0.010	0.090	0.560
SPX	1.320	0.170	0.620	1.060	15.810	0.420	0.150	0.530	3.500
CPI	0.190	0.040	0.140	0.380	0.030	22.420	0.150	0.130	0.870
BRM	0.180	0.320	0.920	0.220	0.760	1.540	22.810	0.560	3.700
TO_ABS	0.260	0.270	0.420	0.30	0.340	0.300	0.060	1.940	
TO_WTH	1.700	1.770	2.760	1.960	2.210	1.990	0.380		12.770
NET	0.131719	0.05003	0.137301	0.213714	0.19651	0.169338	-0.50559		
	Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months								
EPU	3.730	0	0.050	0.210	0.290	0.040	0	0.080	0.420
EXP	0.010	2.490	0.450	0.660	0.270	0.010	0	0.200	1.000
IMP	0.010	0.510	3.180	0.650	0.510	0.010	0	0.240	1.200
GDP	0.780	0.420	0.190	75.260	2.390	0.070	0.010	0.550	2.750

INDIA									
	EPU	**EXP**	**IMP**	**GDP**	**SPX**	**CPI**	**BRM**	**FROM_ABS**	**FROM_WTH**
SPX	1.180	0.010	0.190	6.880	11.420	0.290	0.090	1.230	6.140
CPI	0.070	0.010	0.060	0.040	0	12.360	0.100	0.040	0.200
BRM	0.150	0.130	0.440	0.870	0.310	1.010	12.960	0.420	2.070
TO_ABS	0.320	0.160	0.200	1.330	0.540	0.200	0.0300	2.770	
TO_WTH	1.570	0.770	0.980	6.610	2.690	1.020	0.140		13.780
NET	0.231262	0.04501	-0.04475	0.776274	0.69409	0.164095	-0.38779		

Note: Absolute to measures spillovers from country j to other countries. Absolute from measures spillovers from other countries to country j. Within to measures spillovers from country j to other countries, including from own innovations to country k. Within from measures spillovers from other countries to country j, including from own innovations to country k (see Tiwari et al., 2018, 2019). Positive ***Net*** *denotes that the variable is a* ***net transmitter*** *while negative* ***Net*** *denote* ***net recipient.*** *EPU-economic policy uncertainty, EXP- export, IMP-import, GDP- gross domestic product, SPX- share price index, CPI- consumer price index, BRM- broad money.*

Table 5.7: Pairwise net directional spillover between EPU and macroeconomic variables in India

Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
0.002	-0.017	0.154	0.080	-0.004	0.093	-0.007
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.124	-0.023	-0.062	0.109	0.011	-0.048	-0.105
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
0.001	-0.060	-0.101	-0.010	0.047	0.019	-0.169
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
0.001	0.018	0.007	-0.121	-0.016	-0.021	-0.025
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi -
0.014	0.007	-0.004	-0.043	0.011	-0.011	0.017
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
-0.126	-0.103	-0.048	-0.030	0.056	-0.087	-0.198
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
-0.001	0.006	-0.082	-0.127	-0.005	-0.021	-0.009
exp-gdp -	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.009	0.037	0.0002	-0.017	0.066	0.046	-0.007
imp-brm	gdp-spx -	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
-0.063	0.640	0.004	-0.123	0.042	-0.032	-0.130

Note: epu-economic policy uncertainty, exp- export, imp-import, gdp- gross domestic product, spx- share price index, cpi- consumer price index, brm- broad money.

5.4.1.4 Static spillover connectedness between EPU and Macroeconomic variables in Korea

Korea's average absolute (from) spillover as shown in Table 5.8 was 10.09 in frequency band 1, but declines drastically to 3.50 in the medium-term frequency band. Clearly there exist spillover effects from EPU to macroeconomic variables and vice versa in Korea except for CPI to EPU and export to GDP (all in frequency band 3). The average absolute (from) spillover then increased in the long-term frequency band to 5.44 which is below the value recorded in frequency band 1. It can therefore be concluded that Korea's spillover among the seven variables in dominates in the short-term (frequency band 1). More specifically, the summation of the amount of spillover received by each variable from the rest of the other variables in the short-term frequency are 1.01for EPU, 2.68 for export, 3.48 for import, 0.16 for GDP, 1.36 for SPX, 0.98 for CPI, and 0.41

for broad money. In frequency band 2, the total spillover received by each variable is 0.27 for EPU, 0.51 for export, 0.84 for import, 0.35 for GDP, 0.79 for SPX, 0.34 for CPI, and 0.41 for broad money. In the long-term frequency band, we record EPU (0.17), export (0.65), import (1.21), GDP (1.49), SPX (1.39), CPI (0.19) and broad money (0.35). It is evident from these outputs that, import (3.48) received the highest spillover in frequency band 1, followed by import (0.84) in the medium- term frequency band and GDP (1.49) in the long-term frequency band.

With respect to the spillover shocks received by EPU from the macroeconomic variables, Table 5.5 reveals from “FROM_ABS” column that EPU receives a total of 1.01%, 0.27% and 0.17% spillover shocks for frequency band 1, 2, and 3 respectively. In the short-term frequency band it is also observed that SPX makes the highest contribution of 5.30% spillover shocks to EPU. In the medium-term, EPU receives 1.52% spillover shocks from SPX and 0.90% in the long-term frequency band. It can be inferred that, EPU is not a significant transmitter or recipient of spillover shocks in Korea, however, SPX is a must watch for investors and policy makers since it’s the main source of Korea’s EPU shocks across all the three frequency bands. Just as was recorded for Brazil, China, and India, diversification benefits in Korea is also effective in the medium-term frequency band since we recorded the lowest spillover effects in the medium-term. We also find evidence of causal spillover for each variable across the three (3) frequency bands.

The directional spillover transmitted ‘TO_ABS’ shows the spillover for j variables to other variables. The variable that **contributors** the highest to the other variables in frequency band 1 is import contributing 3.05%, while SPX contribute the highest spillover shocks (0.80%) in the medium-term frequency band. In the frequency band 3 we identify SPX as the highest contributor

(1.77%). Investors should be alert about import and SPX because they are the main transmitters of spillover shocks to the other variables in Korea. Focusing on EPU, we discover that EPU is not a major contributor of spillover shocks in Korea since it transmits only 1.15%, 0.45% and 0.39% of its spillover shocks to the other variables in frequency band 1, frequency band 2 and frequency band 3 respectively. More specifically, the variable that receives the highest fraction of EPU shocks in Korea is the SPX receiving spillover values of 4.92 %, 2.00% and 1.35% in frequency bands 1, 2 and 3 respectively. Clearly, the main recipients of EPU spillover shocks are the SPX and investors must observe its trends for effective predictions and decision making. Table 5.8 also records the net spillover for each variable in Korea on the last row. The output reveals that EPU, GDP and SPX are net transmitter, while import and broad money are net recipients across all three frequency bands. Export is a net transmitter in frequency band 1 and 2 and a net recipient in the long-term frequency. CPI on the other hand is a net recipient in the short-term frequency and a net transmitter in the medium- and long-term frequency. It is observed that GDP maintained the role of a net transmitter across all the frequency bands and SPX maintained its position as a net recipient across all the frequency bands. The **biggest net transmitter** of shocks across the three (3) frequency bands in Korea is GDP. The net pairwise connectedness for Korea in Table 5.9 also shows no pattern of transmission in the whole system as recorded earlier for Brazil, China and India.

Table 5.8: Total spillover and Net spillover indices between EPU and Macroeconomic variables in Korea

KOREA									
	EPU	**EXP**	**IMP**	**GDP**	**SPX**	**CPI**	**BRM**	**FROM_ABS**	**FROM_WTH**
Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)									
EPU	77.340	0.210	0.670	0.190	5.30	0.110	0.600	1.010	1.690
EXP	0.800	66.070	15.830	0.280	0.460	0.910	0.500	2.680	4.490
IMP	0.680	16.090	52.540	1.620	3.370	2.220	0.400	3.480	5.830
GDP	0.050	0.210	0.140	10.010	0.650	0.050	0.010	0.160	0.270
SPX	4.920	0.790	2.110	1.420	47.360	0.240	0.060	1.360	2.280
CPI	1.410	2.240	1.840	0.010	1.230	56.590	0.170	0.980	1.650
BRM	0.210	0.680	0.790	0.040	0.680	0.440	37.470	0.410	0.680
TO_ABS	1.150	2.890	3.050	0.510	1.670	0.570	0.250	10.090	
TO_WTH	1.930	4.840	5.110	0.850	2.790	0.950	0.410		16.890
NET	0.143771	0.207563	-0.43175	0.348551	0.305761	-0.41498	-0.15892		
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)									
EPU	8.420	0.020	0.190	0.090	1.520	0.010	0.030	0.270	1.470
EXP	0.030	4.790	1.990	0.720	0.440	0.380	0.010	0.510	2.830
IMP	0.100	2.150	6.690	1.560	0.810	1.210	0.050	0.840	4.650
GDP	0.110	0.020	0.200	15.340	1.930	0.180	0.020	0.350	1.960
SPX	2.000	0.070	0.920	2.000	15.330	0.440	0.090	0.790	4.370
CPI	0.500	1.120	0.510	0.010	0.170	21.080	0.030	0.340	1.860
BRM	0.390	0.910	0.490	0.030	0.720	0.310	30.050	0.410	2.260
TO_ABS	0.450	0.610	0.620	0.630	0.80	0.360	0.030	3.500	
TO_WTH	2.480	3.410	3.420	3.480	4.440	2.010	0.180		19.400
NET	0.180323	0.104009	-0.22319	0.275165	0.013039	0.026314	-0.37566		
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months									
EPU	4.140	0.010	0.120	0.150	0.900	0	0.010	0.170	0.760
EXP	0.060	2.280	0.550	2.880	0.960	0.050	0.010	0.650	2.900
IMP	0.110	1.020	2.040	5.550	1.560	0.230	0.010	1.210	5.430

	KOREA								
	EPU	**EXP**	**IMP**	**GDP**	**SPX**	**CPI**	**BRM**	**FROM_ABS**	**FROM_WTH**
GDP	0.480	0	0.760	60.660	8.260	0.820	0.080	1.490	6.680
SPX	1.350	0.010	0.870	6.890	12.520	0.590	0.030	1.390	6.250
CPI	0.270	0.650	0.2900	0.060	0.040	11.780	0.010	0.190	0.840
BRM	0.430	0.770	0.310	0.020	0.690	0.200	24.360	0.350	1.550
TO_ABS	0.390	0.350	0.410	2.220	1.770	0.270	0.020	5.440	
TO_WTH	1.730	1.570	1.860	9.980	7.970	1.220	0.100		24.430
NET	0.216152	-0.2952	-0.7957	0.733904	0.381471	0.082997	-0.32362		

*Note: Absolute to measures spillovers from country j to other countries. Absolute from measures spillovers from other countries to country j. Within to measures spillovers from country j to other countries, including from own innovations to country k. Within from measures spillovers from other countries to country j, including from own innovations to country k (see Tiwari et al., 2018, 2019). Positive **Net** denotes that the variable is a **net transmitter** while negative **Net** denote **net recipient.** EPU-economic policy uncertainty, EXP- export, IMP-import, GDP- gross domestic product, SPX- share price index, CPI- consumer price index, BRM- broad money.*

Table 5.9: Pairwise net directional spillover between EPU and macroeconomic variables in Korea

Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
-0.085	-0.003	0.020	0.055	-0.186	0.056	-0.038
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.009	-0.048	-0.189	-0.027	0.211	0.181	0.055
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
-0.056	-0.110	0.006	-0.004	-0.140	-0.089	-0.039
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
-0.002	0.014	-0.003	-0.068	-0.070	-0.051	-0.023
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.099	0.053	-0.106	-0.129	0.193	-0.016	0.099
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
-0.063	-0.010	0.025	-0.0007	0.038	-0.091	-0.040
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
-0.007	0.001	-0.046	-0.065	-0.039	-0.060	-0.066
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.411	0.137	-0.085	-0.109	0.684	0.098	-0.009
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
-0.043	0.196	0.109	0.010	0.078	-0.094	-0.027

Note: epu-economic policy uncertainty, exp- export, imp-import, gdp- gross domestic product, spx- share price index, cpi- consumer price index, brm- broad money.

5.4.1.5 Static spillover connectedness between EPU and Macroeconomic variables in Mexico

Table 5.10 shows the total and net spillover of the variables in Mexico. It is evident that the average absolute (from) spillover among EPU, GDP, broad money, import, export, CPI and SPX are 10.14, 3.95 and 10.05 in frequency bands 1, 2 and 3 respectively. We can infer that spillover in Mexico dominates in the short- and long-term frequencies. The directional spillover “FROM_ABS” (thus, absolute from) shows the spillover from other variables to variable *j*. In other sense, column “FROM_ABS” represents the total spillover received by a variable from all the other variables. Export received the highest amount of spillover (thus, 2.98) from all the other variables in frequency band 1, followed by import (0.93) in frequency band 2 and GDP (4.04) in frequency band 3. Interestingly, EPU receives the least amount of spillover from the other variables in frequency band 2 (with a value of 0.06) and frequency band 3 (0.19). EPU (with a value of 1.63) is however the forth (4th) recipient of spillover from all the other variables in the short-term frequency.

The directional spillover transmitted 'TO_ABS' shows the spillover from j variables to other variables. The variable that **transmits** the highest spillover shock to the other variables in frequency band 1 is import contributing 3.06%, while SPX contribute the highest spillover shocks (1.05%) in the medium-term frequency band. In the frequency band 3 we identify GDP as the highest contributor (2.99%). Investors should therefore be alert about import, SPX and GDP because they are the main transmitters of spillover shocks to the other variables in Mexico. EPU is not a major transmitter of spillover shocks in Korea since it transmits only 0.98%, 0.44% and 0.54% of its spillover shocks to the other variables in frequency band 1, frequency band 2 and frequency band 3 respectively. More specifically, EPU transmits its highest amount of spillover shocks to SPX in the first frequency band (4.10%) and second frequency band (1.48), and to GDP in frequency band 3 (1.97). Clearly, the main recipients of EPU spillover shocks is SPX and GDP. Investors must observe their trends for effective predictions and decision making. There exist spillover effects from EPU to macroeconomic variables, and vice versa in Mexico except for export to broad money (in frequency band 2), and broad money to EPU (in frequency band 3).

The last row recorded the net spillover which is the difference between "FROM" and "TO" spillovers per each variable and indicates the net transmitter and net recipient variable. In the short-term EPU, export and SPX are net recipients while import, GDP, CPI and broad money are net transmitters. In frequency band 2, EPU, GDP, SPX and CPI are net transmitter while export, import and broad money are net transmitter. In frequency band 3, EPU, SPX and CPI are net transmitters while, export, import, GDP and broad money are net recipients. Although all the variables' net transmission vary across frequency bands CPI is identified as a net transmitter and export as a net recipients across all frequency bands.

Table 5.11 shows the net pairwise connected between the seven selected variables in Mexico. It is evident that the amounts of pairwise net directional connectedness recorded across the three frequencies differ in magnitude and except for some few cases the outputs shows alternating signs (positive/negative) across all frequencies for each paired variable. Table 5.11 show evidence of positive signs across all frequencies for pairwise net directional connectedness from import to GDP, export to GDP, import to CPI, import to broad money and from GDP to broad money. On the otherhand, EPU to broad money and CPI to broad money record negative signs across all frequencies. There is therefore no specific pattern of transmission in the whole system. We then conclude that the pairwise net directional connectedness must be analysed on a pair-specific and frequency-dependent bases.

Table 5.10: Total spillover and Net spillover indices between EPU and Macroeconomic variables in Mexico

	MEXICO								
	EPU	**EXP**	**IMP**	**GDP**	**SPX**	**CPI**	**BRM**	**FROM_ABS**	**FROM_WTH**
Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)									
EPU	76.260	1.460	2.570	1.200	4.990	1.140	0.020	1.630	3.000
EXP	0.730	43.910	15.590	0.950	2.550	0.40	0.650	2.980	5.500
IMP	0.970	12.180	43.970	1.100	2.030	0.230	0.970	2.500	4.600
GDP	0.070	0.580	0.240	6.120	0.380	0.090	0.070	0.200	0.380
SPX	4.100	3.120	2.580	2.680	48.810	0.300	2.290	2.150	3.970
CPI	0.430	0.310	0.120	0.770	0.470	44.050	0.220	0.330	0.610
BRM	0.560	0.050	0.330	0.070	1.050	0.390	45.530	0.350	0.640
TO_ABS	0.980	2.530	3.060	0.970	1.640	0.370	0.60	10.140	
TO_WTH	1.810	4.660	5.640	1.780	3.020	0.670	1.110		18.700
NET	-0.64544	-0.45434	0.564805	0.761408	-0.51577	0.034027	0.255307		
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)									
EPU	7.370	0.010	0.010	0.110	1.110	0.120	0.010	0.190	1.010
EXP	0.140	6.300	2.230	1.850	0.980	0.150	0.140	0.780	4.050
IMP	0.180	2.800	5.450	2.400	0.870	0.130	0.140	0.930	4.820
GDP	0.350	1.410	0.700	10.480	2.170	0.470	0.180	0.750	3.900
SPX	1.480	0.710	0.210	0.760	17.410	0.460	0.260	0.550	2.870
CPI	0.540	0.006	0.060	0.660	0.530	31.410	0.210	0.290	1.510
BRM	0.380	0	0.050	0.120	1.710	0.810	29.280	0.440	2.270
TO_ABS	0.440	0.710	0.460	0.840	1.050	0.300	0.130	3.950	
TO_WTH	2.270	3.680	2.400	4.370	5.440	1.580	0.690		20.420
NET	0.243949	-0.0713	-0.46843	0.090298	0.497032	0.013252	-0.3048		
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months									
EPU	3.170	0.010	0.010	0.060	0.280	0.080	0	0.060	0.240
EXP	0.250	8.150	3.210	8.320	3.170	0.090	0.250	2.180	8.260
IMP	0.300	5.710	6.250	10.890	2.890	0.350	0.210	2.910	10.990
GDP	1.970	7.160	3.600	48.390	12.460	2.450	0.640	4.040	15.290
SPX	0.930	0.690	0.180	1.460	11.280	0.260	0.020	0.510	1.920

	MEXICO								
	EPU	**EXP**	**IMP**	**GDP**	**SPX**	**CPI**	**BRM**	**FROM_ABS**	**FROM_WTH**
CPI	0.190	0.210	0.140	0.010	0.040	19.410	0.160	0.110	0.410
BRM	0.150	0.060	0.120	0.160	0.670	0.470	18.040	0.230	0.890
TO_ABS	0.540	1.980	1.040	2.990	2.790	0.530	0.180	10.050	
TO_WTH	2.040	7.490	3.930	11.300	10.550	2.010	0.690		38.010
NET	0.476352	-0.20463	-1.86685	-1.0559	2.281997	0.420459	-0.05144		

Note: Absolute to measures spillovers from country j to other countries. Absolute from measures spillovers from other countries to country j. Within to measures spillovers from country j to other countries, including from own innovations to country k. Within from measures spillovers from other countries to country j, including from own innovations to country k (see Tiwari et al., 2018, 2019). Positive ***Net*** *denotes that the variable is a* ***net transmitter*** *while negative* ***Net*** *denote* ***net recipient.*** *EPU-economic policy uncertainty, EXP- export, IMP-import, GDP- gross domestic product, SPX- share price index, CPI- consumer price index, BRM- broad money.*

Table 5.11: Pairwise net directional spillover between EPU and macroeconomic variables in Mexico

Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
0.104	0.229	0.162	0.127	0.101	-0.077	0.488
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.052	-0.081	0.013	0.086	0.122	-0.078	0.015
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
0.093	-0.329	-0.097	0.0004	-0.024	0.178	-0.025
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
-0.019	-0.025	-0.034	-0.053	-0.060	-0.053	-0.082
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.063	0.039	0.013	0.019	0.243	0.095	0.010
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
0.013	0.200	-0.027	0.008	-0.009	-0.207	-0.086
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
-0.033	-0.041	-0.273	-0.092	-0.016	-0.021	-0.357
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.165	0.354	-0.017	0.027	1.041	0.387	0.029
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
0.012	1.572	0.349	0.069	0.031	-0.093	-0.045

Note: epu-economic policy uncertainty, exp- export, imp-import, gdp- gross domestic product, spx- share price index, cpi- consumer price index, brm- broad money.

5.4.1.6 Static spillover connectedness between EPU and Macroeconomic variables in Russia

From Table 5.12, Russia recorded an average absolute (from) spillover of 6.09 in frequency band 1, but declines drastically to 2.69 in the medium-term frequency band. The average absolute (from) spillover then increased in the long-term frequency band to 7.04 but still below the value recorded in frequency band 1. It can therefore be concluded that Russia's spillover among the seven variables in dominates in the short-term (frequency band 1). More specifically, the summation of the amount of spillover received by each variable from the rest of the other variables in the short-term frequency are 1.13 for EPU, 1.3 for export, 1.3 for import, 0.08 for GDP, 0.47 for SPX, 0.97 for CPI, and 0.85 for broad money. In frequency band 2, the total spillover received by each variable is 0.05 for EPU, 0.44 for export, 0.33 for import, 0.17 for GDP, 0.32 for SPX, 0.48 for

CPI, and 0.9 for broad money. In the long-term frequency band, we record EPU (0.02), export (1.33), import (1.38), GDP (2.03), SPX (0.76), CPI (0.41) and broad money (1.12). It is evident from these outputs that, export (1.30) and import (1.30) received the highest spillover in frequency band 1, followed by broad money (0.90) in the medium- term frequency band and GDP (2.03) in the long-term frequency band, with respect to the spillover shocks received by EPU from the macroeconomic variables.

Table 5.12 reveals from "FROM_ABS" column that EPU receives a total of 1.13%, 0.05% and 0.02% spillover shocks for frequency band 1, 2, and 3 respectively. It is observed that in the short-, medium- and long-term frequency band, CPI makes the highest contribution of 4.82%, 0.29% and 0.06% spillover shocks respectively to EPU. CPI is a must watch for investors and policy makers since it's the main source of Russia's EPU shocks across all the three frequency bands. Diversification benefits in Russia are effective in the medium-term frequency band since we recorded the lowest spillover effects in the medium-term. We also find evidence of causal spillover for each variable across the three (3) frequency bands.

The directional spillover transmitted 'TO_ABS' shows the spillover for j variables to other variables. The variable that **contributors** the highest to the other variables in frequency band 1 is CPI contributing 1.41%, while CPI contributes the highest spillover shocks (0.98%) in the medium-term frequency band. In the frequency band 3 we identify GDP as the highest contributor (2.67%). Investors should be alert about CPI and GDP because they are the main transmitters of spillover shocks to the other variables in Russia. Focusing on EPU, we discover that EPU is not a major contributor of spillover shocks since it transmits only 0.71%, 0.43% and 0.44% of its spillover shocks to the other variables in frequency band 1, frequency band 2 and frequency band 3 respectively. More specifically, the variable that receives the highest fraction of EPU shocks in Russia is the CPI receiving spillover values of 1.61%, 1.94% and 2.00% in frequency bands 1, 2 and 3 respectively.

Clearly, the main recipients of EPU spillover shocks are the CPI and investors must observe its trends for effective predictions and decision making. We find evidence of spillover effects from EPU to macroeconomic variables, and vice versa in Russia except for export to broad money, import to EPU, import to SPX, SPX to EPU, CPI to export (all in frequency band 2), import to EPU, SPX to EPU, EPU to SPX and import to broad money (all in frequency band 3).

Table 5.12 also records the net spillover for each variable in Russia on the last row. The output reveals that GDP, SPX and CPI are net transmitter, while export and import are net recipients across all three frequency bands. EPU is a net recipient in frequency band 1 and a net transmitter in the medium- and long-term frequency bands. Broad money on the other hand is a net transmitter in the short- and medium- term frequency and a net recipient in the long-term frequency band. The **biggest net transmitter**s of shocks are GDP, broad money and CPI in frequency bands 1, 2 and 3 respectively.

The net pairwise connectedness for Russia in Table 5.13 show that the amounts of pairwise net directional connectedness recorded across the three frequencies differ in magnitude and except for some few cases the outputs shows alternating signs (positive/negative) across all frequencies for each paired variable. Thus, Table 5.13 shows that the pairwise net directional connectedness from export to GDP, export to SPX, import to GDP, import to SPX, import to CPI, import to broad money and from SPX to CPI record positive signs (net transmitters) across all frequencies. While negative signs (net recipients) were recorded form EPU to broad money, export to CPI and from GDP to broad money. We find no pattern of transmission in the whole system since we recorded varying signs (positive/ negative) for each of the paired variables across all frequencies (as recorded earlier for the other selected EMEs). We therefore conclude that net pairwise results in Russia must also be analysed on a pair-specific and frequency- dependent bases.

Table 5.12: Total spillover and Net spillover indices between EPU and Macroeconomic variables in Russia

	RUSSIA								
	EPU	**EXP**	**IMP**	**GDP**	**SPX**	**CPI**	**BRM**	**FROM_ABS**	**FROM_WTH**
Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)									
EPU	84.000	0.210	0.760	0.730	0.180	4.820	1.190	1.130	1.980
EXP	1.120	65.700	5.110	0.370	1.810	0.110	0.610	1.300	2.280
IMP	0.230	4.430	65.100	0.210	1.260	1.460	1.510	1.300	2.280
GDP	0.020	0.110	0.020	4.190	0.170	0.040	0.180	0.080	0.140
SPX	0.390	0.510	0.090	1.080	51.750	0.740	0.460	0.470	0.820
CPI	1.610	0.210	1.130	0.350	0.520	26.220	2.970	0.970	1.700
BRM	1.600	0.010	0.130	1.460	0.010	2.730	59.680	0.850	1.490
TO_ABS	0.710	0.780	1.030	0.600	0.570	1.410	0.990	6.090	
TO_WTH	1.250	1.370	1.810	1.050	0.990	2.480	1.730		10.680
NET	-0.41758	-0.52262	-0.26504	0.521294	0.098708	0.445445	0.139792		
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)									
EPU	5.400	0.050	0	0.030	0	0.290	0.010	0.050	0.340
EXP	0.010	7.560	1.460	0.610	0.960	0	0.030	0.440	2.740
IMP	0.050	0.790	8.760	0.550	0.330	0.440	0.150	0.330	2.070
GDP	0.030	0.210	0.030	6.700	0.740	0.130	0.040	0.170	1.040
SPX	0.010	0.020	0	0.720	21.120	1.350	0.150	0.320	2.000
CPI	1.940	0.150	0.260	0.190	0.200	29.490	0.610	0.480	2.990
BRM	0.960	0	0.010	0.650	0.030	4.660	14.130	0.900	5.630
TO_ABS	0.430	0.170	0.250	0.390	0.320	0.980	0.140	2.690	
TO_WTH	2.680	1.090	1.570	2.450	2.020	6.140	0.870		16.810
NET	0.373781	-0.26372	-0.08032	0.224671	0.003688	0.50367	0.761769		
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months									
EPU	2.190	0.050	0	0.010	0	0.060	0.020	0.020	0.070
EXP	0.020	5.240	1.000	5.930	2.280	0.060	0.010	1.330	4.930
IMP	0.010	1.110	5.060	6.180	1.470	0.790	0.120	1.380	5.120
GDP	0.450	2.190	0.360	73.180	9.590	1.600	0.020	2.030	7.530

					RUSSIA				
	EPU	**EXP**	**IMP**	**GDP**	**SPX**	**CPI**	**BRM**	**FROM_ABS**	**FROM_WTH**
SPX	0	0.020	0.010	3.950	16.320	1.220	0.100	0.760	2.800
CPI	2.000	0.140	0.240	0.070	0.160	31.330	0.230	0.410	1.500
BRM	0.590	0.060	0	2.540	0.560	4.070	6.140	1.120	4.140
TO_ABS	0.440	0.510	0.230	2.670	2.010	1.110	0.070	7.040	
TO_WTH	1.620	1.890	0.860	9.890	7.450	4.130	0.260		26.110
NET	0.416994	-0.81977	-1.14961	0.636115	1.253603	0.709431	-1.04676		

Note: Absolute to measures spillovers from country j to other countries. Absolute from measures spillovers from other countries to country j. Within to measures spillovers from country j to other countries, including from own innovations to country k. Within from measures spillovers from other countries to country j, including from own innovations to country k (see Tiwari et al., 2018, 2019). Positive ***Net*** *denotes that the variable is a* ***net transmitter*** *while negative* ***Net*** *denote* ***net recipient.*** *EPU-economic policy uncertainty, EXP- export, IMP-import, GDP- gross domestic product, SPX- share price index, CPI- consumer price index, BRM- broad money.*

Table 5.13: Pairwise net directional spillover between EPU and macroeconomic variables in Russia

Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
-0.131	0.076	0.101	-0.030	0.460	-0.059	0.097
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.037	0.187	-0.014	0.085	0.026	0.168	0.047
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
0.197	-0.130	-0.044	-0.183	0.032	0.064	0.035
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
0.006	-0.006	-0.0008	-0.0004	-0.236	-0.136	0.096
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.058	0.135	-0.022	0.004	0.075	0.048	0.027
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
0.020	0.003	-0.008	-0.087	0.165	0.016	-0.578
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months						
epu-exp	epu-imp	epu-gdp	epu-spx	epu-cpi	epu-brm	exp-imp
0.004	-0.0003	-0.063	0.0001	-0.276	-0.082	-0.015
exp-gdp	exp-spx	exp-cpi	exp-brm	imp-gdp	imp-spx	imp-cpi
0.535	0.323	-0.011	-0.007	0.831	0.209	0.078
imp-brm	gdp-spx	gdp-cpi	gdp-brm	spx-cpi	spx-brm	cpi-brm
0.017	0.806	0.219	-0.359	0.151	-0.066	-0.549

Note: epu-economic policy uncertainty, exp- export, imp-import, gdp- gross domestic product, spx- share price index, cpi- consumer price index, brm- broad money.

5.4.2 Inter-country static spillover connectedness across selected EMEs.

This session firstly conducts an inter-country analysis on the static spillover connectedness between the EPU of the selected EMEs. We then focus on a second session which adds GDP and SPX to the inter-country static spillover analysis because i) intra-counrty analysis showed that GDP and SPX are major spillover shock transmitters across all the selected EMEs in this study. ii) GDP and SPX are the main recipients of EPU spillover shocks across the selected EMEs. This analysis enabled us to investigate evidence of spillover and causal spillover among the EPU of the selected EMEs and secondly among EPU, GDP and SPX of the selected EMEs. We ascertained the main transmitters of shocks to each EME. We also discovered that EPU does notdominate in the transmission or receiving of spillover shocks in all the selected EMEs

5.4.2.1 Static spillover connectedness among the EPU of the selected EMEs.

Table 5.14 shows the total and net spillover of EPU across the selected EMEs. We find evidence of spillover transmission across all the selected EMEs except form Korea-EPU to Brazil-EPU in the medium term and from Russia-EPU to Brazil-EPU, China-EPU, India-EPU and Korea-EPU all in the long-term. It is evident that spillover dominates in the short-term. This is evident from the average absolute (from) spillover values of 13.56%, 0.93% and 0.39 on frequency bands 1, 2 and 3 respectively. The directional spillover transmitted 'To' shows that the highest EPU contributor to the other EMEs is Korea-EPU contributing the highest EPU that amounts 3.86%, followed by Russia-EPU with a value of 2.64% in the short-term. In the medium-term the highest contributor of EPU shocks is Korea-EPU (0.55%) followed by India-EPU (0.20%). And in the long-term we identify Korea-EPU (0.24%) as the highest contributor of EPU shocks to the rest of the selected EMEs which is followed by China-EPU (0.09%). It is clear that Korea-EPU is the highest transmitter/ contributor of EPU shocks among the selected EMEs.

The EME that receives the highest spillover from the rest of the five (5) EMEs in the short-term is Korea-EPU receiving 4.47. In the medium-term, China-EPU and Mexico-EPU receives the highest spillover shocks valued at 0.22%, while Mexico-EPU receives the highest transmission of 0.10% in the long-term. Brazil-EPU transmits its highest spillover shocks to Russia-EPU (1.26%) in frequency band 1, India-EPU (0.03%) in frequency band 2 and in frequency band 3, Brazil-EPU transmits 0.01% each to India-EPU, Korea-EPU and Mexico-EPU. China-EPU on the other hand transmits its highest spillover shocks to Korea-EPU across all frequencies with values 6.54%, 0.70% and 0.30% respectively. Thirdly, India-EPU transmits its highest spillover shocks to Korea-

EPU in frequency band 1 (6.25%) and frequency band 2 (0.08%) and Russia-EPU (0.03%) in frequency band 3. Fourthly, Korea-EPU transmits its highest spillover shocks to China-EPU (8.39%) in frequency band 1, and transmits 1.09% and 0.47% to Mexico-EPU in both frequency band 2 and frequency band 3. Mexico-EPU also transmits its highest amount of spillover to Korea-EPU in the short-term (6.91%) medium-term (0.34%) and long-term (1.74%). Finally Russia-EPU highest transmission is to Korea-EPU in the short-term. Russia-EPU transmits 0.03% each to Korea-EPU and Mexico-EPU in the medium term and transmits 0.01% to Russia-EPU in the long-term.

The results therefore suggest that investors should rather be alert about Korea-EPU because it's the main transmitters of spillover EPU shocks to the EPU of the selected EMEs across frequency bands 1, 2 and 3. We also discover the highest amount and direction of spillover transmitted from and received by each of the EMEs. Secondly, it is clear that although we find evidence of connected, the degree of EPU volatility shock spillover across the selected EMEs is generally low. Thirdly, diversification benefits are effective in the long-term since we record less spillover effects in the long-term. Fourthly, there is also evidence of causal spillover among the EMEs across the three (3) frequency bands. The last row recorded the net spillover for each variable. As explained earlier, the net spillover calculates the difference between "FROM" and "TO" spillovers per each variable and indicates the net transmitter and net recipient variable. A positive net spillover value of a variable denotes that the variable is a net transmitter while negative net spillover denotes a net recipient. It is therefore evident from Table 5.14 that in the short-term India-EPU, Mexico-EPU and Russia-EPU are net transmitters while Brazil-EPU, China-EPU and Korea-EPU are net recipients. Korea-EPU is the only transmitter in frequency band 2 and frequency band 3 while the other EMEs are net recipients. We record that except for Brazil-EPU and China-EPU that are net recipients across all frequency bands, the net transmission for the rest of the EMEs vary across frequency bands. We also identified that although Korea-EPU is the highest transmitter of EPU shocks to other EMEs, total spillover Korea-EPU received in the short-term is higher than its transmissions.

For a more detailed investigation of connectedness we now focus on net pairwise spillover which shows the detailed amount of transmission between pairs of the EPU-values of the selected EMEs. Table 5.15 shows the net pairwise connected between the EPU of the selected EMEs. It is evident that except for some few cases where paired variables record the same signs (positive or negative) for pairwise net directional transmission across all three frequencies, we find no pattern of transmission in the whole system. The paired variables that exhibit positive signs (net pairwise directional transmitter) are the pairwise net directional connectedness from Brazil to China, China to Korea, China to Mexico and from India to Mexico. On the otherhand, net pairwise directional connectedness from China to India and from India to Russia record negative signs for transmission. We then conclude that the pairwise net directional connectedness have no specific pattern therefore outputs must be analysed on a pair-specific and frequency-dependent bases across the selected EMEs for the purposes of effective applications of these findings. This study confirms arguments that EMEs have influenced the rise in EPU by transmitting these negative shocks to other countries (Dizioli, Guajardo, Klyuev, Mano, & Raissi, 2016; and Russel, 2016). Unlike other studies that find China EPU as a main transmitter of EPU shocks to other economies (Biljanovska, Grigoli, & Hengge, 2017; Luk, Cheng, Ng, & Wong, 2020), this study rather identify China EPU as a recipient of EPU shocks from other EMEs.

Table 5.14: Total spillover and Net spillover indices between EPU of selected EMEs

	Brazil	China	India	Korea	Mexico	Russia	FROM_ABS	FROM_WTH
Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)								
Brazil	87.650	0.640	1.980	0.340	0.990	2.050	1.000	1.070
China	0.380	78.510	1.830	8.390	1.520	1.950	2.350	2.520
India	1.000	2.550	79.720	5.130	2.180	3.110	2.330	2.500
Korea	0.210	6.540	6.250	64.100	6.910	6.930	4.470	4.810
Mexico	0.7300	1.090	0.850	6.700	81.090	1.770	1.860	2.000
Russia	1.260	0.800	4.010	2.600	0.680	85.830	1.560	1.670
TO_ABS	0.590	1.940	2.490	3.860	2.050	2.640	13.560	
TO_WTH	0.640	2.080	2.670	4.150	2.200	2.830		14.570
NET	-0.405	-0.409	0.159	-0.614	0.189	1.080		
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)								
Brazil	4.310	0.050	0.020	0	0.020	0.010	0.020	0.330
China	0.010	3.870	0.070	0.990	0.210	0.020	0.220	4.420
India	0.030	0.140	3.400	0.840	0.050	0.020	0.180	3.670
Korea	0.020	0.700	0.080	5.180	0.340	0.030	0.200	4.030
Mexico	0.020	0.170	0.030	1.090	4.110	0.030	0.220	4.590
Russia	0.010	0.130	0.060	0.360	0.060	2.760	0.100	2.120
TO_ABS	0.010	0.200	0.040	0.550	0.110	0.020	0.930	
TO_WTH	0.300	4.070	0.900	11.200	2.310	0.370		19.170
NET	-0.001	-0.017	-0.135	0.350	-0.111	-0.085		
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months								
Brazil	1.900	0.020	0.010	0	0.010	0	0.010	0.310
China	0	1.700	0.020	0.440	0.090	0	0.090	4.420
India	0.010	0.050	1.410	0.350	0.020	0	0.070	3.460
Korea	0.010	0.300	0.020	2.240	0.130	0	0.080	3.690
Mexico	0.010	0.070	0.010	0.470	1.740	0.010	0.100	4.590
Russia	0	0.060	0.030	0.160	0.020	1.180	0.050	2.190
TO_ABS	0.010	0.090	0.010	0.240	0.040	0	0.390	
TO_WTH	0.290	4.110	0.720	11.380	2.060	0.110		18.660
NET	0.0006	-0.006	-0.057	0.160	-0.053	-0.043		

*Note: Absolute to measures spillovers from country j to other countries. Absolute from measures spillovers from other countries to country j. Within to measures spillovers from country j to other countries, including from own innovations to country k. Within from measures spillovers from other countries to country j, including from own innovations to country k (see Tiwari et al., 2018, 2019). Positive **Net** denotes that the variable is a **net transmitter** while negative **Net** denote **net recipient.***

Table 5.15: Pairwise net directional spillover between the EPU of selected EMEs

Band 1: 3.14 to 0.79; corresponds to 1 month to 4 months (quarter)				
Brazil-China	Brazil-India	Brazil-Korea	Brazil- Mexico -	Brazil-Russia
0.043	0.164	0.022	0.044	0.132
China-India	China-Korea	China-Mexico	China-Russia	India-Korea
-0.119	0.309	0.070	0.193	-0.187
India-Mexico	India-Russia	Korea-Mexico	Korea-Russia	Mexico-Russia
0.222	-0.1496	0.035	0.723	0.182
Band 2: 0.79 to 0.26; corresponds to 4 months (quarter) to 12 months (annual)				
Brazil-China	Brazil-India	Brazil-Korea	Brazil-Mexico	Brazil-Russia
0.007	-0.0004	-0.004	-0.0008	-0.0003
China-India	China-Korea	China-Mexico	China-Russia	India-Korea
-0.012	0.048	0.008	-0.020	0.126
India-Mexico	India-Russia	Korea-Mexico	Korea-Russia	Mexico-Russia
0.004	-0.007	-0.125	-0.054	-0.004
Band 3: 0.26 to 0.00; corresponds to 12 months (annual) to infinite months				
Brazil-China	Brazil-India	Brazil-Korea	Brazil-Mexico	Brazil-Russia
0.003	-0.0002	-0.002	-0.0005	-0.0002
China-India	China-Korea	China-Mexico	China-Russia	India-Korea
-0.006	0.023	0.002	-0.009	0.055
India-Mexico	India-Russia	Korea-Mexico	Korea-Russia	Mexico-Russia
0.001	-0.005	-0.057	-0.027	-0.002

5.4.2.2 Static spillover connectedness between the EPU, GDP and SPX of selected EMEs.

This session investigates evidence of the static spillover connectedness across the selected EMEs with focus on specific variables which are EPU, GDP and SPX. For all the results in this session, we find records of spillovers between EPU, GDP and SPX across the selected EME. These findings are similar to Ciccarelli, Ortega, and Valderrama (2016) and Hegerty (2016) who also found significance evidence of spillover across countries and between macroeconomic and financial variables. From Table 5.8 we record an average absolute (from) spillover of 18.39 in the short-term frequency band, 9.32 in the medium-term frequency band and 15.77 in the long-term frequency band. Clearly, spillover dominates in the short- and long-term frequency band. We first proceed to investigate the major external sources of Brazil's EPU shocks which are displayed in row 1 of Table 5.16. In frequency band 1, Table 5.16 shows evidence of spillover transmissions from China, India, Korea, Mexico and Russia to Brazil. In other words, the least transmission to Brazil -EPU was from China-EPU and Mexico-GDP with a value of 0.03% and the highest transmission was from India- EPU transmitting a value of 2.02%. However, in frequency band 2 and 3 India-SPX is the main source of shocks transmission to Brazil -EPU with very low values of 0.15% and 0.07% respectively. This implies that in the medium-and long-frequency band there is a significant decline in spillover transmissions to Brazil -EPU. We also find zero (0) spillover transmissions from China-EPU to Brazil -EPU as well as from Korea-EPU to Brazil -EPU. The main transmitters of spillover shocks to Brazil -EPU are India-EPU, India-SPX and India- SPX in frequency band 1, 2, and 3 respectively. Clearly, India as an economy is the main transmitter of spillover shocks to Brazil-EPU. The findings are similar to Yildirtan (2007) who recorded SPX spillovers to and from other macroeconomic variables.

Studies on China-EPU in frequency band 1 also shows evidence of spillover transmission from the other EMEs to China. There was no record of zero (0) transmission and the highest transmission of external shock to China-EPU was from Korea-EPU with a value of 5.77%. In frequency band 2, we identify that, there was no spillover from Brazil -EPU to China-EPU. The highest transmitter of shocks to China-EPU was recorded from Brazil -SPX (0.88%) followed by Korea-SPX (0.85%). It is evident that in the medium-term frequency bands, SPX (rather than EPU) is the major transmitter of spillover shocks to China-EPU. In the long-term frequency band we record a low percentage spillover shock of 0.39% from Korea- EPU which is the major transmitter of spillover shocks to China EPU. There was no spillover from Brazil -EPU, Brazil -GDP, Korea-GDP and

Russia-GDP to China-EPU. We conclude that the main transmitters of spillover shocks to China-EPU are Korea-EPU, Brazil -SPX and Korea- EPU in frequency band 1, 2, and 3 respectively. Thirdly, India-EPU received its major external spillover shocks from Korea- EPU valued at 5.3% and Brazil - SPX valued at 3.98%.Clearly, there was minimal transmission from Mexico and Russia to India-EPU. Korea- EPU is the main transmitter of spillover shocks to India-EPU in the medium- term (0.96%) and long-term (0.42%) frequency bands. The second major contributor was Brazil -EPU at both frequency band 2 and 3 recording transmission values of 0.63% and 0.24% respectively. There was no spillover between China-SPX and India-EPU in the long term frequency band. It is evident that the degree of spillover shock transmission reduces as the frequency band approaches 0.00. We conclude that the main transmitter of spillover shocks to India-EPU is Korea- EPU across all the frequency bands.

Moving on to Korea, it is evident from row labelled “KOREA-EPU” that Korea received large amounts of spillover shocks from the EPU of the other EMEs except Brazil -EPU that recorded the least amount of 0.15%. Korea-EPU received 5.08% spillover shocks from China-EPU, 4.17% from India-EPU, 3.93% from Mexico-EPU and 3.07% from Russia-EPU. In the medium- and long-term frequency bands, Korea-EPU receives its highest external spillover transmission from Mexico-SPX. The amounts of spillover transmitted are 0.89% in frequency band 2 and 0.31% in frequency band 3. We recorded zero (0) transmission between Brazil -EPU, Brazil -GDP, Russia-GDP and Russia-SPX in the long-term frequency band. It is however evident that the magnitude of spillover reduces as the frequency band approaches 0.00. We conclude that the main transmitter of spillover shocks to Korea-EPU is China-EPU, Mexico-SPX and Mexico-SPX in frequency bands 1, 2, and 3 respectively.

A closer inspection on Mexico-EPU in the short-term shows that, the main transmitters of spillover shocks to Mexico-EPU are Korea-EPU (4.33%) and Brazil -SPX (2.49%). In the medium- and long-term frequency bands, Mexico-EPU receives its highest external spillover transmission from Korea-EPU. Thus Korea-EPU transmits 0.89% in frequency band 2 and 0.39% in frequency band 3. We record evidence of spillover across all the EMEs in the sort- and medium-term frequency bands. However, in the long-term frequency band we recorded zero (0) transmission from China-SPX, India-EPU, India-GDP, India-SPX and Russia-GDP. It is however evident that the magnitude of spillover reduces as the frequency band approaches 0.00. We conclude that the main transmitter of spillover shocks to Mexico-EPU is Korea-EPU across all the frequency bands.

And lastly, Russia-EPU received its major spillover shocks from Korea-EPU (3.99%) and India-EPU (2.9%). In the medium- and long-term frequency bands, Russia-EPU receives its highest external spillover transmission from Korea-EPU. Thus Korea-EPU transmits 0.6% in frequency band 2 and 0.26% in frequency band 3. This implies that, Korea-EPU is main transmitter of spillover shocks to Russia EPU across all frequency bands. We record evidence of spillover to Russia-EPU across all the EMEs only in the short-term frequency bands. In the medium-term frequency band we recorded zero (0) transmission to Russia-EPU from Brazil-GDP, Brazil-SPX and Russia-GDP. In the long-term frequency band we recorded eight (8) zero (0) transmissions out of eighteen (18) results of spillover transmission to Russia-EPU. Specifically, zero transmissions to Russia-EPU was recorded from Brazil-GDP, Brazil-SPX, China- SPX, India-GDP, Korea GDP, Korea- SPX, Mexico-EPU and Mexico- SPX. It is however evident that the magnitude of spillover reduce drastically in the long-term frequency band.

As we conclude this session, we also record high transmission of spillover between the SPX and GDP of the selected EMEs. The EMEs that transmitted the highest amounts of SPX spillover to all the other EMEs was Brazil -SPX (2.66%), Brazil -SPX (1.13%) and China-SPX (0.82%) in frequency band 1, 2 and 3 respectively. Likewise, the EMEs that transmitted the highest amounts of GDP spillover to all the other EMEs was Mexico-GDP (0.42%), India-GDP (0.89%) and India-GDP (4.59) in frequency band 1, 2 and 3 respectively. For all the selected EMEs, the selected variables (GDP and SPX) respond to EPU shocks since they are recepients of EPU shocks. These findings are comparable to that of Miescu (2019), who found evidence that macroeconomic and financial variables (including GDP and SPX) in 15 EMEs respond significantly to domestic uncertainty shocks. The resulting spillovers from our analysis can be regarded as marginal connectedness (dependence) which provides rich information on the selected EMEs which would otherwise go unnoticed. Portfolio diversification potentials are strong in the short-term while policy efforts may be directed at all frequencies across both large and small markets. In Table 5.16, in terms of EPU, GDP and SPX we find that the spillover among the EMEs is dominated at the long-term frequencies as indicated by average absolute (from) spillovers of 2.88, 3.01, and 3.06 all on frequency bands 3. The dynamics imply that, diversification benefits are possible in the short-, and medium-term as opposed to the long-term where spillovers are stronger. It is also evident that all the EMEs dominate causal spillovers at various scales. This means that the effect of spillover is minimal across the EMEs. There is therefore no need for policy implications on cross-market integration and interdependence within the EMEs since the EMEs are already dependent across the frequency bands. Focus should rather be placed on advanced economies that can promote trade, investment and growth.

Table 5.16: Total spillover and Net spillover indices among EPU, GDP and SPX in selected EMEs.

	BR_ EPU	BR_G DP	BR_S PX	CH_ EPU	CH_G DP	CH_S PX	IN_ EPU	IN_ GDP	IN_ SPX	KOR_ EPU	KOR_ GDP	KOR_ SPX	MEX_ EPU	MEX_ GDP	MEX_ SPX	RUS_E PU	RUS_ GDP	RUS_S PX	FROM_ ABS	FROM_ WTH
Band 1: 3.14 To 0.79; Corresponds To 1 Month To 4 Months (Quarter)																				
BR_ EPU	82.300	1.3.500	0.010	0.030	0.100	0.060	2.020	0.120	0.840	0.040	0.110	0.220	0.460	0.030	0.160	0.710	0.220	1.100	0.420	0.780
BR_ GDP	0.030	1.470	0.090	0.020	0.190	0.030	0.030	0.670	0.010	0.010	0.150	0.030	0.040	0.580	0.040	0	0.060	0.070	0.110	0.210
BR_ SPX	0.020	0.390	24.900	0.490	0..350	1.110	1.700	0.360	7..94	1.800	0.090	9.530	1.060	0.740	10.610	0.100	0.180	5.790	2.350	4.360
CH_ EPU	0.070	0.220	1.780	63.700	0.030	0.740	1.100	0.580	2.690	5.770	0.180	1.970	1.100	0.270	1.590	0.660	0.690	2.790	1.240	2.300
CH_ GDP	0	1.130	0.030	0.360	18.010	0..300	0.130	0..540	0.140	0.070	0..270	0.050	0.080	0.480	0.100	0.040	0.750	0.160	0.260	0.480
CH_ SPX	1.430	0.060	1.930	1. 200	0.650	42. 300	0. 240	0.060	1.080	0.460	0.140	0.640	0. 500	0.040	0.460	0.120	0. 370	1. 240	0 . 590	1.100
IN_ EPU	0. 360	0. 380	3. 980	1.470	0. 230	0. 300	61.400	0.630	2. 980	5. 300	1.460	2. 590	0.450	0. 070	1. 630	0.780	0. 650	0. 590	1. 330	2.460
IN_ GDP	0.130	0.180	0. 070	0.150	0. 310	0.100	0.140	8. 980	0. 050	0. 040	0.160	0.050	0.130	0.030	0.040	0.060	0.010	0.140	0.100	0.180
IN_ SPX	0. 850	0.170	8. 370	0.100	0. 310	0. 580	1. 510	0.130	28. 900	0.190	0.480	8.000	0. 370	1.130	7.830	0.060	0. 210	4. 300	1. 920	3. 570
KOR_ EPU	0.150	0.050	2.800	5.080	0.100	1. 340	4.170	0. 050	0. 320	55. 510	0. 070	3. 940	3. 930	0.110	2.700	3.070	0. 500	0. 210	1. 590	2. 950
KOR_ GDP	0. 020	1. 270	0. 090	0.110	0.110	0. 220	0. 270	0. 550	0.190	0.080	12.770	0. 380	0.040	0.430	0.150	0. 230	0.190	0. 280	0. 260	0.480
KOR_ SPX	0.100	0.160	9.120	0.870	0.040	0. 350	1.130	0. 210	7. 330	2.180	0. 530	24.840	0. 580	0.830	11. 230	0.020	0.030	4. 530	2.180	4.050
MEX_ EPU	0. 360	0.080	2.490	1. 350	0.040	0.170	0. 390	0.820	1.030	4. 330	0. 220	1.190	64.850	1.030	4.420	1.650	0. 920	1. 520	1. 220	2. 270
MEX_ GDP	0.020	0.180	0. 200	0.010	0. 330	0.100	0.010	0. 280	0.180	0.070	0.080	0.160	0.100	10. 900	0. 240	0.040	0.180	0.140	0.130	0. 240
MEX_ SPX	0.080	0.190	10.470	0.810	0. 260	0.110	0.790	0.040	7. 250	1. 220	0.070	11.610	2. 060	0. 980	24.76	0.160	0.030	5. 050	2. 290	4. 250
RUS_ EPU	0.790	0.050	0.120	0. 570	0.060	0.120	2. 900	0.810	0.150	3. 990	1.460	0.090	0.690	0.150	0.170	77. 900	0.030	0.460	0.700	1.3.000
RUS_ GDP	0.040	0.050	0.030	0. 220	0. 230	0.090	0. 030	0. 940	0. 030	0.130	0.130	0.010	0.100	0.110	0.070	0	5. 680	0. 050	0.130	0. 230
RUS_ SPX	0.420	0. 560	6. 310	0. 580	0. 270	0. 560	0. 380	0. 290	4.690	1. 250	0.430	5. 210	0.690	0.480	5. 960	0. 300	0.08	29. 310	1. 580	2. 940
TO_ ABS	0. 270	0. 360	2.660	0.750	0. 200	0. 350	0. 940	0. 390	2.050	1. 500	0. 330	2. 540	0.690	0.420	2.630	0.450	0. 280	1. 580	18. 390	
TO_ WTH	0. 500	0.670	4. 940	1. 380	0. 370	0.650	1.750	0.730	3.800	2.780	0.620	4.710	1. 280	0.770	4.890	0.830	0. 530	2. 930		34.140
NET	-0.150	0. 250	0. 310	-0.490	-0.060	-0. 200	-0. 390	0. 300	0.130	-0.090	0.078	0.357	-0. 535	0. 287	0. 345	-0. 260	0.158	-0.001		
Band 2: 0.79 To 0.26; Corresponds To 4 Months (Quarter) To 12 Months (Annual)																				
BR_ EPU	6. 280	0.080	0	0.010	0.010	0.010	0.040	0	0.150	0.010	0.020	0.030	0.060	0.020	0.020	0.090	0.030	0.050	0.030	0.180
BR_ GDP	0.080	4. 550	0. 390	0.070	1. 980	0. 270	0.050	2.670	0.070	0.050	1. 330	0.140	0.120	2.490	0. 210	0.010	0. 580	0. 350	0.600	3. 200
BR_ SPX	0.020	0. 380	8. 320	0.400	0.610	0.090	0. 530	0. 530	1. 590	0.840	0.060	2.430	0.430	0. 300	3. 520	0.010	0. 270	1.110	0.730	3.880

CH_ EPU	0	0.040	0.880	5.070	0.010	0.120	0. 360	0.020	0.120	0.810	0.030	0.850	0. 280	0.140	0.760	0.050	0.100	0. 330	0. 270	1.450
CH_ GDP	0	2. 270	0.090	0. 230	20.600	1.070	0. 250	2.090	0.430	0.040	0. 540	0.010	0.030	1.430	0.090	0	1.480	0. 390	0. 590	3.110
CH_ SPX	0. 370	0. 300	1.660	0.090	1.790	19.190	0.120	0.690	0. 900	0. 370	0. 380	0.460	0. 320	0. 390	0. 580	0.060	0.440	0. 940	0. 550	2. 920
IN_ EPU	0.020	0.030	0.630	0. 290	0.050	0.030	6.160	0.100	0.440	0. 960	0.070	0. 380	0.110	0.060	0. 370	0. 200	0.070	0.070	0. 220	1.150
IN_ GDP	0.050	0.810	0.160	0. 380	2.490	0. 550	0.090	10.080	0. 220	0.130	0. 990	0.160	0.010	0. 350	0. 230	0.030	0.090	0. 330	0. 390	2.090
IN_ SPX	0.030	0.490	3.810	0.060	0.880	0.120	0.650	0.730	7.640	0.150	0. 590	3.040	0.180	0.810	2. 560	0	0. 230	1. 550	0.880	4.700
KOR_ EPU	0.010	0.050	0.630	0.670	0.010	0.020	0.400	0.140	0.070	5.730	0.050	1.010	0.660	0. 200	0.890	0. 340	0.050	0.020	0. 290	1. 550
KOR_ GDP	0.010	2. 910	0.440	0.410	0.710	0.800	0.160	2. 350	0. 300	0. 270	15.120	0. 930	0.010	2.120	0.480	0. 330	1.490	0. 940	0.81	4. 330
KOR_ SPX	0.030	0.410	3. 280	0. 260	0.110	0.130	0. 270	0.780	1. 950	1.020	1.060	7.600	0. 260	0.830	3.740	0.010	0.120	1. 520	0.880	4.660
MEX_ EPU	0.030	0.070	0. 260	0.080	0.020	0.010	0.020	0.120	0.040	0.890	0.010	0.130	6. 250	0.170	0.790	0.130	0.100	0.180	0.170	0. 900
MEX_ GDP	0.020	1.190	0. 500	0.1500	2.6800	0.4100	0.030	1.720	0. 300	0.100	0.870	0. 500	0. 270	17.690	0.660	0.020	0.790	0.690	0.610	3. 230
MEX_ SPX	0.050	0. 300	3. 550	0.480	0. 360	0.040	0.150	0. 310	1. 530	0.600	0.120	3.170	0.750	0.400	7.430	0.020	0.090	1.890	0.770	4.080
RUS_ EPU	0.020	0	0	0.120	0.010	0.010	0.040	0.060	0.010	0.600	0.100	0.010	0.010	0.040	0.030	5. 540	0	0.010	0.060	0. 310
RUS_ GDP	0	0.640	0. 260	0.410	2.170	0.470	0.020	3.100	0.130	0.120	1.050	0.140	0. 310	0. 550	0. 290	0.030	7.480	0. 380	0. 560	2. 980
RUS_ SPX	0.070	0.740	3.760	0.430	0.870	0.130	0.140	0.660	0.850	0. 560	0.710	2. 270	0.430	0. 590	3.840	0.030	0.410	9.740	0. 920	4.880
TO_ ABS	0.050	0.600	1.130	0. 250	0.820	0. 240	0.190	0.890	0. 510	0.420	0.440	0.880	0. 230	0.600	1.060	0.080	0. 350	0.600	9. 320	
TO_ WTH	0. 240	3.170	6.000	1. 340	4. 360	1. 270	0. 980	4.750	2.690	2. 220	2. 350	4.660	1. 240	3. 220	5. 640	0.400	1. 870	3.180		49.610
NET	0.010	-0.007	0.400	-0.020	0. 230	-0. 310	-0.030	0. 500	-0. 380	0.126	-0. 370	-0.0004	0.064	-0.002	0.292	0.017	-0. 210	-0. 320		
Band 3: 0.26 To 0.00; Corresponds To 12 Months (Annual) To Infinite Months																				
BR_ EPU	2.97	0.03	0	0	0.01	0.01	0.01	0.02	0.07	0	0.01	0.02	0.03	0.01	0.01	0.04	0.04	0.02	0.02	0.06
BR_ GDP	0.37	29.21	0.55	0.09	8.44	1.32	0.04	11.66	0.15	0.23	6.37	0.09	0.21	21.59	0.09	0.01	0.21	0.45	**2.88**	10.54
BR_ SPX	0	0.02	3.81	0.31	0.44	0.14	0.56	1.48	0.96	0.48	0.01	1.06	0.09	0	1.6	0	0.01	0.42	0.42	1.54
CH_ EPU	0	0	0.35	2.27	0.04	0.02	0.16	0.04	0.02	0.39	0	0.33	0.09	0.03	0.29	0.02	0	0.08	0.1	0.37
CH_ GDP	0	1.56	0.02	0.21	26.54	1.73	0.7	12.69	0.46	0.02	0.11	0	0.21	1.75	0.01	0.06	0.03	0.12	1.09	4
CH_ SPX	0.32	0.28	0.57	0.11	0.9	12.2	0.26	1.68	0.61	0.24	0	0.18	0.05	0.07	0.21	0.01	0.01	0.34	0.32	1.18
IN_ EPU	0.01	0.1	0.24	0.09	0.02	0	2.91	0.11	0.18	0.42	0.01	0.18	0.03	0.04	0.15	0.09	0.06	0.02	0.1	0.35
IN_ GDP	0	1.76	0.02	0.95	2.77	0.88	1.14	60.8	0.47	0.21	0.01	0.1	0.29	1.22	0.2	0.17	1	0.09	0.63	2.29
IN_ SPX	0.01	0	1.56	0.02	0.38	0.15	0.62	2.6	4.17	0.11	0.12	1.42	0	0.07	1.07	0.01	0.01	0.59	0.49	1.78

KOR_ EPU	0	0	0.2	0.26	0.13	0.03	0.15	0.15	0.01	2.74	0	0.38	0.22	0.2	0.31	0.14	0	0	0.12	0.44
KOR_ GDP	0.01	0.42	0.2	1.52	1.81	2.19	0.08	19.1	0.79	0.76	19.21	1.07	0.12	2.58	0.51	0.23	1.17	1.04	1.87	6.83
KOR_ SPX	0	0.15	1.28	0.28	0.03	0.13	0.29	1.87	1.04	0.74	0.35	3.86	0.04	0.05	1.81	0	0	0.63	0.48	1.77
MEX_ EPU	0.01	0.06	0.07	0.01	0.01	0	0	0	0	0.39	0.05	0.01	2.71	0.18	0.26	0.04	0	0.03	0.06	0.23
MEX_ GDP	0.04	2.88	1.26	1.41	17.7	2.37	0.68	15.3	1.94	0.26	4.58	1.44	0.02	3.92	1.74	0	0.46	2.21	**3.01**	11.02
MEX_ SPX	0.02	0.01	1.69	0.45	0.22	0.1	0.24	1.95	0.96	0.44	0.01	1.6	0.23	0	3.89	0	0	1	0.49	1.81
RUS_ EPU	0.01	0	0	0.04	0.01	0	0.02	0	0.01	0.26	0	0	0	0.02	0	2.5	0.02	0	0.02	0.08
RUS_ GDP	0.01	1.77	0.83	3.61	19.0	5.35	0.78	12.2	1.28	1.31	5.3	0.6	0.14	0.57	0.86	0.02	19.46	1.42	**3.06**	11.18
RUS_ SPX	0.07	0	1.74	0.49	0.89	0.34	0.32	1.86	0.63	0.47	0.24	1.2	0.12	0.05	2.16	0	0.14	5.24	0.6	2.18
TO_ ABS	0.05	0.5	0.59	0.55	2.93	0.82	0.34	4.59	0.53	0.37	0.95	0.54	0.1	1.58	0.63	0.05	0.18	0.47	15.77	
TO_ WTH	0.18	1.84	2.15	2	10.7	3	1.23	16.8	1.95	1.37	3.49	1.97	0.38	5.78	2.29	0.17	0.64	1.72		57.67
NET	0.03	-2.4	0.16	0.45	1.84	0.50	0.24	3.97	0.05	0.253	-0.91	0.055	0.042	-1.44	0.131	0.025	-2.88	-0.13		

Note: Absolute to measures spillovers from country j to other countries. Absolute from measures spillovers from other countries to country j. Within to measures spillovers from country j to other countries, including from own innovations to country k. Within from measures spillovers from other countries to country j, including from own innovations to country k (see Tiwari et al., 2018, 2019). Positive ***Net*** *denotes that the variable is a* ***net transmitter*** *while negative* ***Net*** *denote* ***net recipient.***

5.4.3 Intra-country time-varying spillover index with rolling-window analysis.

In this session, we consider the intra-country time-varying total connectedness and pairwise net spillovers obtained from a rolling window technique. For time-frequency domain analysis, we use a 12-months (equivalent to 1 year) ahead forecast horizon (*H*) and a rolling window size of 36 months (equivalent to 3 years). This time frame is enough to account for a time-varying phenomenon. The time-frequency domain analysis helped us to determine whether the spillover shocks that create the various sharp increases (large connectedness) in the system occur (or impact) in the short-, medium-, or long-term. This is important because investors make investment decisions at different frequencies as has been discussed in literature by Bandi and Tamoni (2016). This implies that, the sources of the shocks as well as the different responses to theses shocks create short-, medium-, and long-term spillover effects.

Periods in which we have evidence of high connectivity in the short-term (high frequency) simply implies that information is processed rapidly in that whole system in the short-term. It also implies that a shock transmitters to a variable in the whole system mainly affects the short-term behavior of key players (such as investors and policy makers) thereby resulting to spillover responses in the short-term (high frequency). On the other hand, shocks transmitted in the long-term (lower-frequency) implies that spillover shocks are been transmitted for longer periods and the responses to these shocks are in the long-term (low frequencies). An example is the changes in investors' expectations that have long-term effect. It therefore implies that information is not processed rapidly because these shocks create more uncertainty about the effect of the shocks on economic activities (situations) which leads to more volatility causing a delay in the response and transmission of shocks until the long-term (low frequency).

The rolling pairwise net spillovers presented in the study specifically presents analysis and plots for the pairs between the selected variables (EPU, export, import, GDP, CPI,SPX and broad money) in the short-, medium-, and long-terms within each EME. We therefore present twenty-one (21) pairs for each of the three frequencies. We proceed to investigate evidence of time-varying spillover index between EPU, export, import, GDP, CPI, SPX and broad money within each EME.

5.4.3.1 Intra-country time-varying spillover index with rolling-window analysis in Brazil.

The evidence of overall connectedness for **Brazil** is displayed in Figure 5.1 (a). We see that the overall connectedness decreases in magnitude as the frequency increases. Thus, in the short-term (frequency band 1) we record fluctuations from 23% to 68%, followed by fluctuations ranging from 5% to 32% in the medium- term and finally recording a value range of 3% to 40% in the long-term. We record evidence of high connectedness in all three frequencies. Starting with the short-term, we observe that the "high" levels of connectedness of the whole system that is driven by high-frequency (movements from one to four months) responds to shocks which lead to an increase in the spillover shocks in the short-term.

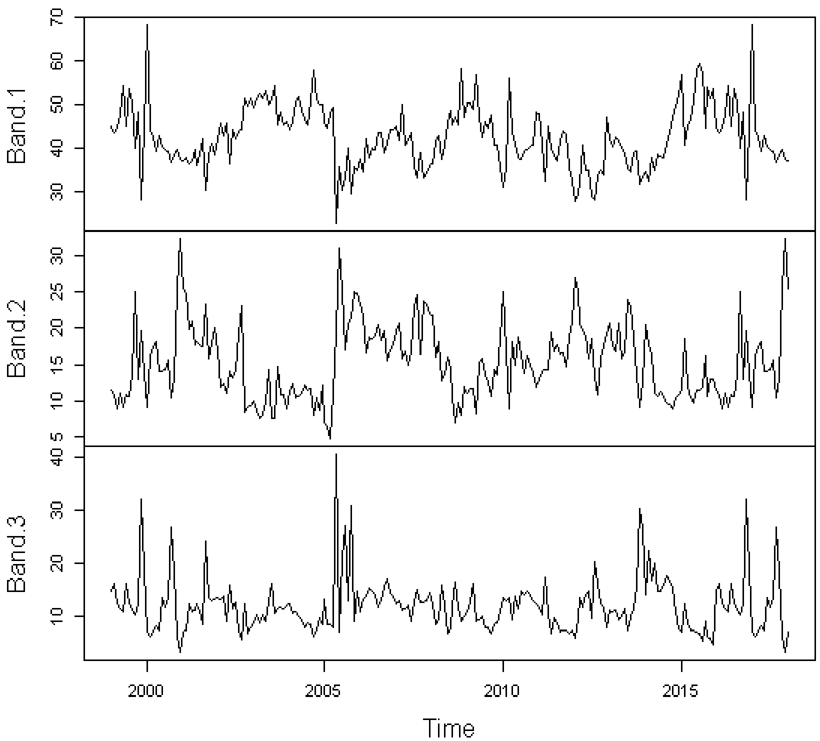
In other words, although we find significant evidence of spillover variations in Brazil, spillover shocks in the short-term drive "high" connectedness from late 1999 to the span of 2000, 2005 and from late 2016 to the span 2017 periods. Heightened values rose to about 68% and going as low as 21% as against average fluctuations of 27% to 57% across the frequency band. These variations are largely expected because 1999 to 2018 (the period under study) includes both calm and turbulent periods (significant economic and financial crises periods) where shocks of different magnitudes are transferred to other systems (in our case variables).

The medium-term shocks transmission implies that spillover shocks are been transmitted for longer periods and the responses to these shocks are in the medium-term (medium frequencies). Highlights of spillover shocks in the medium-term drive "high" connectedness around 2001, 2005 and 2018. Heightened values rose to about 34% against average fluctuations of 25% across the frequency band. The long-term (low frequency) also implies that spillover shocks are been transmitted for longer periods and the responses to these shocks happen in the long-term. Highlights of spillover shocks in the long-term drive "high" connectedness from late 2005 to the span of 2006 with value rising to about 41% as compared to average fluctuations of 32% across frequency band 3. Clearly, the frequencies that recorded high total connectedness in Brazil are recorded in the high- and medium-frequency bands.

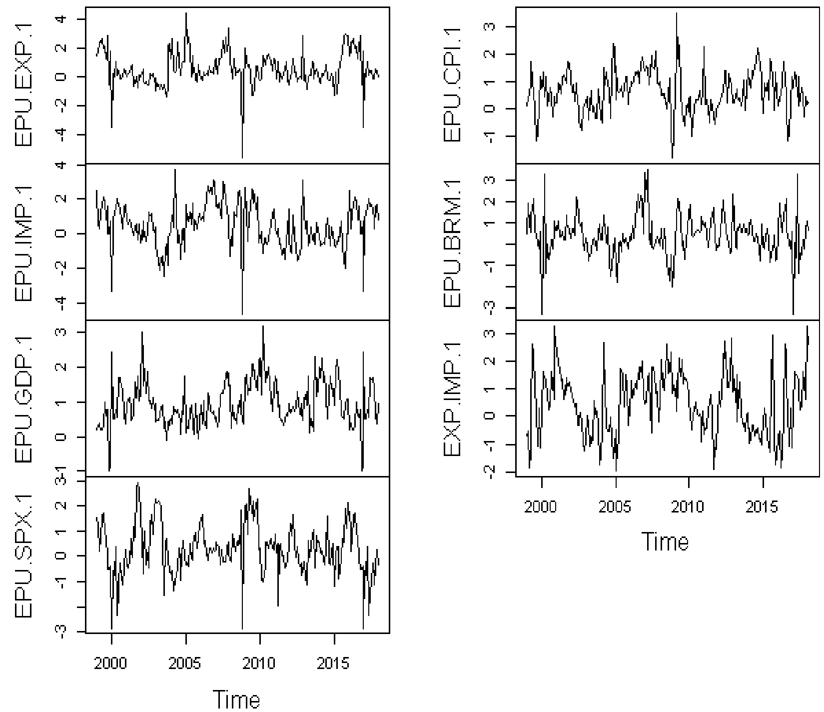
Specifically, the identified high connected relate to the 1997 -1999 Asian financial crisis, 2005 oil crises, 2007-2009 Global Financial Crisis and 2016 Brexit Referendum, 2016 US presidential elections and 2016 European immigration crisis respectively. It can be concluded that economic and financial crisis or incidence intensifies the total spillovers in Brazil. The high valued connectedness can also be attributed to further uncertainty transmission resulting from the insecurities about the effect of the shock on other economic situations. This is a clear indication that spillover effect of the Asian financial crisis that commenced in 1997 delayed until late 1999 in Brazil. The second and third waves recorded in 2005 and 2016 directly coincides with the oil crisis in 2005 and 2016 Brexit Referendum, 2016 US presidential elections and 2016 European immigration crisis respectively. This incidence is an indication of immediate spillover effects. Studies that also recorded higher spillovers during crisis periods are (Antonakakis, Cunado, Filis, Gabauer, & De Gracia, 2018; Batten, Kinateder, Szilagyi, & Wagner, 2021; Akhtaruzzaman, Boubaker, & Sensoy, 2021).

The pairwise net directional spillovers for the elected variables in **Brazil** is displayed in Figure 5.1 from (b) to (d), where (a), (b)and (c) represent the short-, medium-, and long-term respectively. We record multiple sudden increases in the values of spillover connectedness for all the paired variables across the selected time frame (date) and frequency. The level of connectedness is stronger in the short- and long-term with no domineering net recipient and transmitter association.

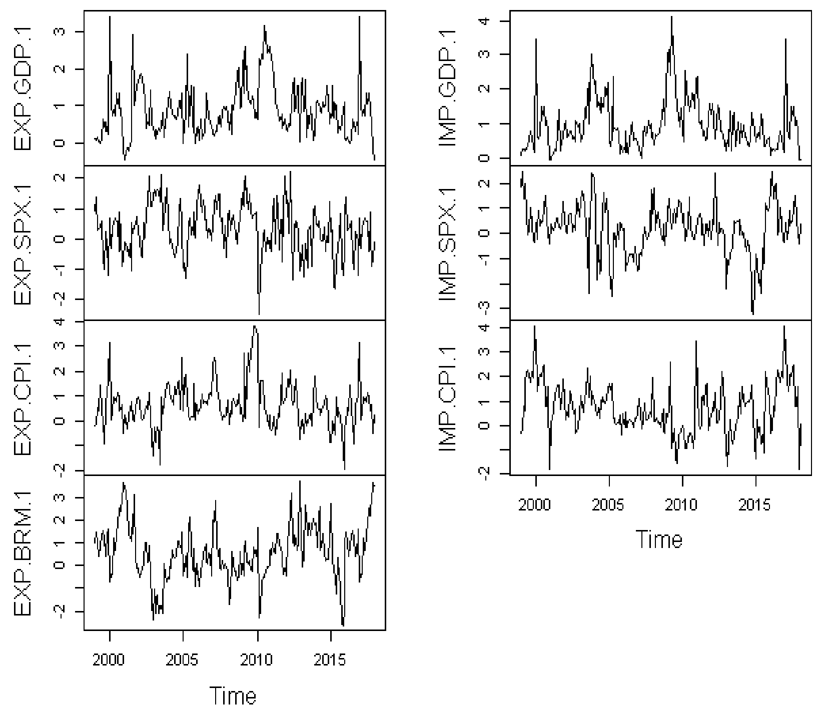
(a) Overall Rolling Spillovers on Bands 3.14 to 0.00 for Brazil



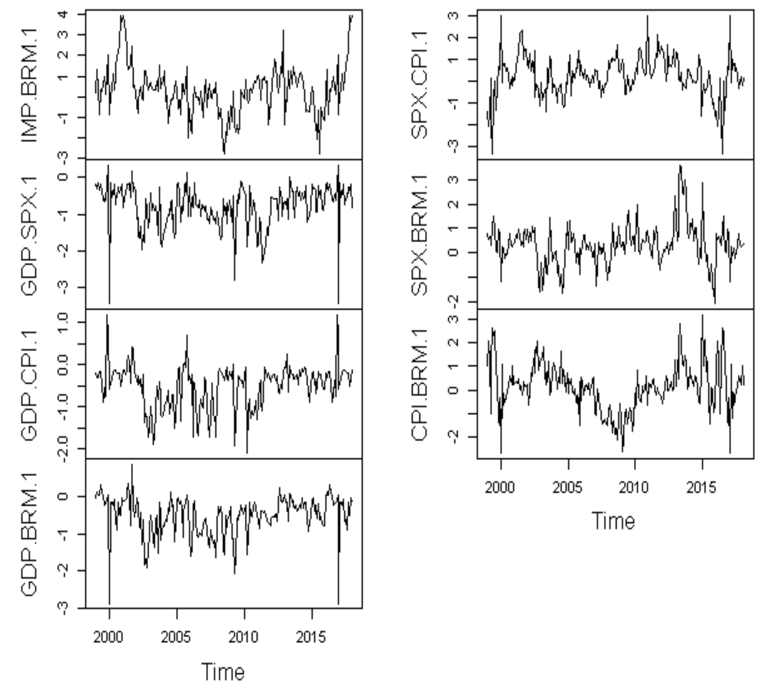
(b) i) Pairwise net rolling spillover on Band 3.14 to 0.79 for Brazil (Short-term frequency)



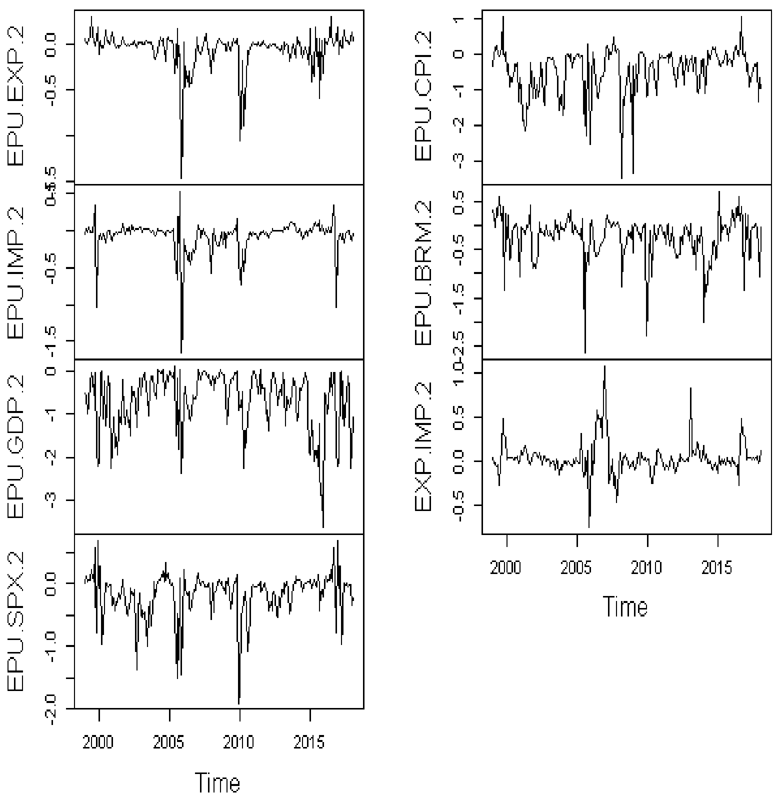
(b) ii) Pairwise net rolling spillover on Band 3.14 to 0.79 for Brazil (Short-term frequency)



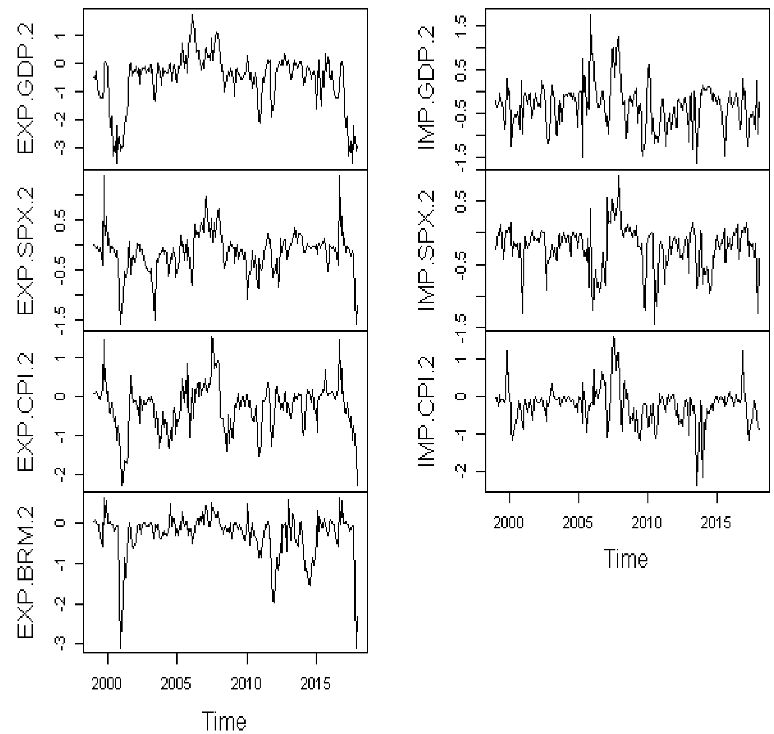
(b) iii) Pairwise net rolling spillover on Band 3.14 to 0.79 for Brazil (Short-term frequency)



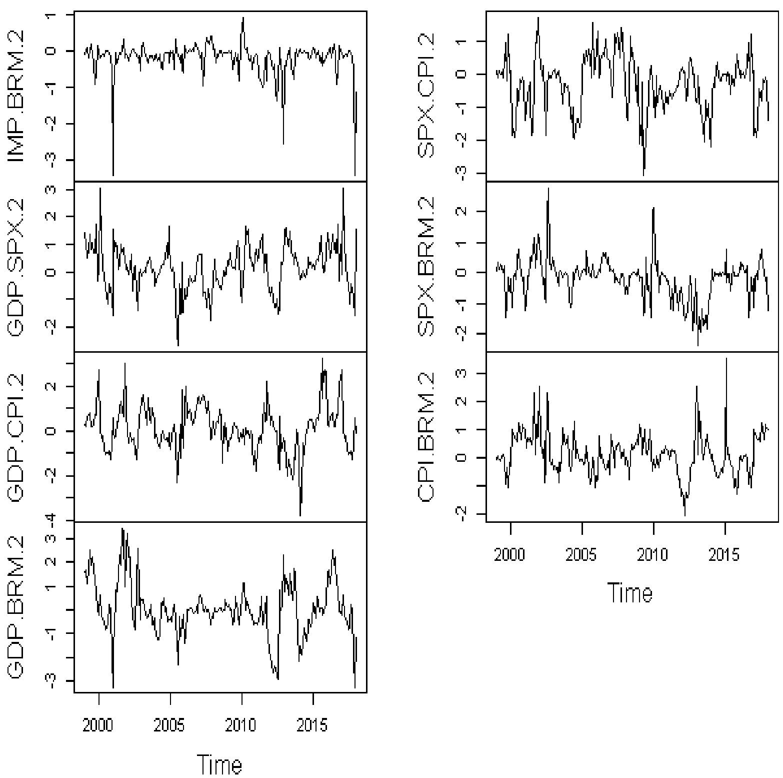
(c) i) Pairwise net rolling spillover on Band 0.79 to 0.26 for Brazil (Medium-term frequency)



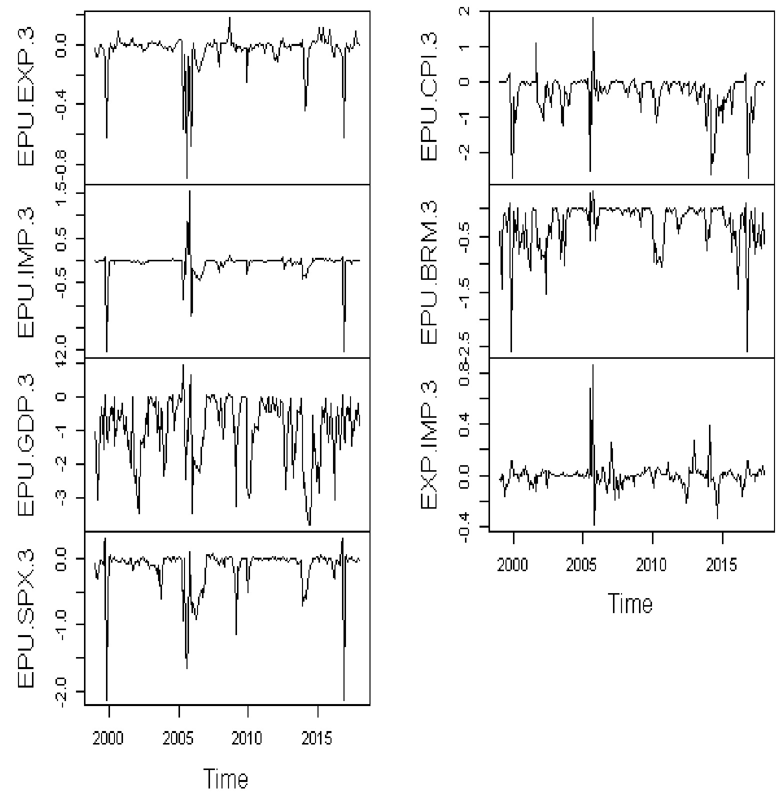
(c) ii) Pairwise net rolling spillover on Band 0.79 to 0.26 for Brazil (Medium-term frequency)



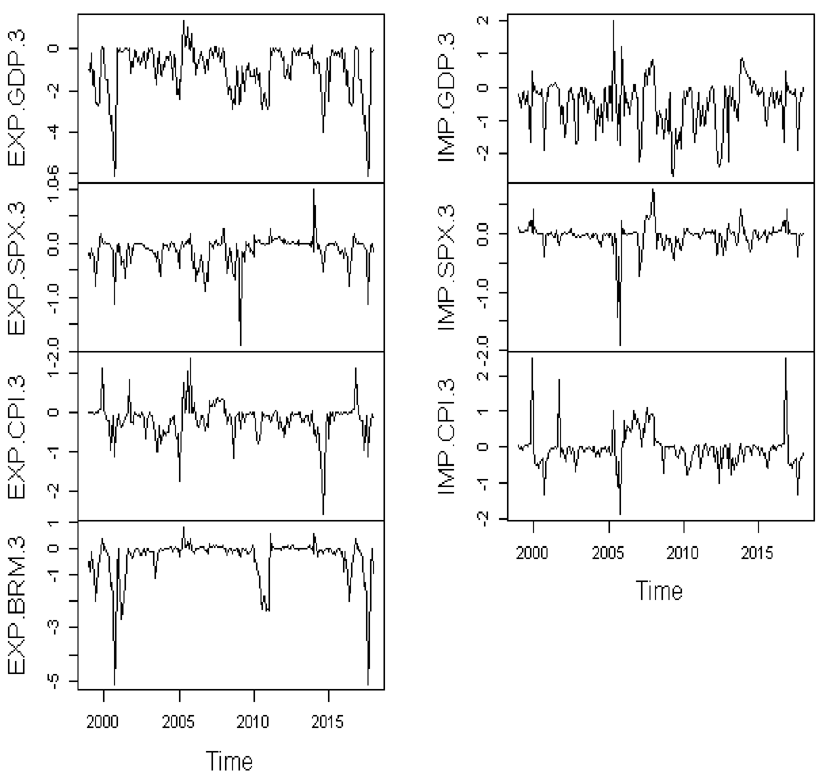
(c) iii) Pairwise net rolling spillover on Band 0.79 to 0.26 for Brazil (Medium-term frequency)



(d) i) Pairwise net rolling spillover on Band 0.26 to 0.00 for Brazil (Long-term frequecy)



(d) ii) Pairwise net rolling spillover on Band 0.26 to 0.00 for Brazil (Long-term frequency)



(d) iii) Pairwise net rolling spillover on Band 0.26 to 0.00 for Brazil (Long-term frequency)

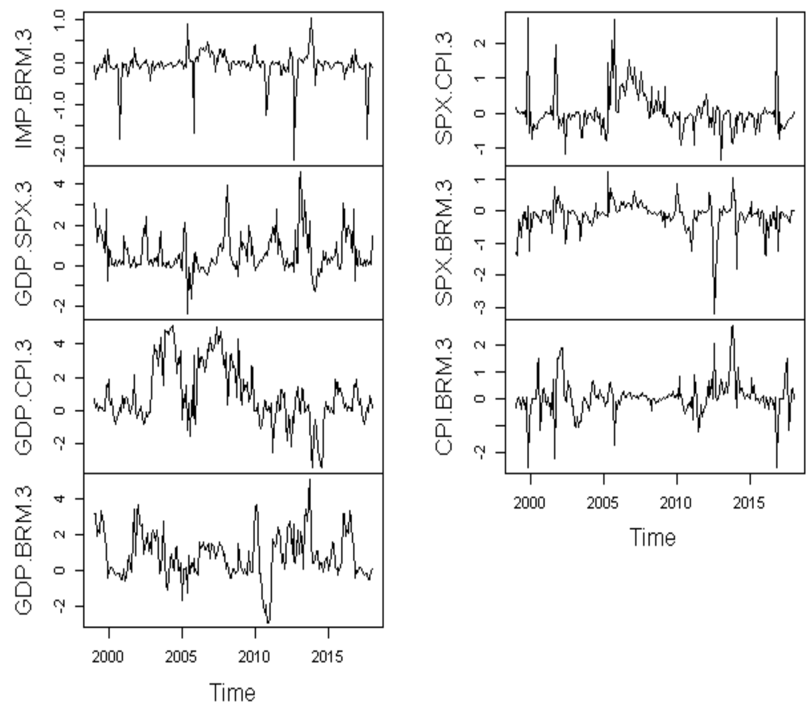


Figure 5.1: Overall rolling and Pairwise net rolling spillovers of selected variables in Brazil

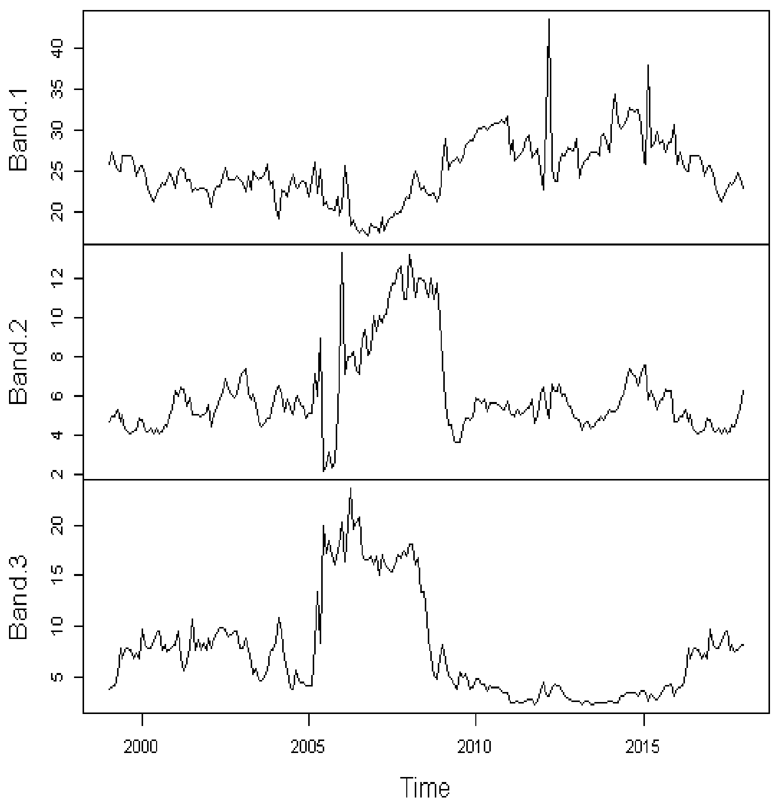
5.4.3.2 Intra-country time-varying spillover index with rolling-window analysis in China.

We now focus on evidence of overall connectedness in **China.** We see from Figure 5.2 (a) that the overall connectedness decreases in magnitude as the frequency increases. In the short-term (frequency band 1) we record fluctuations from 16% to 43%, followed by fluctuations ranging from 2% to 13% in the medium- term and finally recording a value range of 2% to 23% in the long-term. We record evidence of high connectedness within each of the three frequencies. The short-term (high frequency) drives "high" connectedness during 2012 and 2015 periods. Heightened values rose to about 43% as against average fluctuations of 30% across the frequency band. Highlights of spillover shocks in the medium-term drive "high" connectedness from late 2005 to early 2006 and 2009 periods. Heightened values rose as high as 13% and dropped as low as 2% against average fluctuations from 5% to 7% across the frequency band. In the long-term, we record "high" connectedness around 2005, 2006 and 2009 with value rising to about 23% as compared to average fluctuations of 7% across frequency band 3.

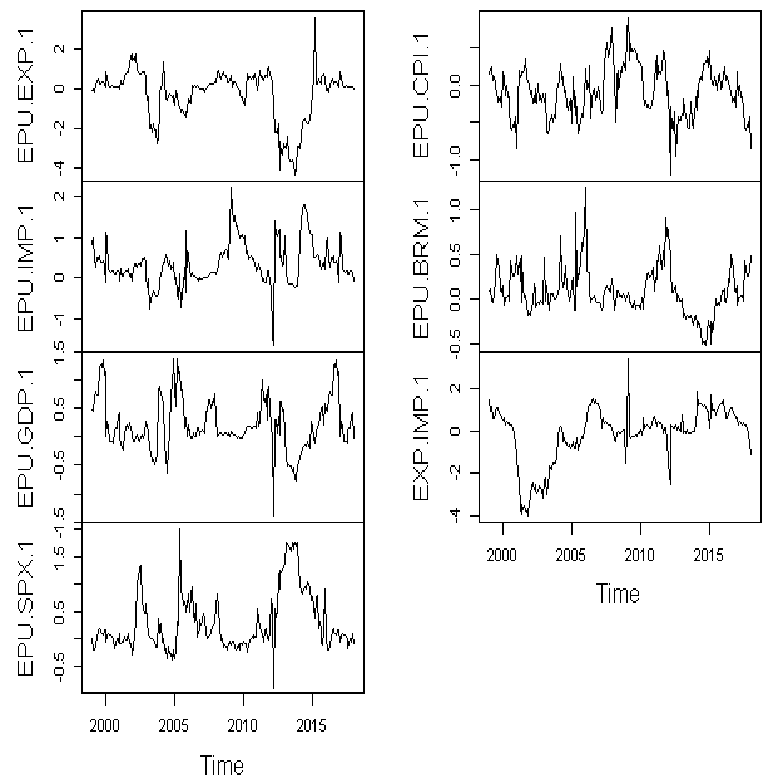
We therefore conclude that the long-term received the highest magnitude of heightened levels of connectedness in China which overlaps 2005 oil crises, 2007-2009 Global Financial Crisis, Eurozone Crises, US Fiscal Fights, and China Leadership Transition (all occurring round 2012) and 2016 Brexit Referendum, 2016 US presidential elections and 2016 European immigration crisis respectively. China also responds to economic and financial crisis or incidence. Clearly the 1997-1999 Asian crises did not significantly affect China like in the case of Brazil since we do not record any heightened spillover connectedness around the period 1999 to 2000. And specifically to China they received high levels of uncertainties as a result of the Latin America and Caribbean elections that occurred in January 2006. This could be the likely cause of the fluctuations around late 2005 through 2006 in the medium- and long-term frequency bands.

The pairwise net directional spillover for the selected variables in China is displayed in Figure 5.2 from (a) to (b) where (a), (b) and (c) represent the short, medium, and long-term frequencies respectively. We record multiple high values of spillover connectedness for each of the paired variables across time and frequency with the strongest levels of connectedness recorded in the short-term. The levels of connectedness in the short-term reached heights of 4% as compared to an average of 2% in the medium-, and long-term. It is therefore evident that there are records of high connectedness in China with heightened values that overlapped some global even such as the oil crises in 2005, Eurozone Crises, US Fiscal Fights (all in 2012) and country specific events such China Leadership Transition which occurred in 2012. We also find evidence of varying positive (net transmitters) and negative (net recipients) connectedness across all the frequencies, thereby showing no clear pattern of which variables are dominating as net recipients or transmitters of each paired variables.

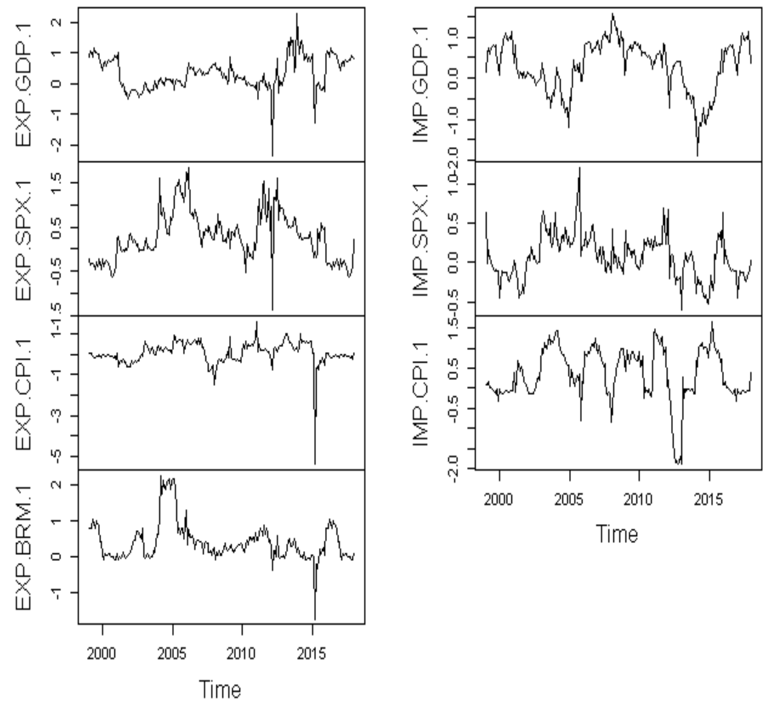
(a) Overall Rolling Spillover on Band 3.14 to 0.00 for China



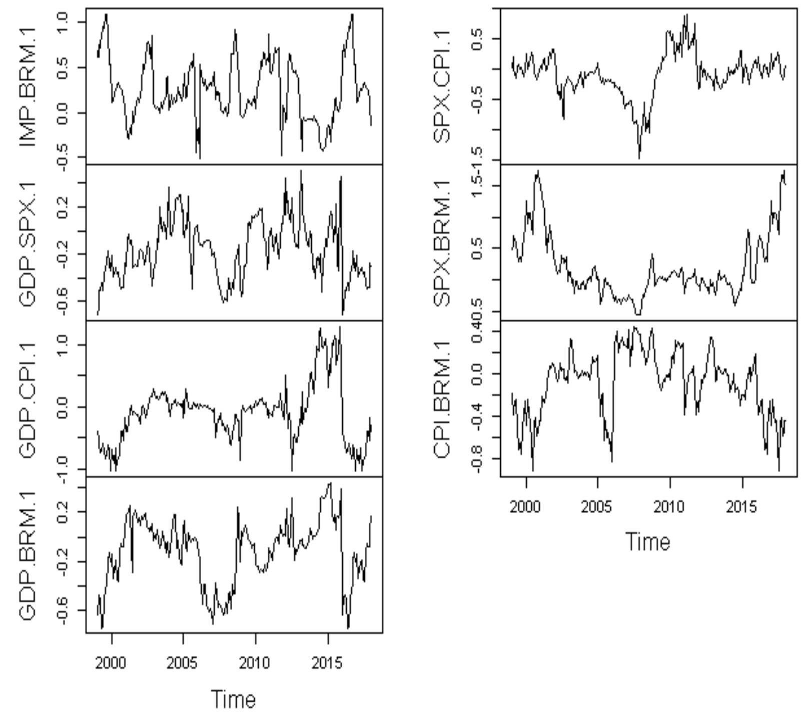
(b) i) Pairwise net rolling spillover on Band 3.14 to 0.79 for China (Short-term frequency)



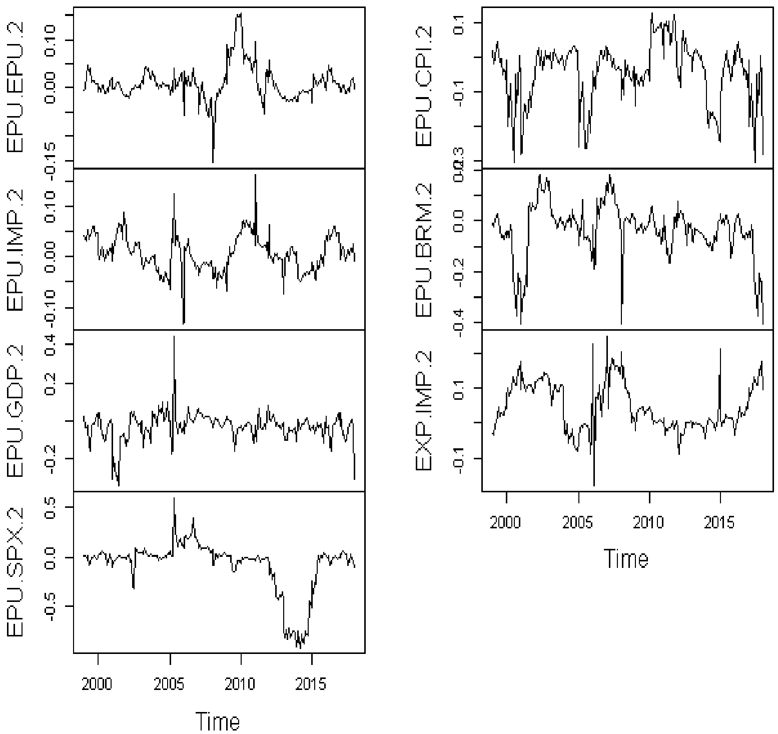
(b) ii) Pairwise net rolling spillover on Band 3.14 to 0.79 for China (Short-term frequency)



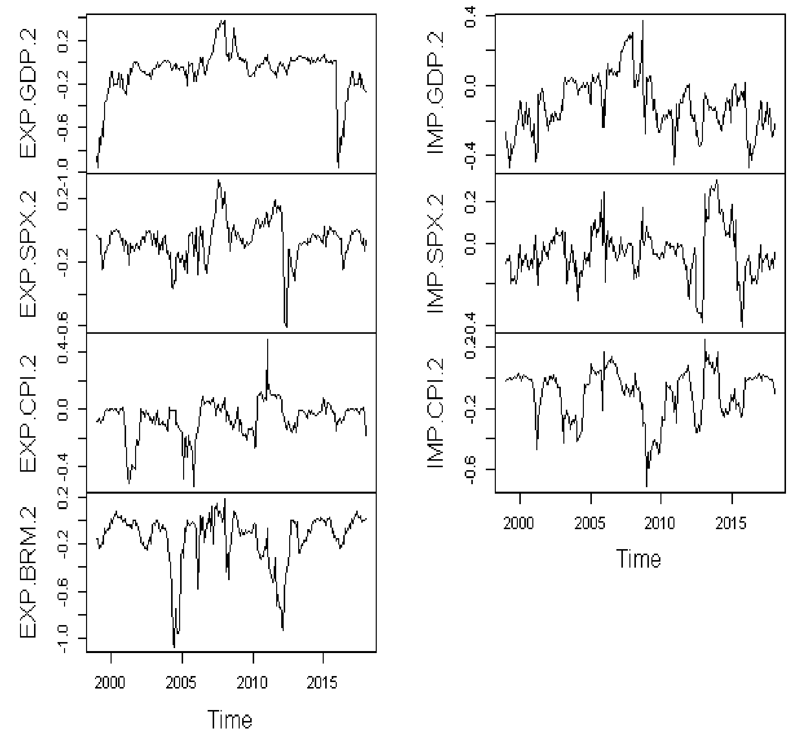
(b) iii) Pairwise net rolling spillover on Band 3.14 to 0.79 for China (Short-term frequency)



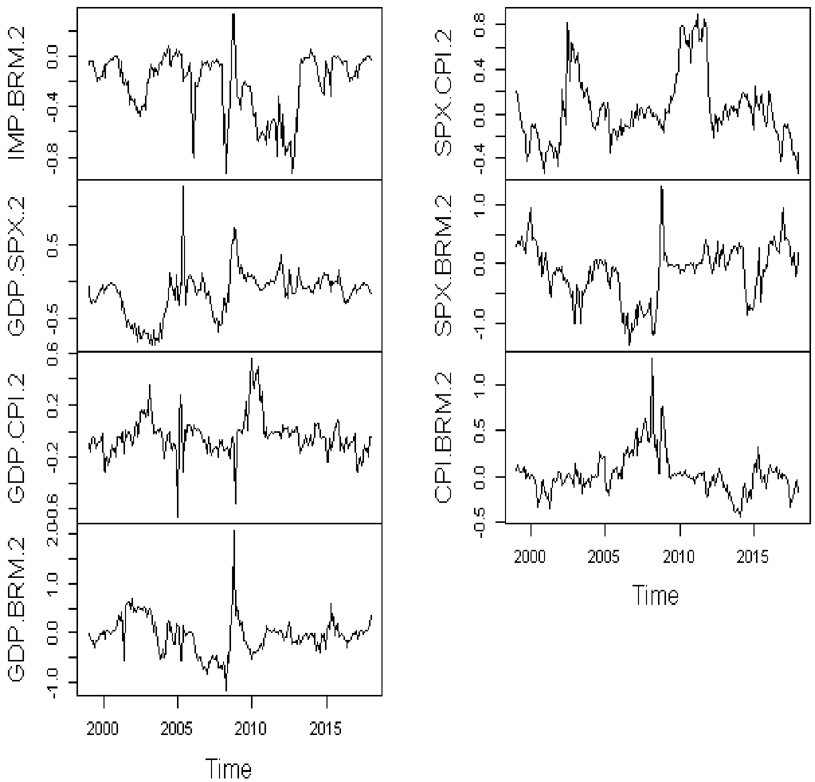
(c) i) Pairwise net rolling spillover on Band 0.79 to 0.26 for China (Medium-term frequency)



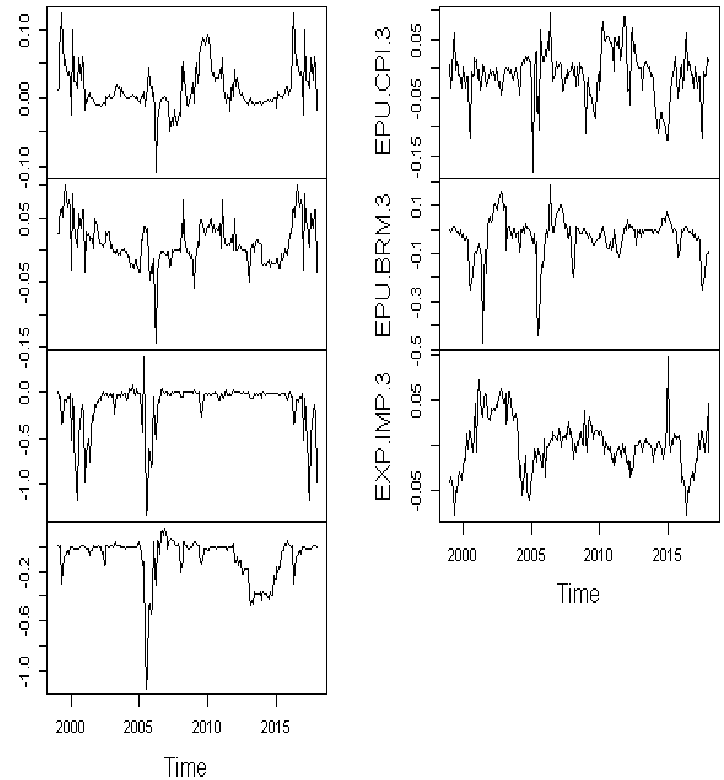
(c) ii) Pairwise net rolling spillover on Band 0.79 to 0.26 for China (Medium-term frequency)



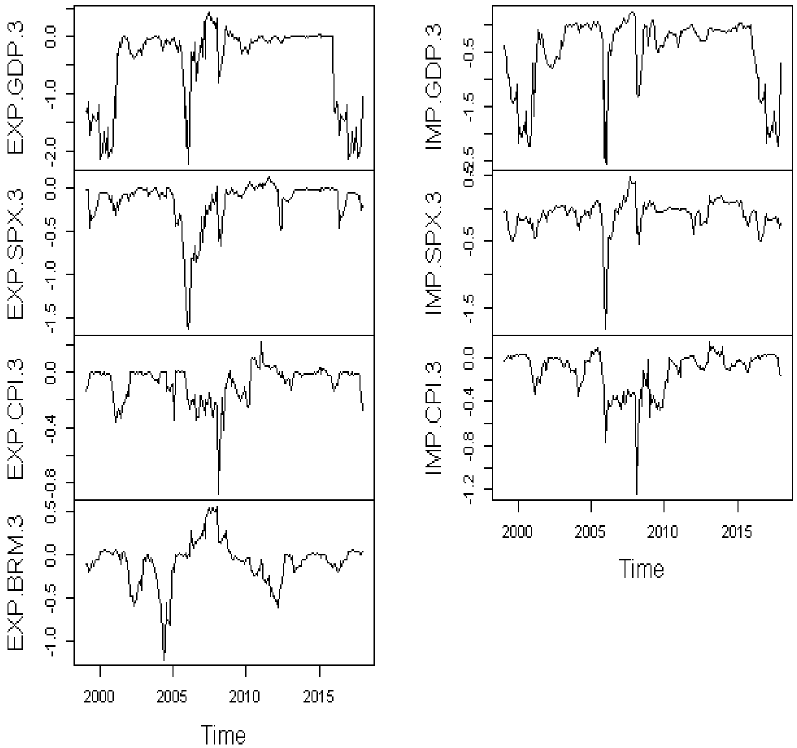
(c) iii) Pairwise net rolling spillover on Band 0.79 to 0.26 for China (Medium-term frequency)



(d) i) Pairwise net rolling spillover on Band 0.26 to 0.00 for China (Long-term frequency)



(d) ii) Pairwise net rolling spillover on Band 0.26 to 0.00 for China (Long-term frequency)



(d) iii) Pairwise net rolling spillover on Band 0.26 to 0.00 for China (Long-term frequency)

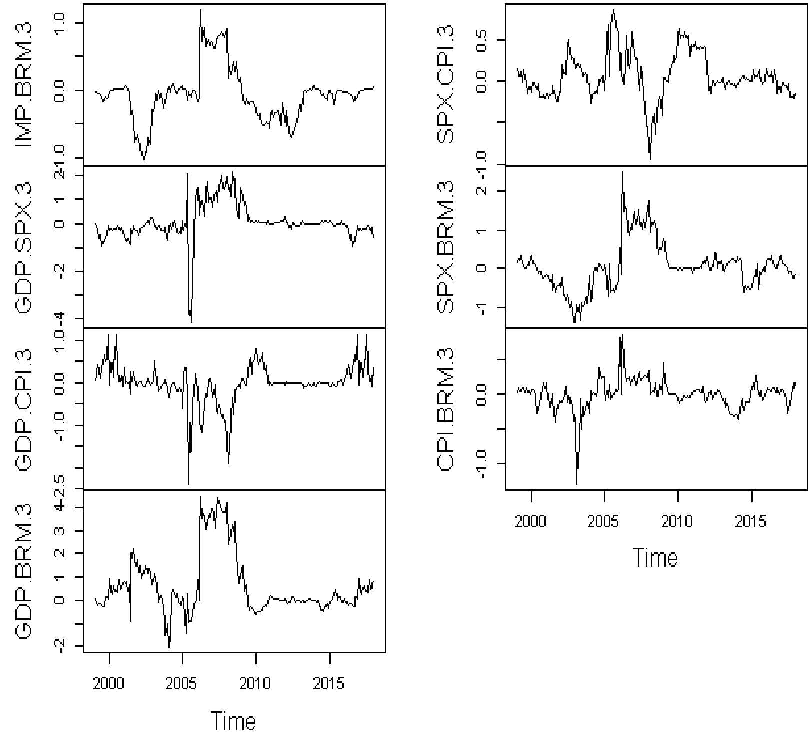
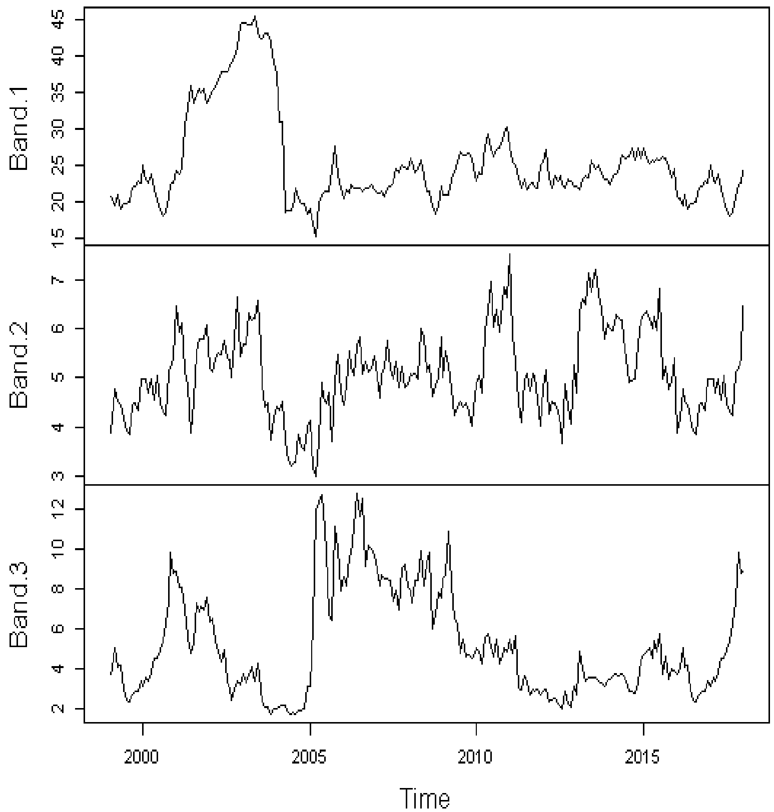


Figure 5.2: Overall rolling and Pairwise net rolling spillovers of selected variables in China

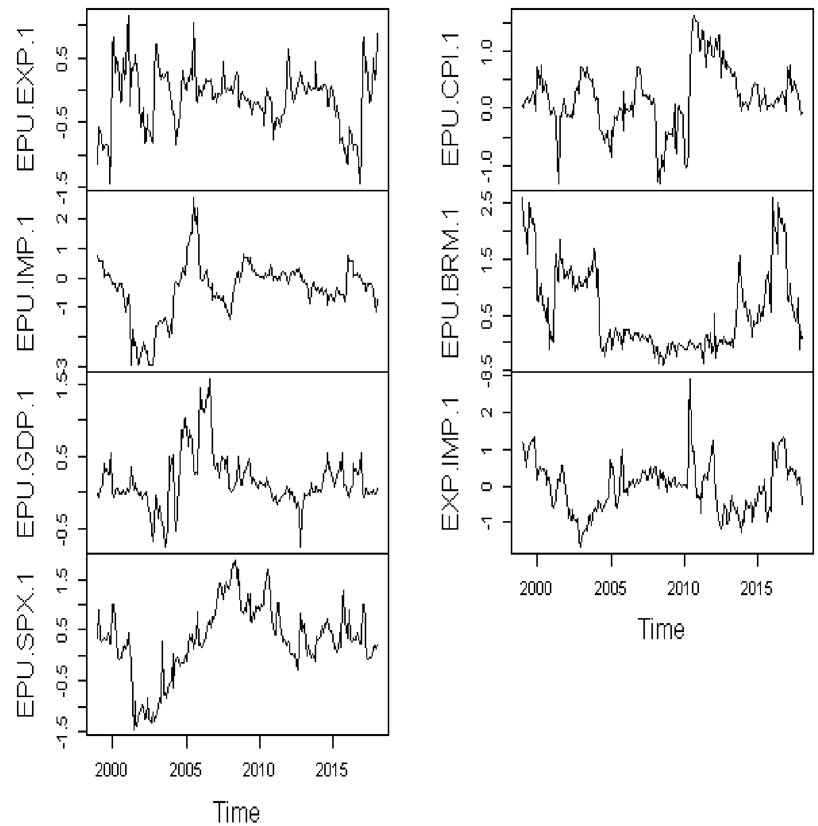
5.4.3.3 Intra-country time-varying spillover index with rolling-window analysis in India

This session focuses on evidence of overall connectedness in **India**. We see from Figure 5.3 that the overall connectedness decreases in magnitude as the frequency increases. We record fluctuations from 15% to 45% in the short-term, followed by fluctuations ranging from 3% to 7% in the medium- term and finally recording a value range of 2% to 13% in the long-term. We record evidence of high connectedness within each of the three frequencies. The short-term (high frequency) drives "high" connectedness during 2002 (with value 35%) and 2003 (with value 45%) periods. Interestingly we record very significant fluctuations in the medium-term with the highest connectedness recorded at 2001 (with values 7.5% and 7%), 2003 (with value 7.3) and 2015 (with value 7%). In the long-term, we also record "high" connectedness around early 2005 (with value 13%), mid 2006 (with values 13%), in 2009 (with value 11%) and we recorded 11% for 2001, 2008 and 2018.We therefore conclude that the medium- and long-term received the highest magnitude of heightened levels of connectedness in India of which some overlap with economic and financial global incidence as stated earlier. India also responds to economic and financial crisis or incidence. The pairwise net directional spillovers for the elected variables in India is displayed in Figure 5.3 from (b) to (d), where (a), (b)and (c) represent the short-, medium-, and long-term respectively. We record multiple sudden increases in the values of spillover connectedness for all the paired variables across the selected time frame (date) and frequency. The level of connectedness is stronger in the long-term with the highest value rerecorded at 3% as compared to an average of 1.5% in the medium-, and long-term. The pairwise net directional connectedness show varying positive connectedness (net transmitter) and negative connectedness (net recipients) across all the levels of frequencies thereby showing no evidence of a domineering variable.

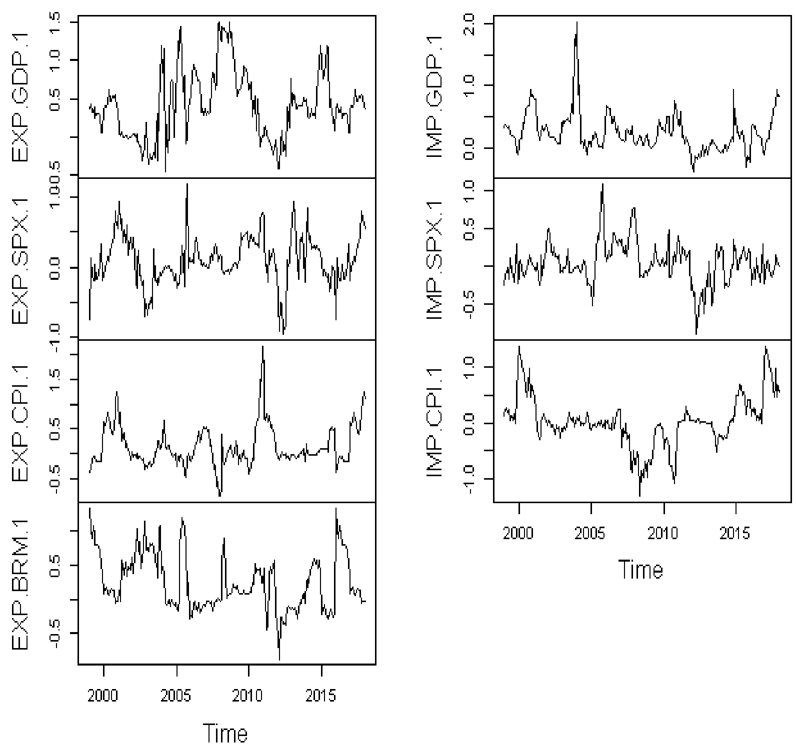
(a) Overall Rolling Spillover on Band 3.14 to 0.00 for India



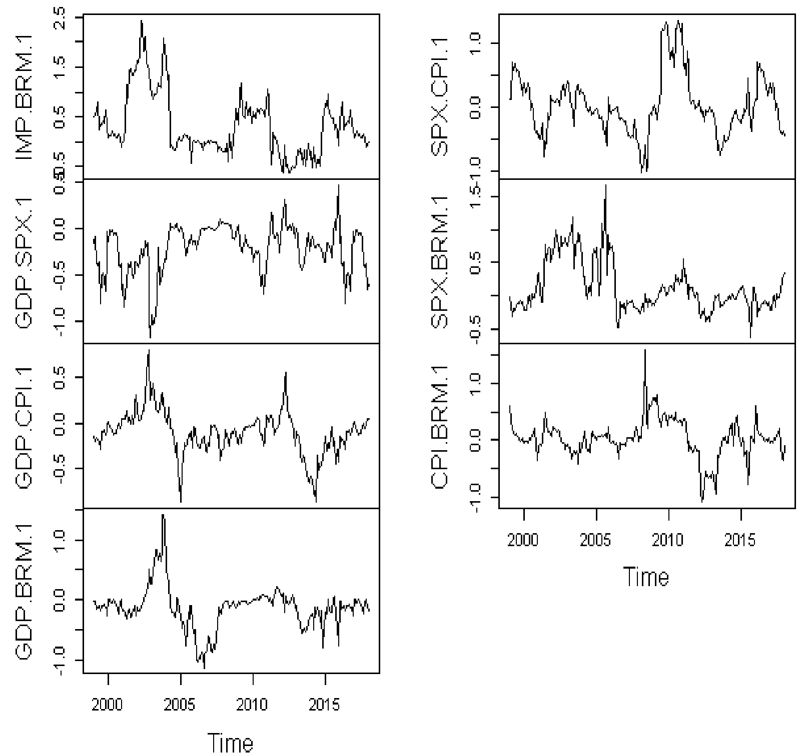
(b) i) Pairwise net rolling spillover on Band 3.14 to 0.79 for India (Short-term frequency)



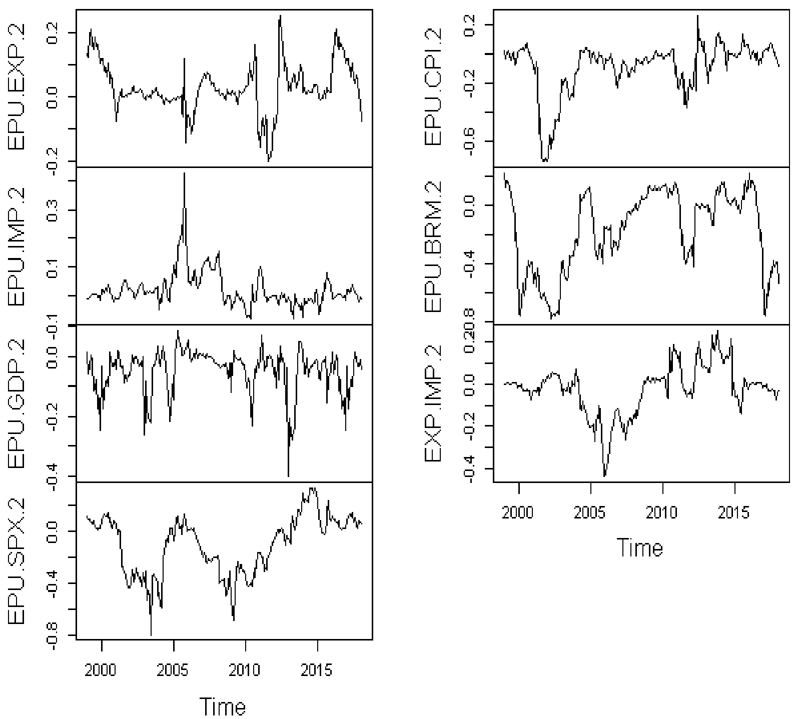
(b) ii) Pairwise net rolling spillover on Band 3.14 to 0.79 for India (Short-term frequency)



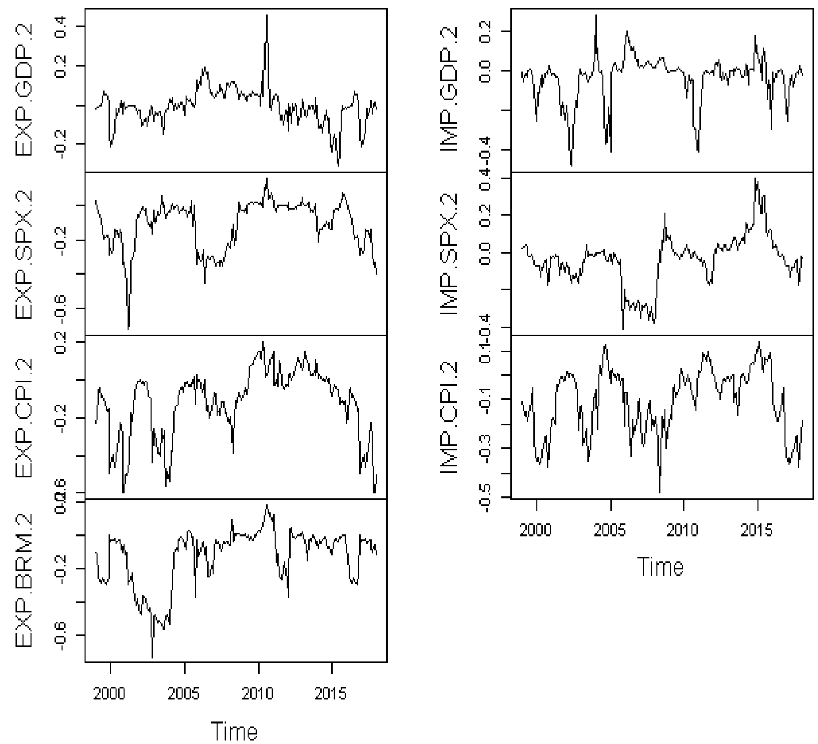
(b) iii) Pairwise net rolling spillover on Band 3.14 to 0.79 for India (Short-term frequency)



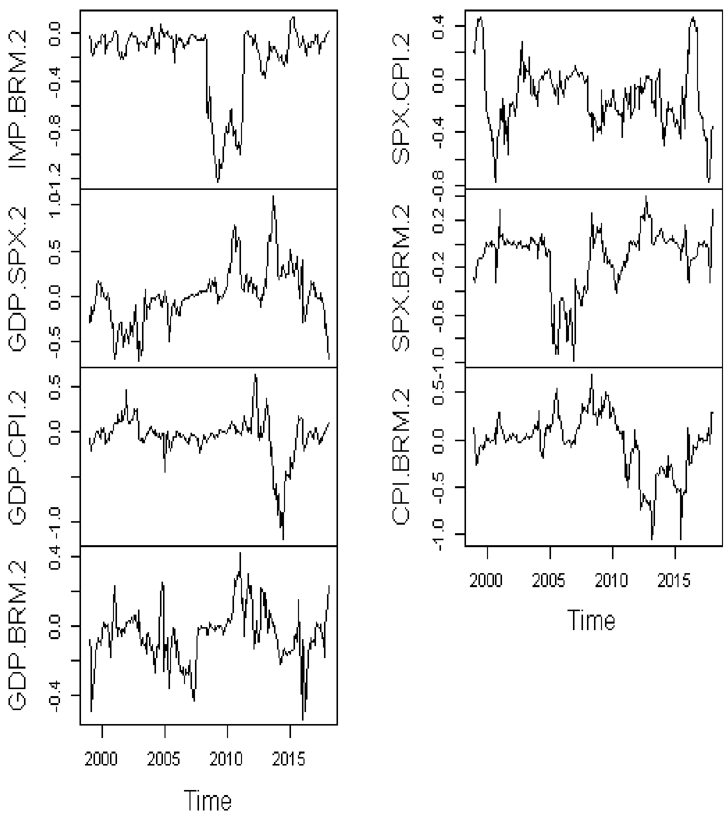
(c) i) Pairwise net rolling spillover on Band 0.79 to 0.26 for India (Medium-term frequency)



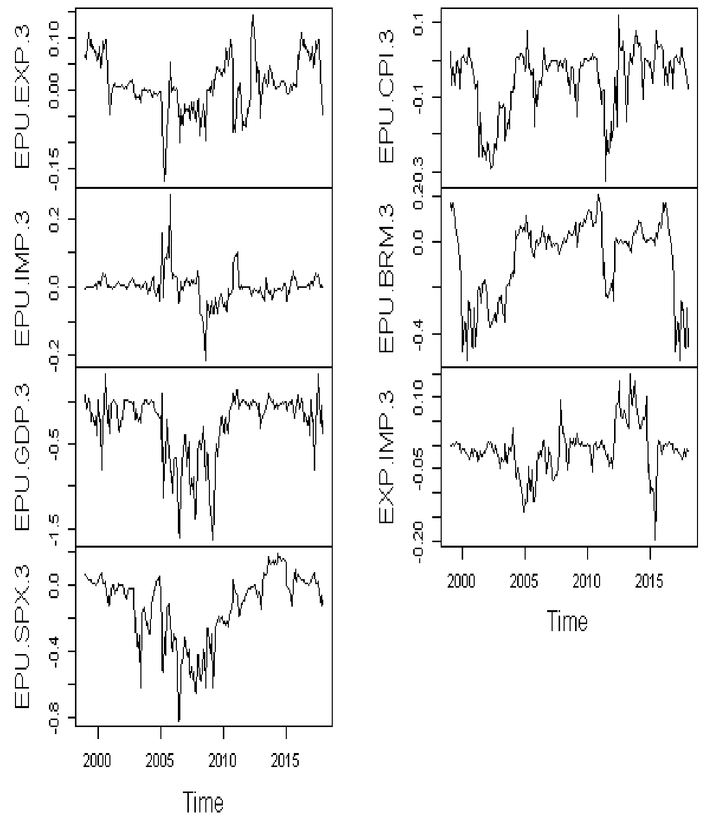
(c) ii) Pairwise net rolling spillover on Band 0.79 to 0.26 for India (Medium-term frequency)



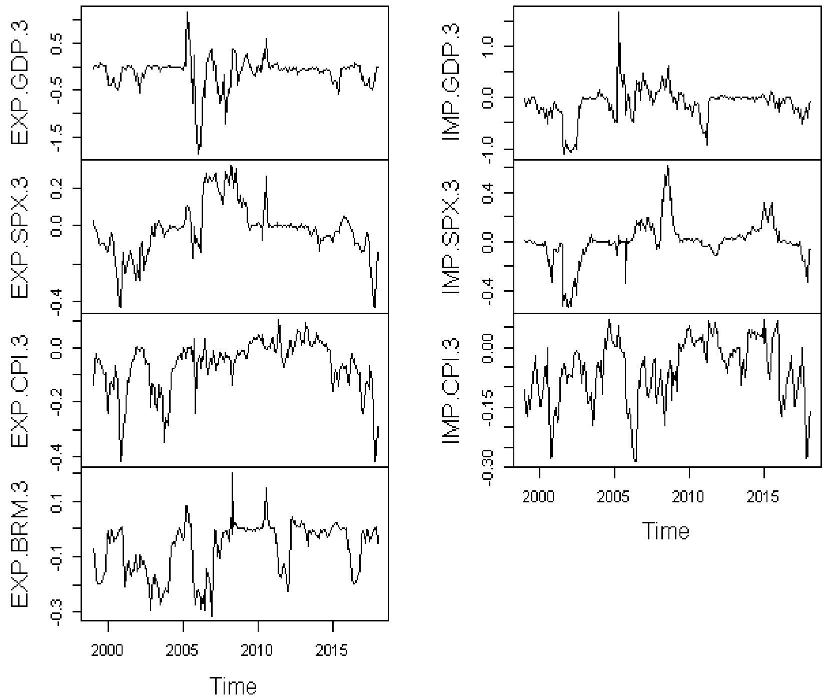
(c) iii) Pairwise net rolling spillover on Band 0.79 to 0.26 for India (Medium-term frequency)



(d) i) Pairwise net rolling spillover on Band 0.26 to 0.00 for India (Long-term frequency)



(d) ii) Pairwise net rolling spillover on Band 0.26 to 0.00 for India (Long-term Frequency)



(d) iii) Pairwise net rolling spillover on Band 0.26 to 0.00 for India (Long-term Frequency)

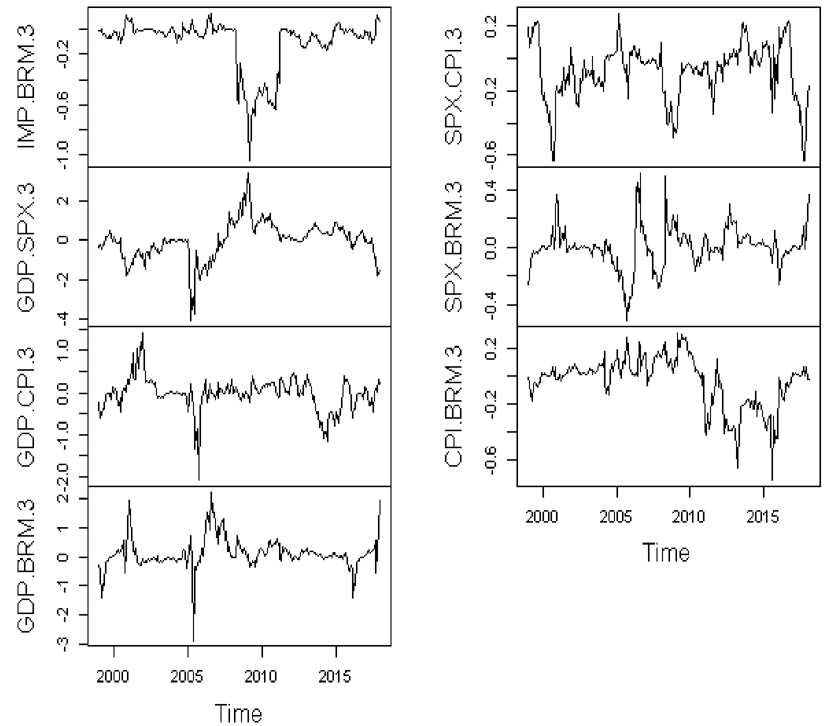
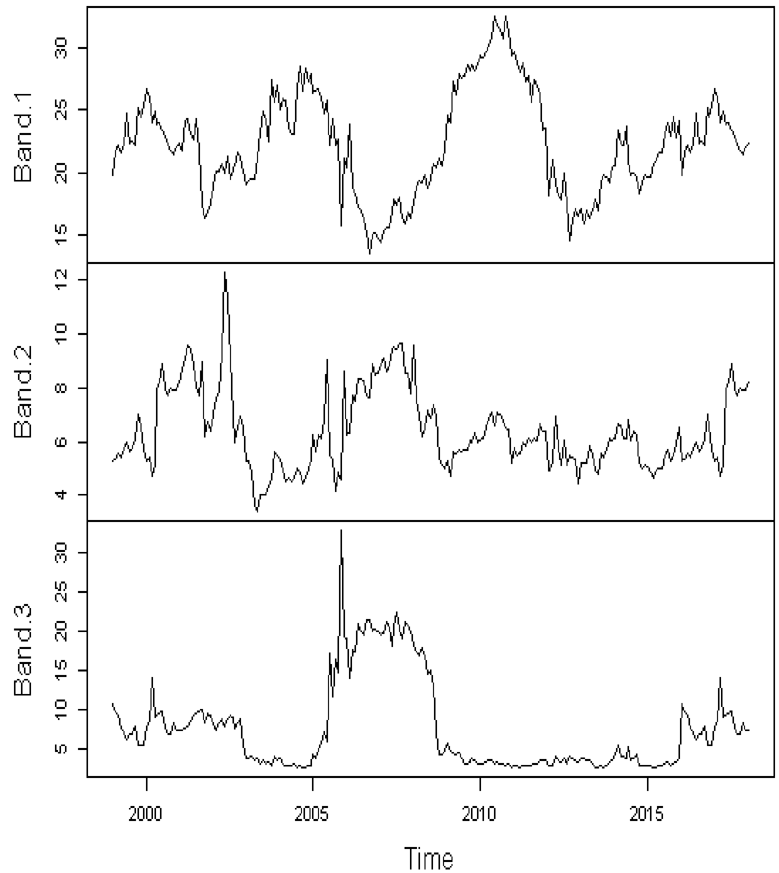


Figure 5.3: Overall rolling and Pairwise net rolling spillovers of selected variables in India

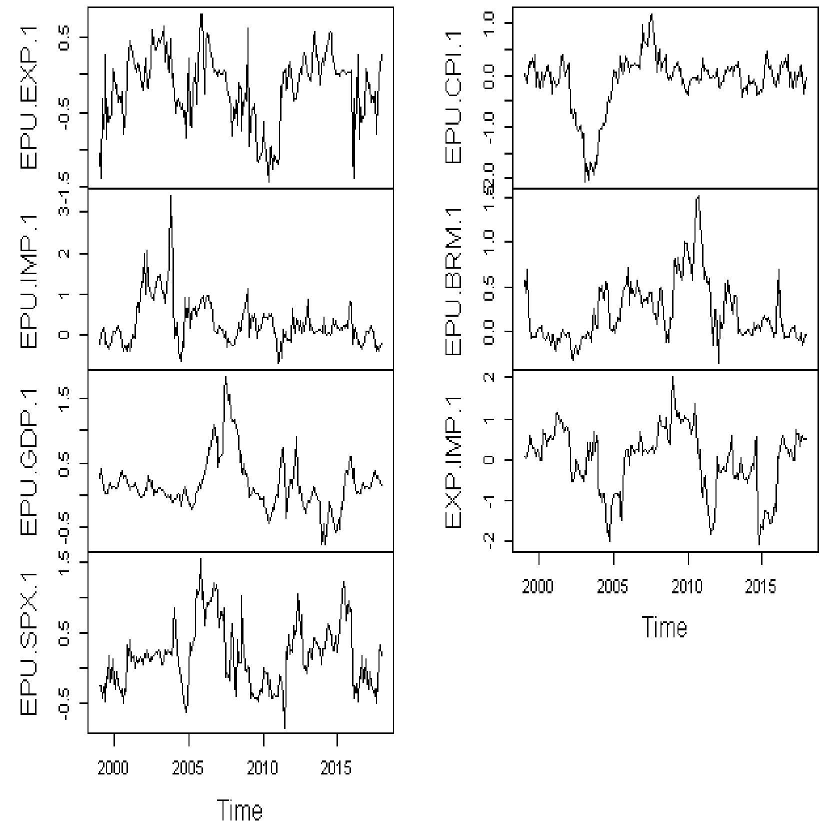
5.4.3.4 Intra-country time-varying spillover index with rolling-window analysis in Korea

We see from Figure 5.4 (a) that the overall connectedness in Korea decreases in magnitude as the frequency increases as recorded in the other EME. The fluctuations range from 13% to 32% in the short-term, followed by fluctuations ranging from 3% to 12% in the medium- term and finally recording a value range of 2% to 22% in the long-term. We record evidence of spillover connectedness within each of the three frequencies. We generally record heightened fluctuations in Korea. Specifically, we record a consistent rise from 2008 reaching a peak at 2011 (with a value of 33%) and then consistently falls till 2013. We also record two peaks during 2003 to 2004 with values 28% and 29% respectively. And finally, we record 27% spillover connectedness during 2000 and 2017. In the short-term, we record heightened values in the first half. The highest spillover shocks was recorded in 2002 with a value of 12.5% and 8.5 at the latter part of 2005. Also, 9% was recorded between 2007 and 2008 and around 2001. In the long-term, we discover that 2006-2009 was consistently high averaging at 23% with a peak of 34% 2006. These heightened values clearly reflect the 2001 US recession, oil crisis Global Financial Crisis and 2016 Brexit Referendum just to mention a few. The pairwise net directional spillover in Korea is presented in Figure 5.4 from (a) to (b) where (a), (b) and (c) represent the short, medium, and long-term frequencies of twenty-one (21) pairs respectively. We record multiple high values of spillover connectedness for each of the paired variables across time and frequency. We also identified heightened values during 2005 and 2012 which correspond with the 2005 oil crises, 2009 global financial crises and 2012 Eurozone Crises and US Fiscal Fights. Stronger levels of connectedness were recorded in the short-term and long-term. We record weak spillover connectedness between import and broad money, GDP and SPX, GDP and CPI, and lastly GDP and broad money all in the long-term.

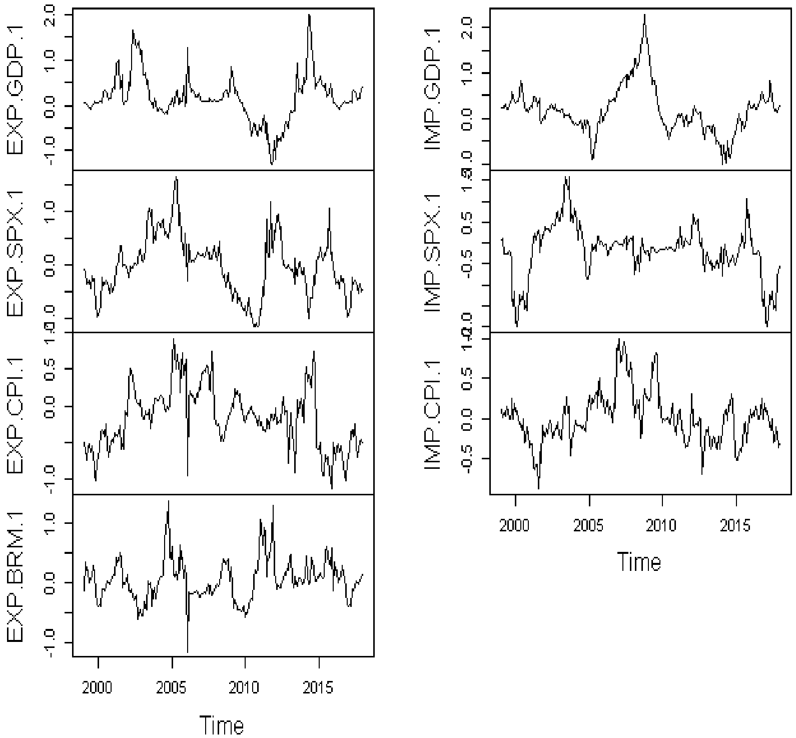
(a) Overall Rolling Spillover on Band 3.14 to 0.00 for Korea



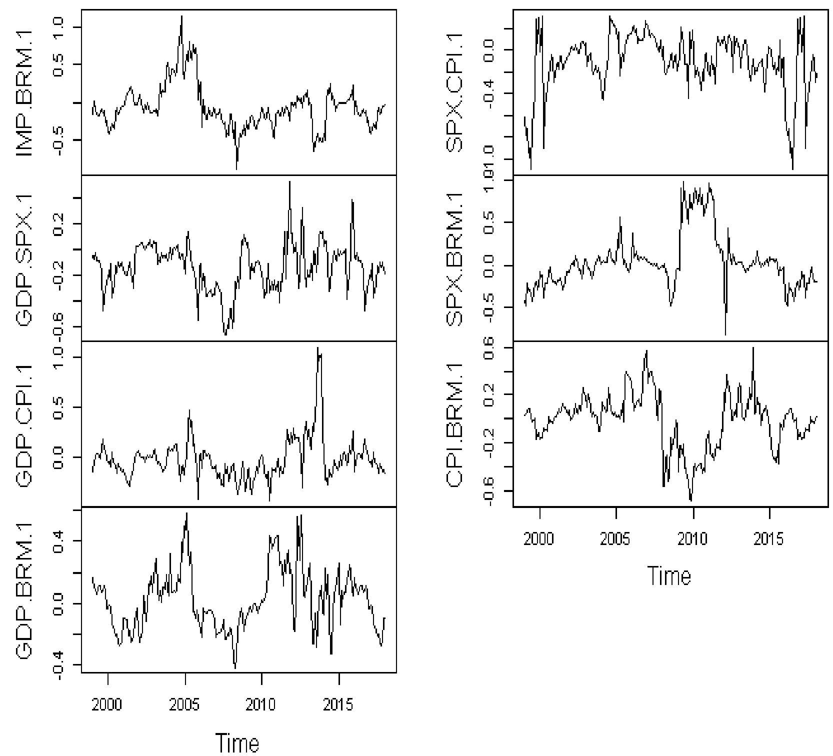
(b) i) Pairwise net rolling spillover on Band 3.14 to 0.79 for Korea (Short-term Frequency)



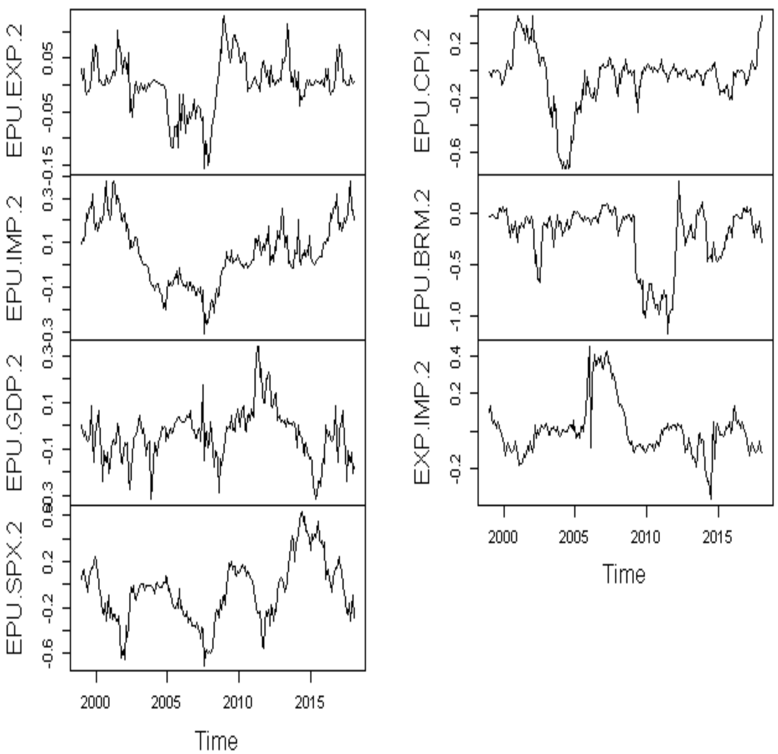
(b) ii) Pairwise net rolling spillover on Band 3.14 to 0.79 for Korea (Short-term Frequency)



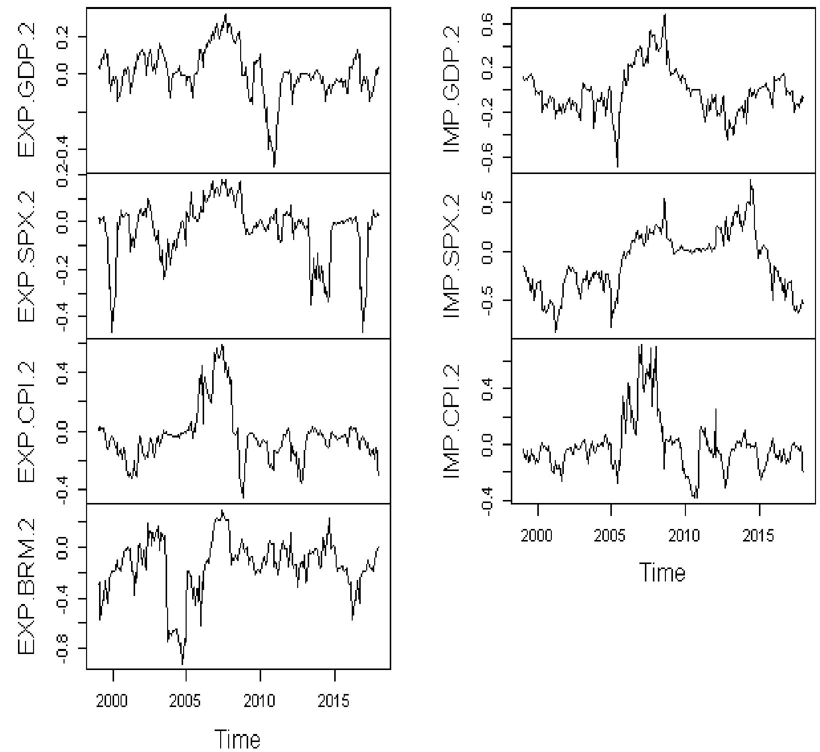
(b) iii) Pairwise net rolling spillover on Band 3.14 to 0.79 for Korea (Short-term Frequency)



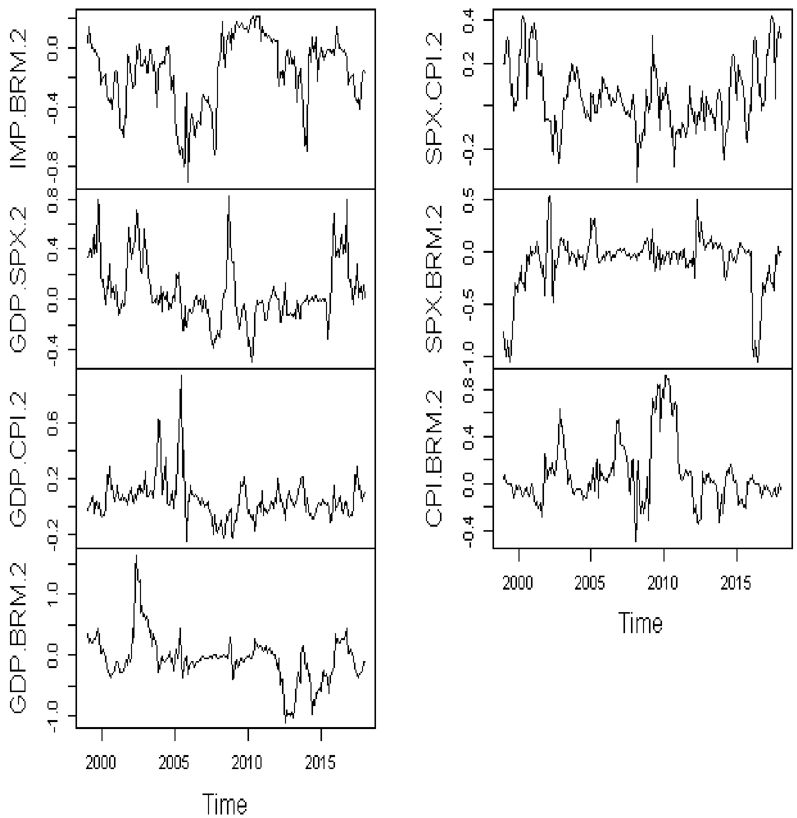
(c) i) Pairwise net rolling spillover on Band 0.79 to 0.26 for Korea (Medium-term Frequency)



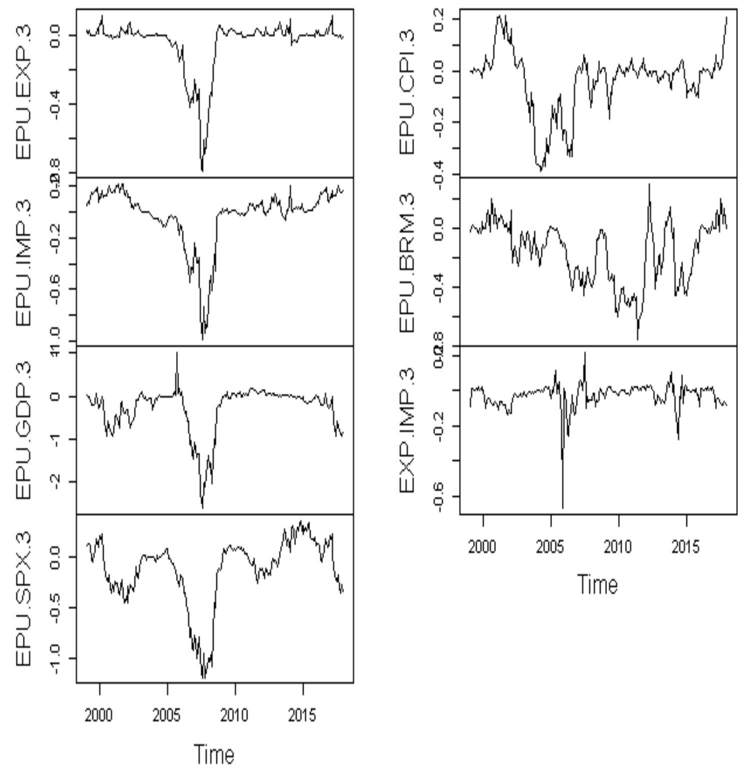
(c) ii) Pairwise net rolling spillover on Band 0.79 to 0.26 for Korea (Medium-term Frequency)



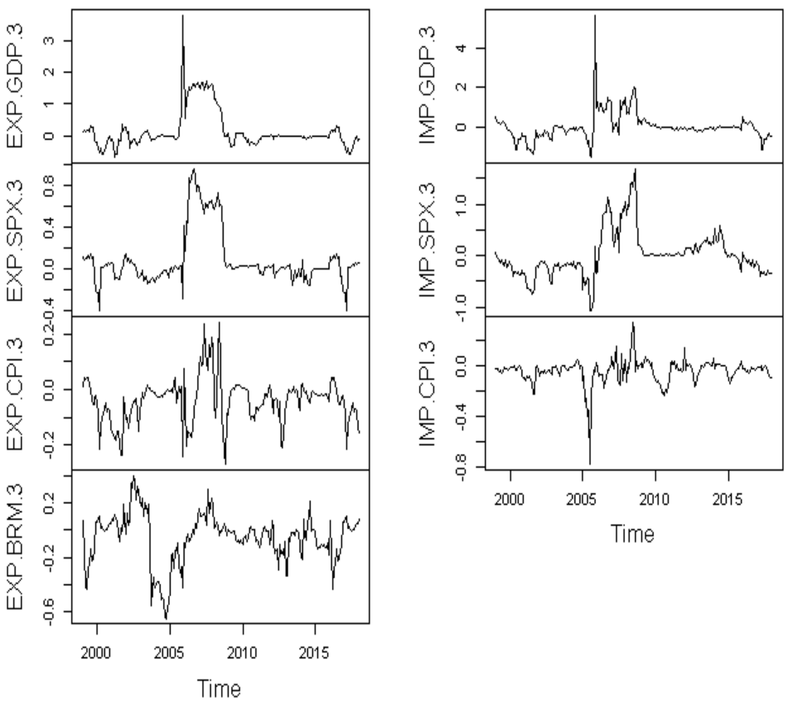
(c) iii) Pairwise net rolling spillover on Band 0.79 to 0.26 for Korea (Medium-term Frequency)



(d) i) Pairwise net rolling spillover on Band 0.26 to 0.00 for Korea (Long-term Frequency)



(d) ii) Pairwise net rolling spillover on Band 0.26 to 0.00 for Korea (Long-term Frequency)



(d) iii) Pairwise net rolling spillover on Band 0.26 to 0.00 for Korea (Long-term Frequency)

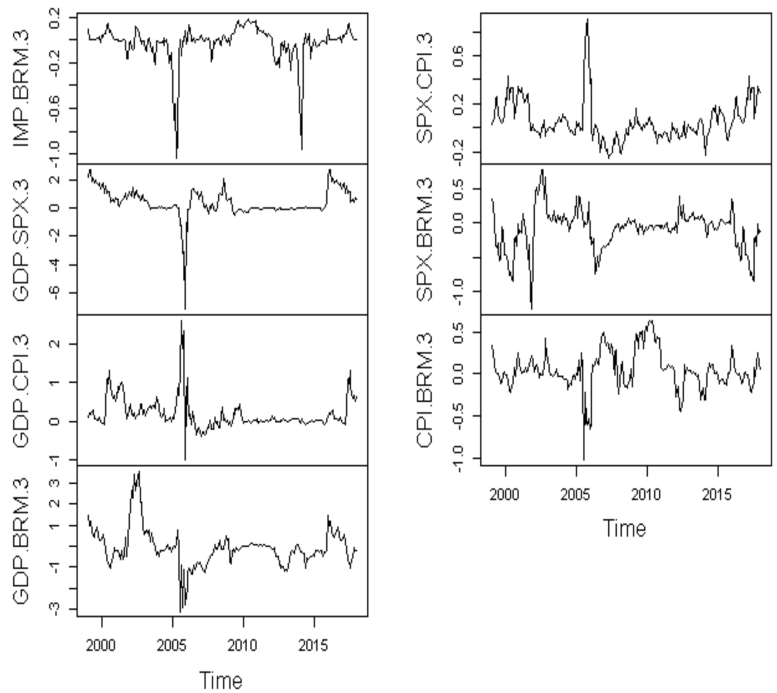


Figure 5.4: Overall rolling and Pairwise net rolling spillovers of selected variables in Korea

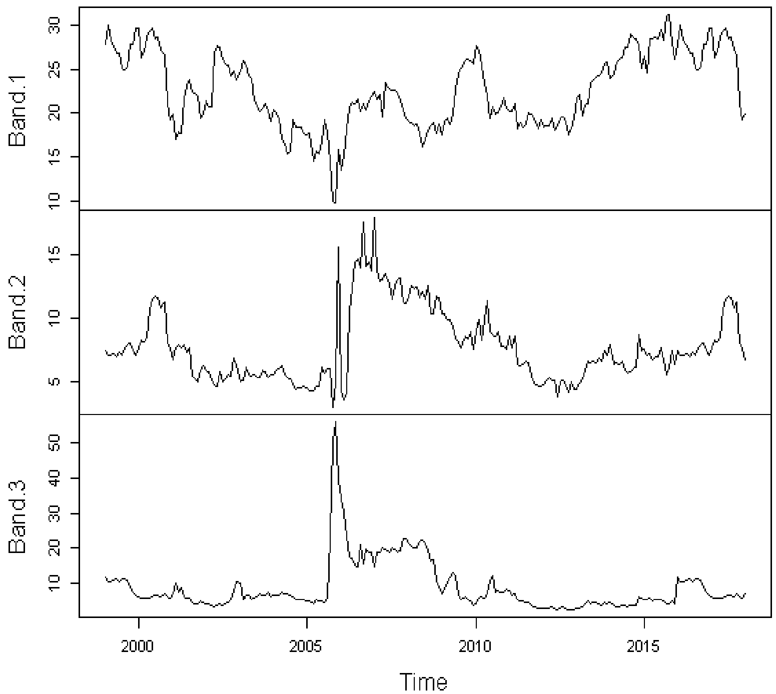
5.4.3.5 Intra-country time-varying spillover index with rolling-window analysis in Mexico

This session focuses on evidence of overall connectedness in **Mexico**. Interestingly we see from Figure 5.5 (a) that Mexico's overall connectedness is highest in the long-term (low frequency) having a frequency value of as high as 56%. We record fluctuations from 10% to 31% in the short-term, followed by fluctuations ranging from 3% to 15% in the medium- term and finally recording a value range of 2% to 50% in the long-term. We record evidence of high connectedness within each of the three frequencies. In frequency band 1, we record relatively high fluctuating values right from 2000 to 2017. This implies that the short-term (high frequency) quickly responds to incidence hence spillover shocks, which reflects the consistent fluctuations across the whole time frame.

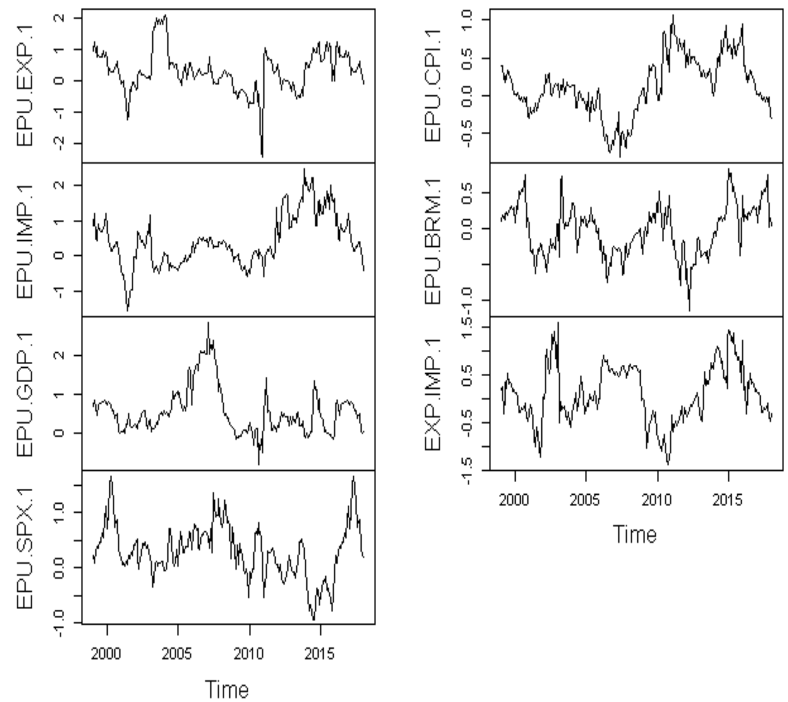
We wish to add that Mexico has persistently over the period under study experienced countless number of economic and financial incidences leading to heightened uncertainty and shock transmissions. These incidences includes Daewoo Motor Bankruptcy and Financial Fraud and Accounting Scandals in 2000, Gulf War II in 2003, impeachment of President Roh Moo-hyun and the constitutional court overturning the move (all in 2004), Eurozone fears in 2011, Brexit and Korean industry reconstruction in 2016 and finally when parliament impeaches President Park in late 2016. In frequency band 2, we first record a sharp rise of 16% which is above the average value of 7% during the late part of 2005. The spillover connectedness reduced drastically afterwards to a values of 2.5% only to increase again to 18% in 2007. We also record heightened values of 12% around 2000, 2011 and 2017. In the long-term, the spillover connectedness rises above the average values of 10% to 56% during the late session of 2005. Clearly the medium, and long-term show less records of spillovers above average values as compared to the short-term, however the highest level of connectedness was recorded in the long-term. It can also be concluded that economic and financial incidence intensifies the total spillover in Mexico just as was recorded earlier in other EMEs.

Figure 5.5 (b), (c) and (c) shows the pairwise net directional spillover connectedness between the seven selected variables in Mexico. The amounts of pairwise net directional connectedness recorded across the three frequencies all differ in magnitude across all the frequency bands. We also record varying signals (positive/negative) across all frequencies for each of the paired variables. The net recipients' and transmitters' relationship between the paired variables do not show any clear evidence of the domineering net recipients and transmitters in Mexico. Although we record multiple high values of spillover connectedness for each of the paired variables across time and frequency we identify very weak pairwise net directional connectedness in the long-term. We also find evidence that some of the heightened spillover connectedness in Mexico overlaps with some global even such as the oil crises in 2005 and the global financial crises in 2007 to 2009. Hence, pairwise net directional spillover outputs must be analysed on a pairwise bases focusing also on specific times and frequencies.

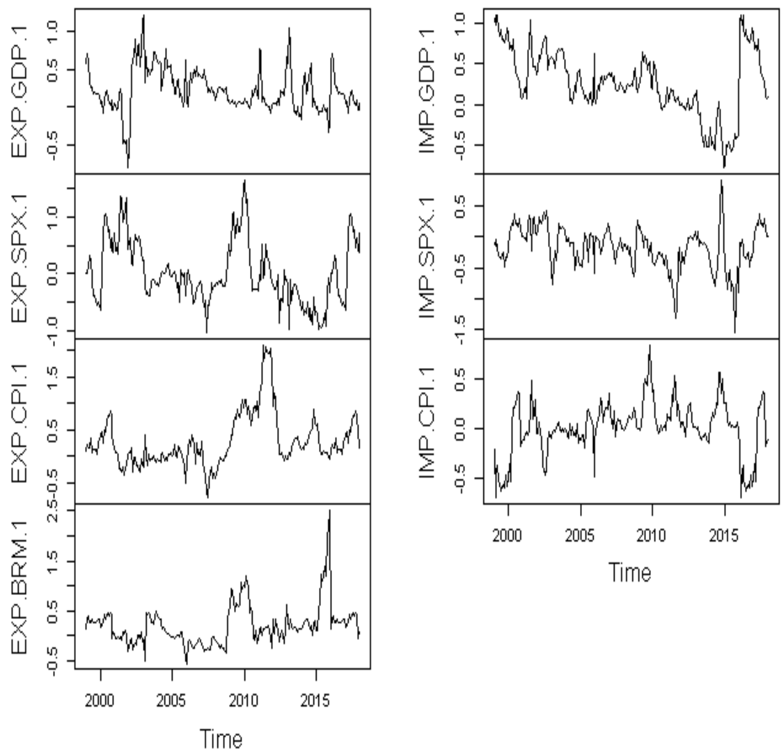
(a) Overall Rolling Spillover on Band 3.14 to 0.00 for Mexico



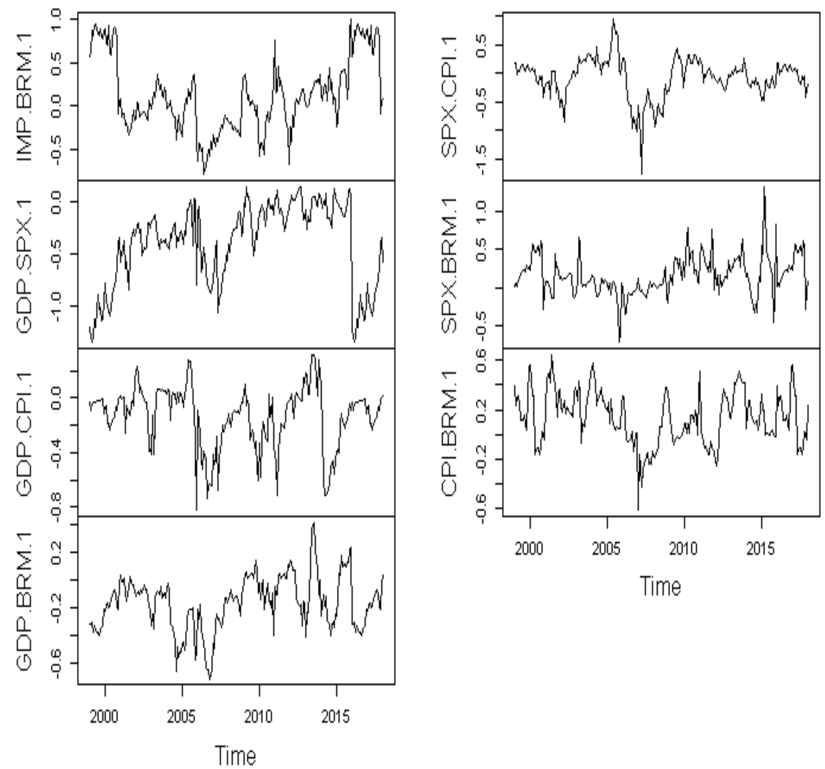
(b) i) Pairwise net rolling spillover on Band 3.14 to 0.79 for Mexico (Short-term Frequency)



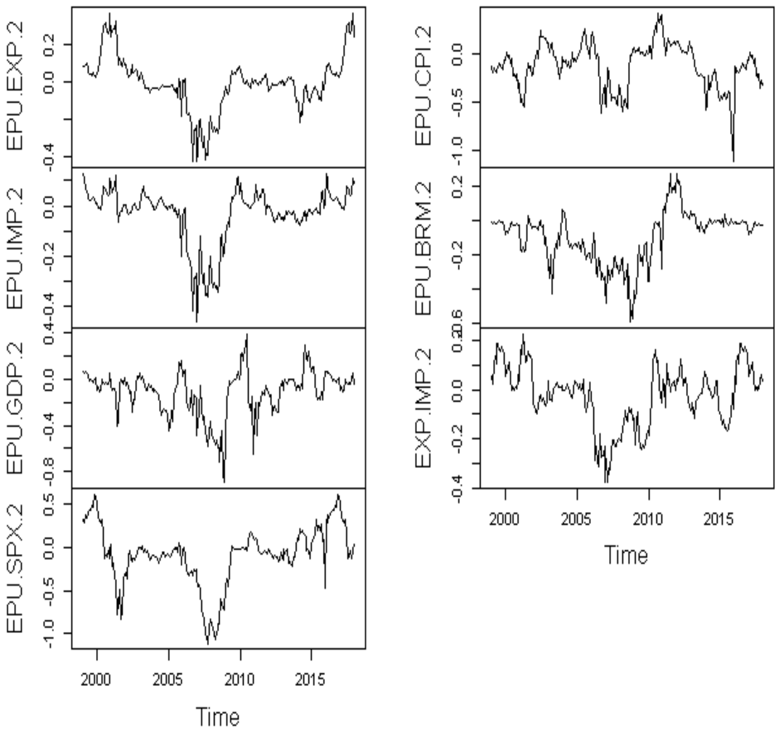
(b) ii) Pairwise net rolling spillover on Band 3.14 to 0.79 for Mexico (Short-term Frequency)



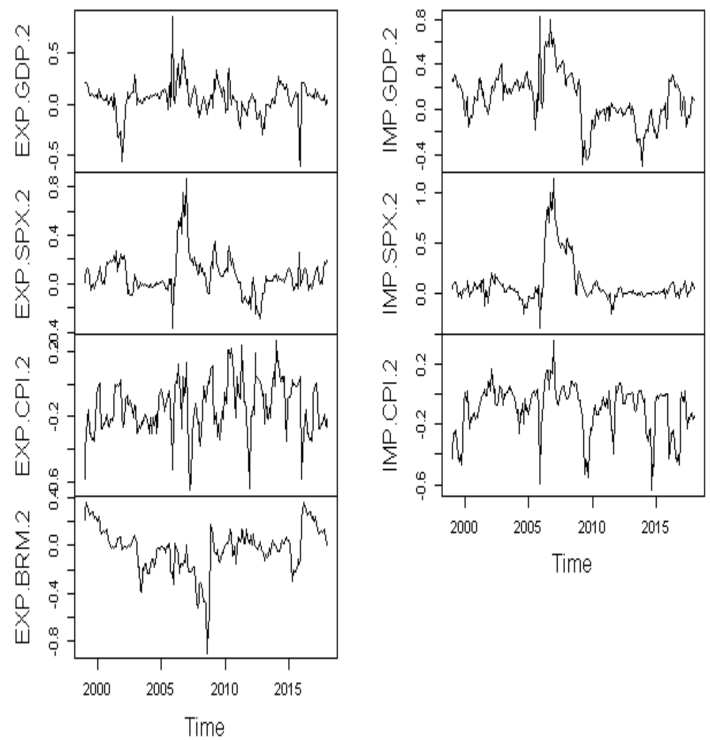
(b) iii) Pairwise net rolling spillover on Band 3.14 to 0.79 for Mexico (Short-term Frequency)



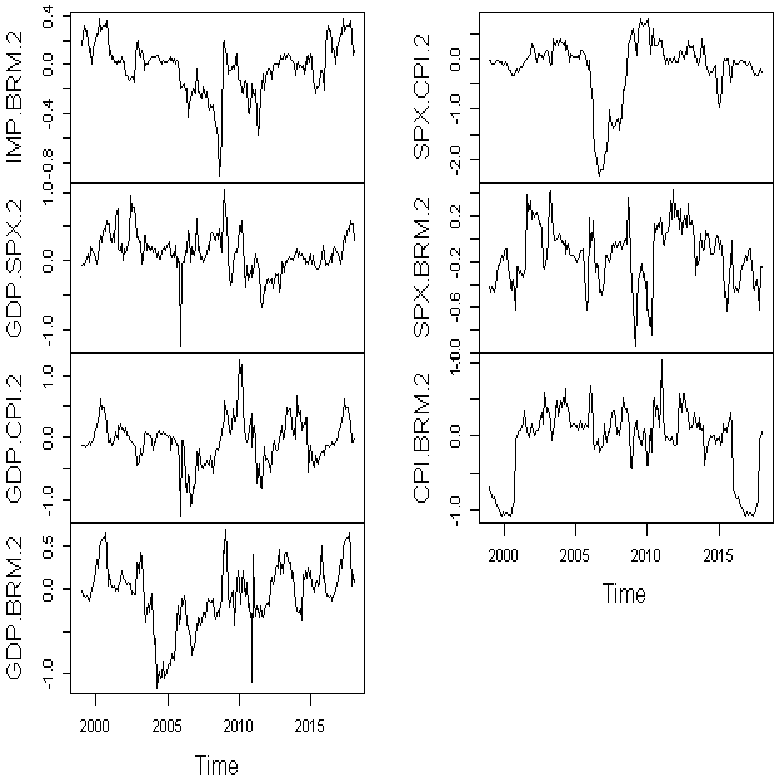
(c) i) Pairwise net rolling spillover on Band 0.79 to 0.26 for Mexico (Medium-term Frequency)



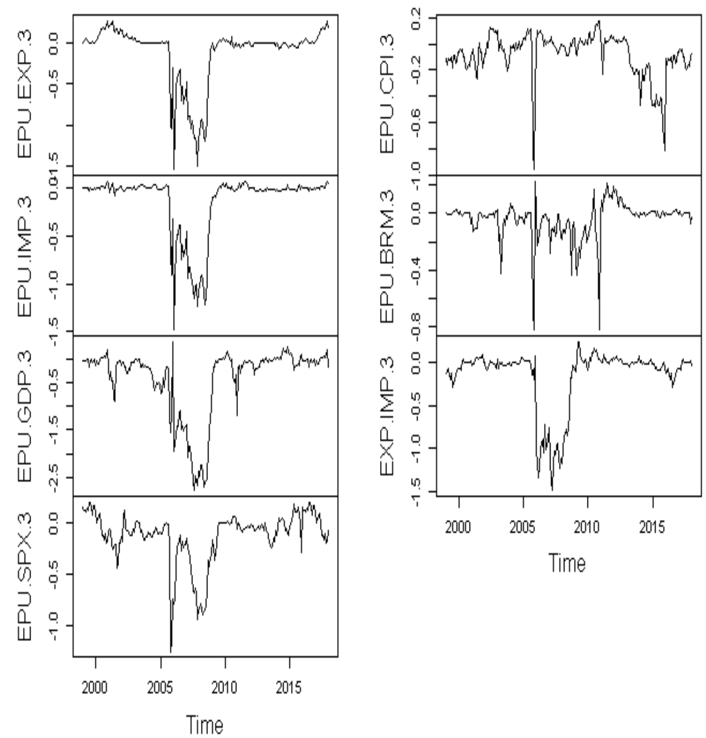
(c) ii) Pairwise net rolling spillover on Band 0.79 to 0.26 for Mexico (Medium-term Frequency)



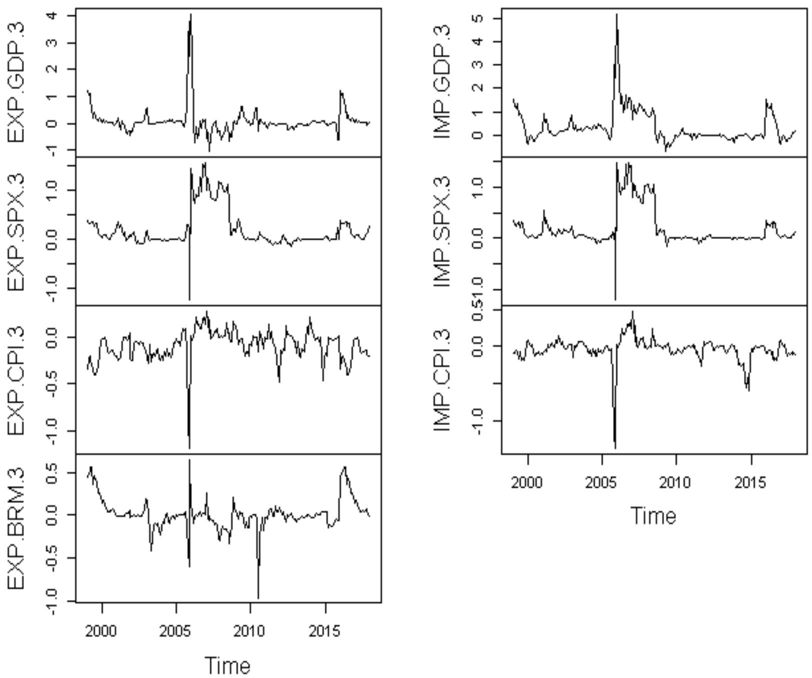
(c) iii) Pairwise net rolling spillover on Band 0.79 to 0.26 for Mexico (Medium-term Frequency)



(d) i) Pairwise net rolling spillover on Band 0.26 to 0.00 for Mexico (Long-term Frequency)



(d) ii) Pairwise net rolling spillover on Band 0.26 to 0.00 for Mexico (Long-term Frequency)



(d) iii) Pairwise net rolling spillover on Band 0.26 to 0.00 for Mexico (Long-term Frequency)

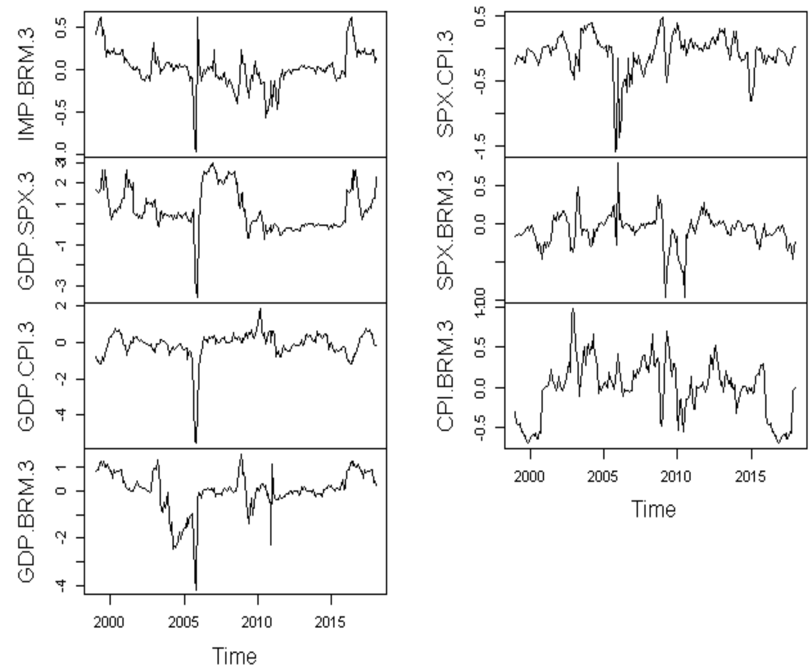


Figure 5.5: Overall rolling and Pairwise net rolling spillovers of selected variables in Mexico

5.4.3.6 Intra-country time-varying spillover index with rolling-window analysis in Russia

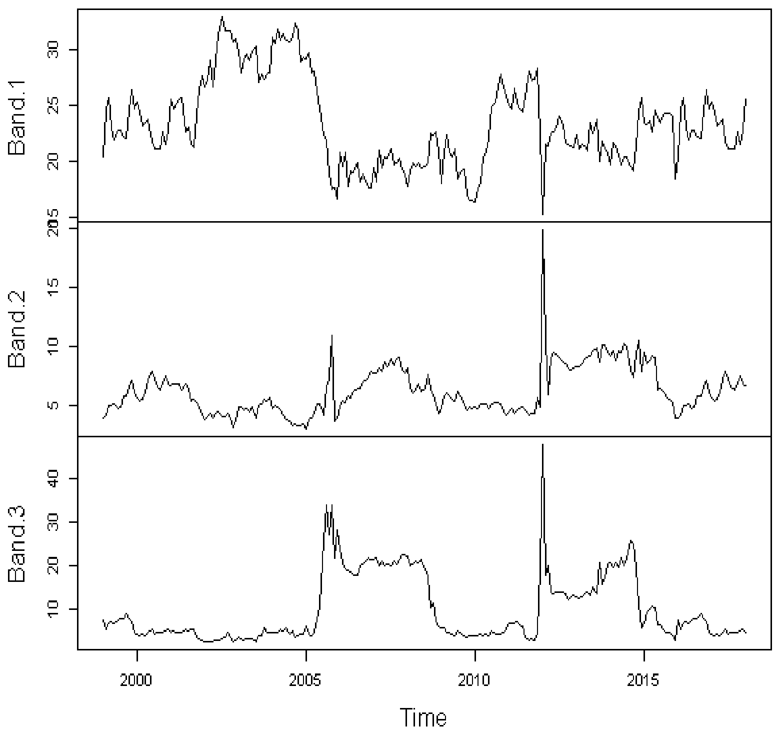
In the case of **Russia**, it evident from Figure 5.6 (a) that Russia's overall connectedness is highest in the long-term (low frequency) having a frequency value of as high as 48%. We record fluctuations from 15% to 32%, 3% to 19% and 2% to 48% in the short-, medium- and long-term. We record evidence of high connectedness within each of the three frequencies in Russia. In frequency band 1, we record relatively high fluctuating values right from 2002 to 2005 with heightened values ranging around 33% and around late 2010 through to late 2012 with value heightening at 28%. In frequency band 2 we record 11% spillover connectedness in 2006 and 20% in 2012. In frequency band 3 we also record spillover connectedness of 35% in 2006, 49% in 2012 and 25% around the latter part of 2014. We realise that 2006 and 2012 record heightened values across all three frequencies.

This implies that Russia experienced specific economic and financial incidences in their economy leading to heightened uncertainty and shock transmissions. Specifically, heightened values in 2006 can be attributed to Timoshenko's resignation and Terror attack in Nalchik. Likewise, in 2012 Russia was affected by Duma elections and the protests against election fraud as well as the Putin election. The year 2014 (as evident in fluctuations in the short-term) records the Ukraine conflicts which involved Kiev Euromaidan and Crimea annexation. Global incidence that affected the spillover shocks include the European Financial Stability Pact 2010 and Greek debt crisis. It is therefore evident that across all the selected EMEs the overall time-varying total spillover index are very responsive to country specific and global events, which makes us conclude that economic and financial occurrences and crises intensify the total spillover connectedness. We can confidently answer our question that there exit spillover effect within each EME even in the time-varying domain with rolling-window analysis.

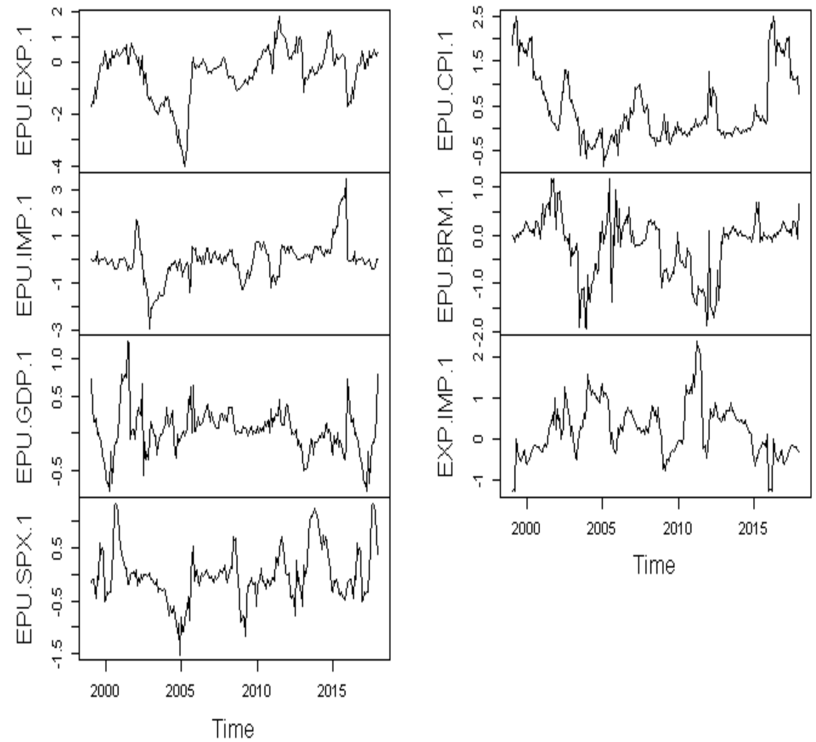
Figure 5.6 (b), (c) and (c) shows the pairwise net directional spillover connectedness between the seven selected variables in Russia for the short-, medium-, and long-term. We record multiple sudden increases in the values of the spillover connectedness for all the paired variables across time and frequency. The highest level of connectedness was recorded in the long-term (around 2005 and 2012) reaching a value of 5% against a maximum value of 2.5 in the short-term and 1.5% in the medium term. The high connectedness in 2005 and 2012 coincide with the 2005 oil crises and 2012 Duma elections and the protests against election fraud as well as the Putin election in Russia. However, in general the weakest spillover connected across the whole system is recorded in the long term.

The amounts of pairwise net directional connectedness recorded across the three frequencies all differ in magnitude and signals (positive/negative) across all frequencies for each of the paired variables. The net recipients' and transmitters' relationship between the paired variables do not show any clear evidence of the domineering net recipients and net transmitters variables in Russia. We do not find any distinct patterns across the whole system but rather discover detailed pairwise net directional spillover outputs for each paired variables across all frequency. The net directional spillover outputs must be analysed on a pairwise bases.

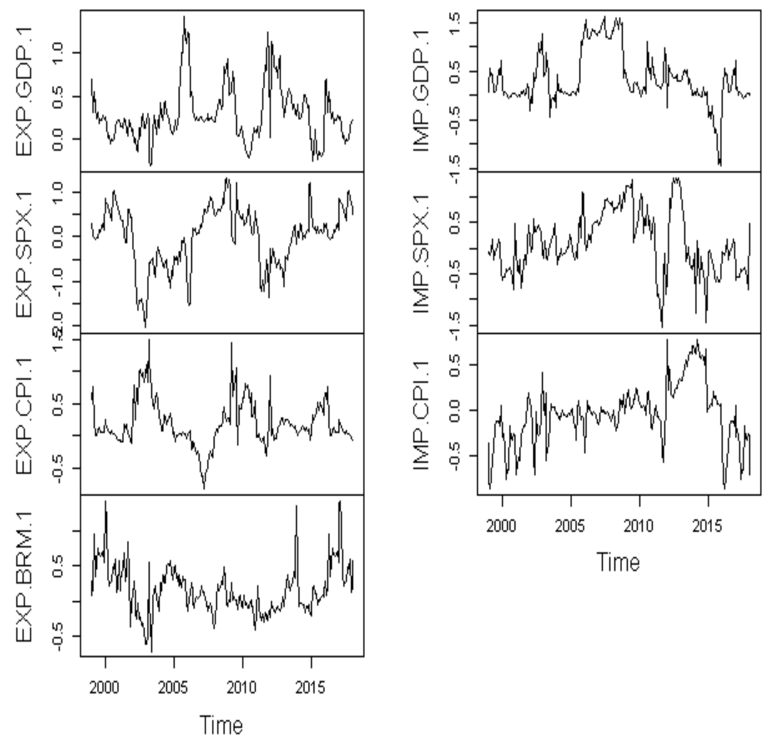
(a) Overall Rolling Spillover on Band 3.14 to 0.00 for Russia



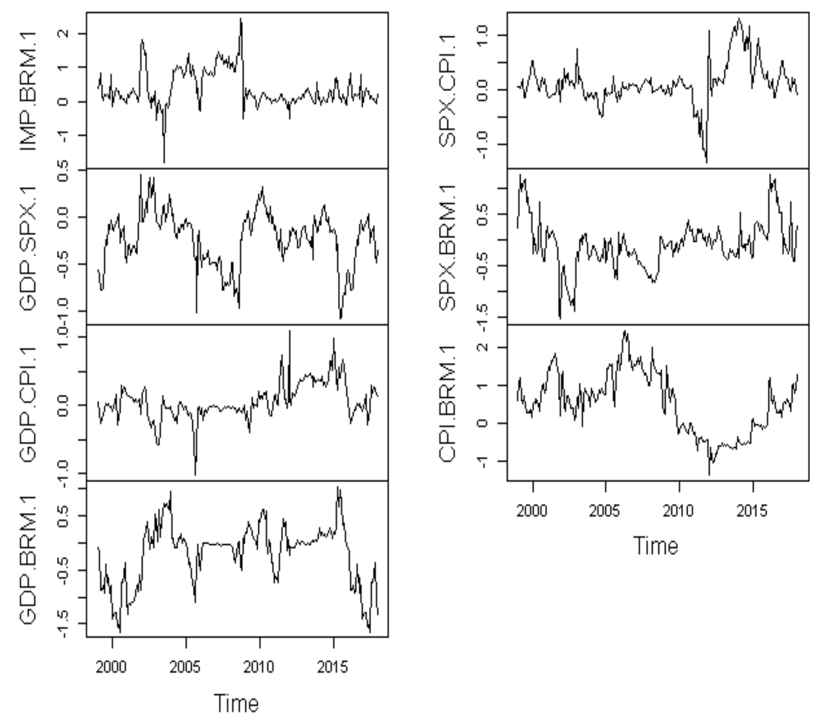
(b) i) Pairwise net rolling spillover on Band 3.14 to 0.79 for Russia (Short-term Frequency)



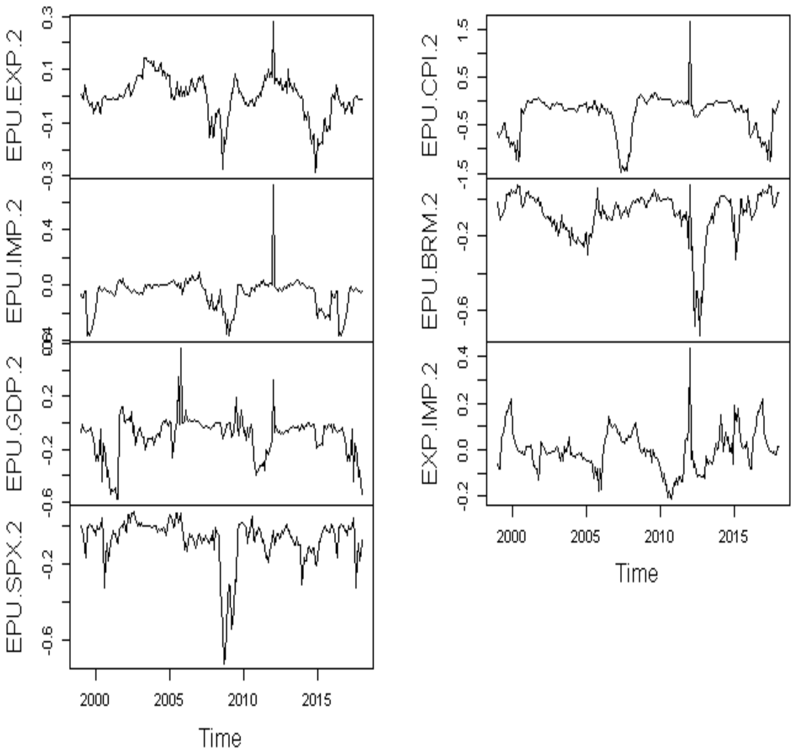
(b) ii) Pairwise net rolling spillover on Band 3.14 to 0.79 for Russia (Short-term Frequency)



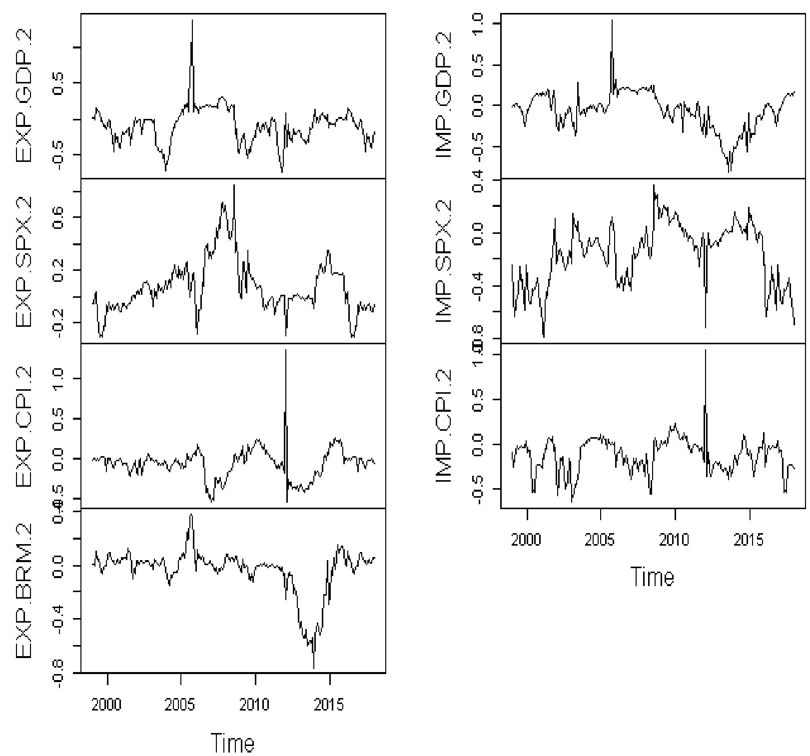
(b) iii) Pairwise net rolling spillover on Band 3.14 to 0.79 for Russia (Short-term Frequency)



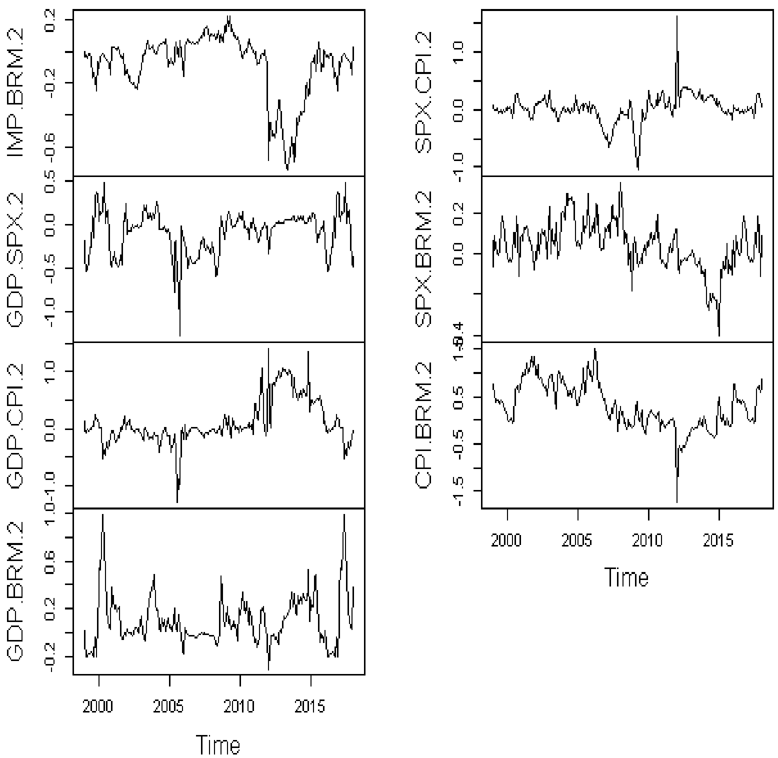
(c) i) Pairwise net rolling spillover on Band 0.79 to 0.26 for Russia (Medium-term Frequency)



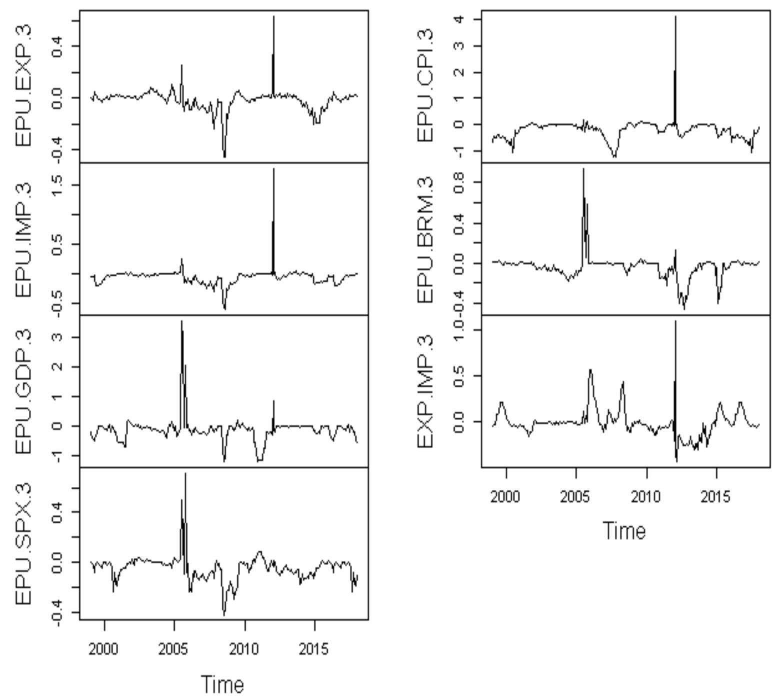
(c) ii) Pairwise net rolling spillover on Band 0.79 to 0.26 for Russia (Medium-term Frequency)



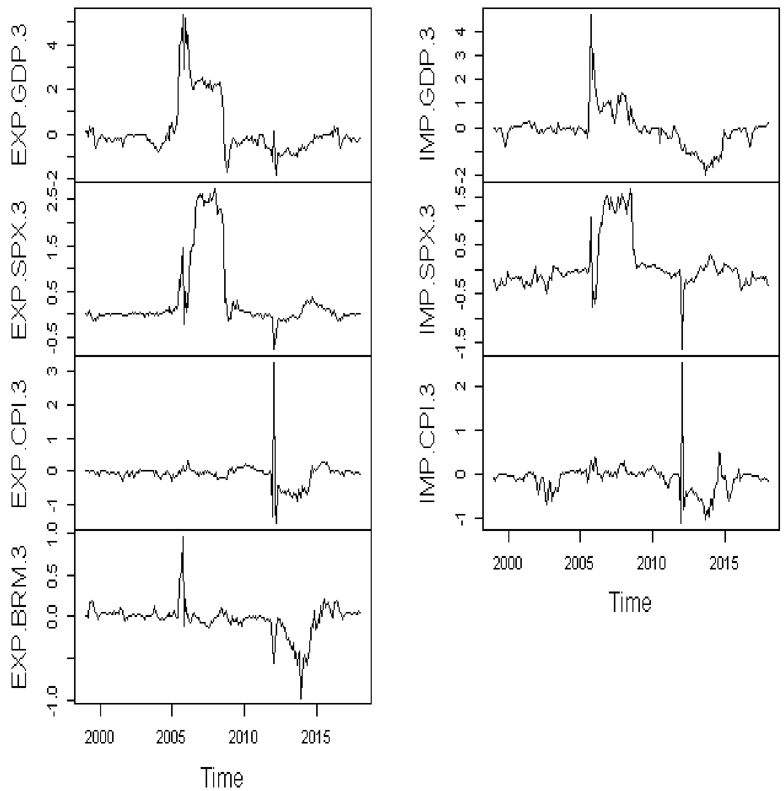
(c) iii)Pairwise net rolling spillover on Band 0.79 to 0.26 for Russia (Medium-term Frequency)



(d) i)Pairwise net rolling spillover on Band 0.26 to 0.00 for Russia (Long-term Frequency)



(d) ii) Pairwise net rolling spillover on Band 0.26 to 0.00 for Russia (Long-term Frequency)



(d) iii) Pairwise net rolling spillover on Band 0.26 to 0.00 for Russia (Long-term Frequency)

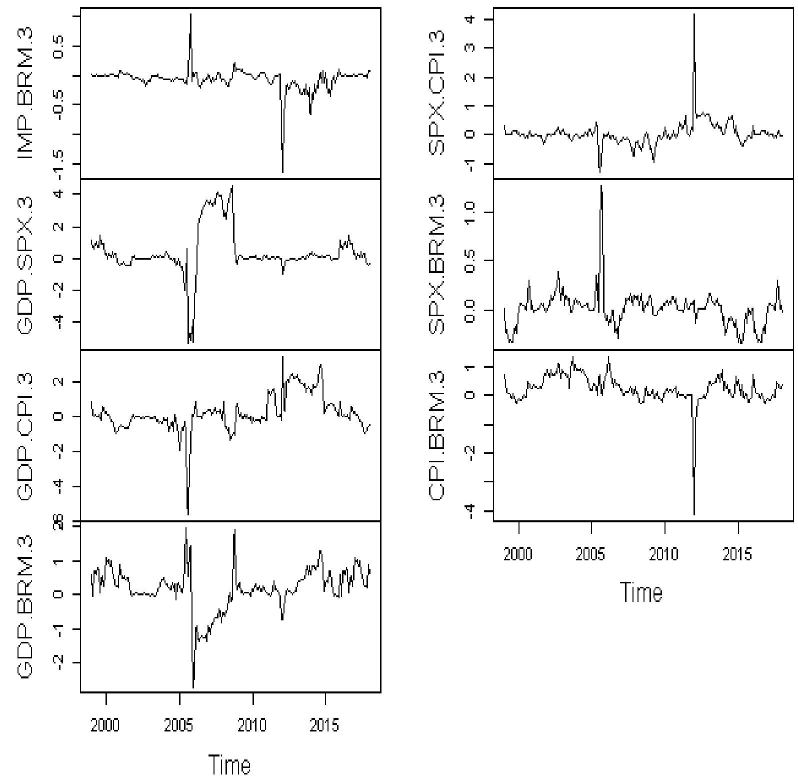


Figure 5.6: Overall rolling and Pairwise net rolling spillovers of selected variables in Russia

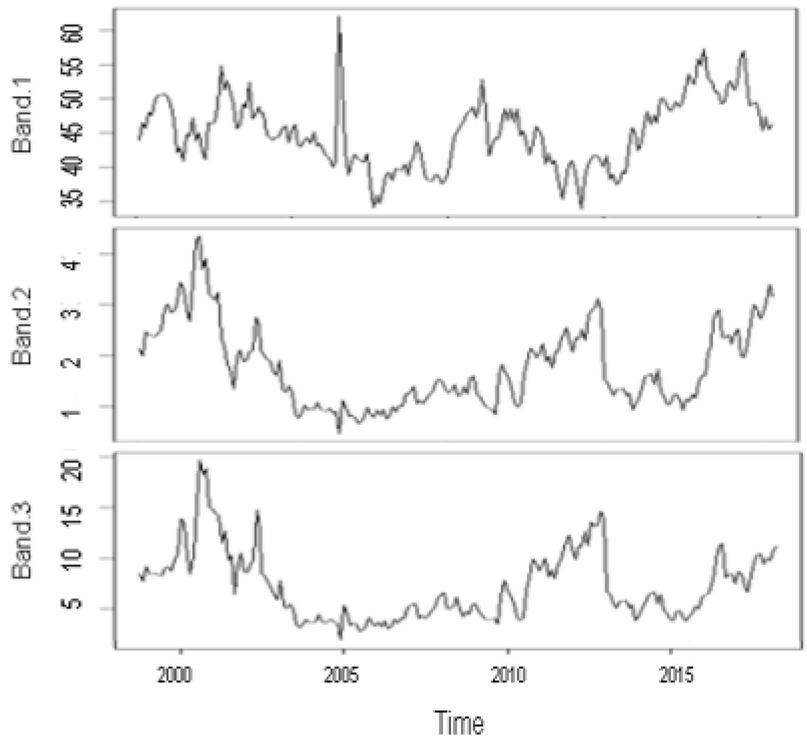
5.4.4 Inter-country time-varying spillover index with rolling-window analysis.

The first session of the inter-country analysis focused on time-varying spillover of EPU across the selected EMEs. This provides enormous insight into the connectedness between the EPU of selected EMEs with rolling-window analysis. Although this session specifically focus on EPU, the second investigation further adds GDP and SPX to the inter-country time-varying spillover analysis because i) intra-country analysis showed that GDP and SPX are major spillover shock transmitters across all the selected EMEs in this study. ii) GDP and SPX are the main recipients of EPU spillover shocks across the selected EMEs. The second session focuses on evidence of overall time-varying connectedness between the EPU, GDP and SPX of the selected EMEs in one system with rolling window analysis. Findings help investors and policy makers to highlight the time and frequencies where significant spillovers occur for effective forecasting, portfolio diversification and decision making. It also assists them to understand the spillover pattern of the three most influential variables (EPU, SPX and GDP) with respect to the transmission and recipients of spillover shocks across all the selected EMEs.

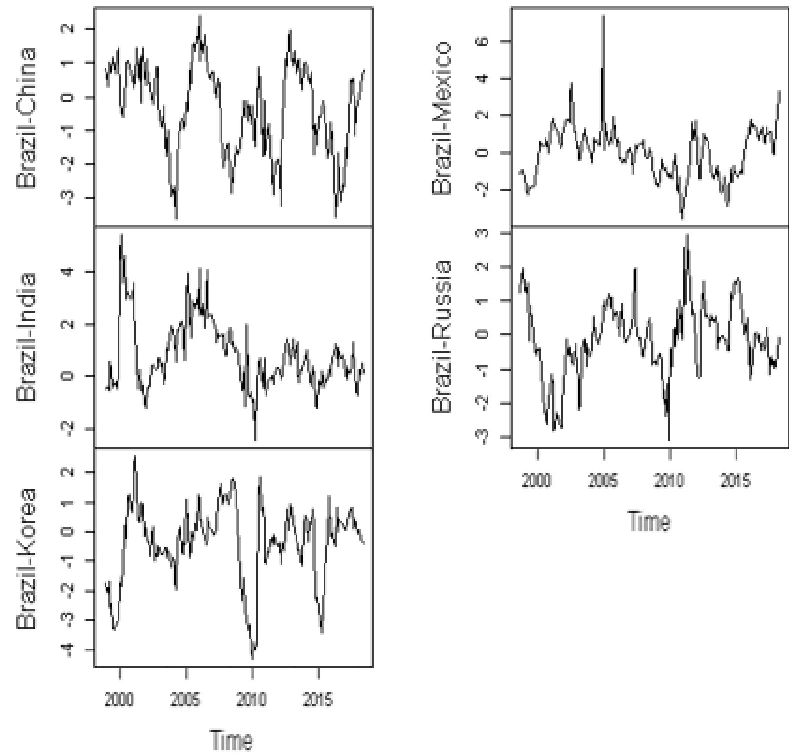
5.4.4.1 Time-varying spillover index with rolling window analysis between the EPU of selected EMEs.

The overall connectedness among the selected EMEs (see Figure 5.7 (a)) recorded the highest magnitude of connectedness in the frequency band 1 (valued at 60%), followed by frequency band 3 (30%) with the least magnitude recorded in frequency band 2 (15%). We record evidence of connectedness within each of the three frequencies. The short-term (high frequency) drives “high” connectedness during 2001, 2010 and between 2017and 2018 time periods. Heightened values rose to about 55% in 2001, 60% in 2010 and 55% in 2016 and 55% in 2017. Highlights of spillover shocks in the medium-term drive “high” connectedness at three significant time periods. With an average spillover fluctuation rate of 1.5% we record high connectedness in 2000 (with a spillover value of 4%), in 2013 (with a spillover value of 3%), in 2016 (3%) and in 2018 (3%). In the long-term, we record “high” connectedness around 2000, 2002 and 2013 with value rising to 20%, 15% and 15% respectively as compared to average fluctuations of 7% across frequency band 3. The heightened spillover values recorded overlap with some global incidents such as 1997-1999 Asian crises, Eurozone Crises (2012), US Fiscal Fights (2012), China Leadership Transition (2012), 2016 Brexit Referendum, 2016 US presidential elections and 2016 European immigration crisis. Which also confirms previous studies that argue that economic and financial crises intensify the levels of uncertainties in an economy. We also argue that economic and financial occurrences heighten the volatility spillover of EPU as well as key macroeconomic variables. The pairwise net directional spillover is displayed in Figure 5.7 from (a) to (d) where (a), (b) and (c) represent the short, medium, and long-term frequencies respectively. We record weak spillover connectedness between Mexico and Russia in the short-term and between China and Mexico in the medium-term. In the long-term, we record low connectedness between Brazil and China, Brazil and Mexico, China and Mexico and lastly Mexico and Russia. The highest positive value was recorded from Brazil to Mexico (8%) in 2005 which coincides with the 2005 oil crises. The lowest negative value was recorded between Mexico and Russia (-8%) in 2010 all in the short-term. We discover that the pattern of connectedness is unique for each of the paired economies. The implementations of policies to reduce the spillover transmissions of EPU to other economies should be handled on a pairwise bases rather than the implementation of general policies that have the tendency to affect the outcome of a fraction of economies.

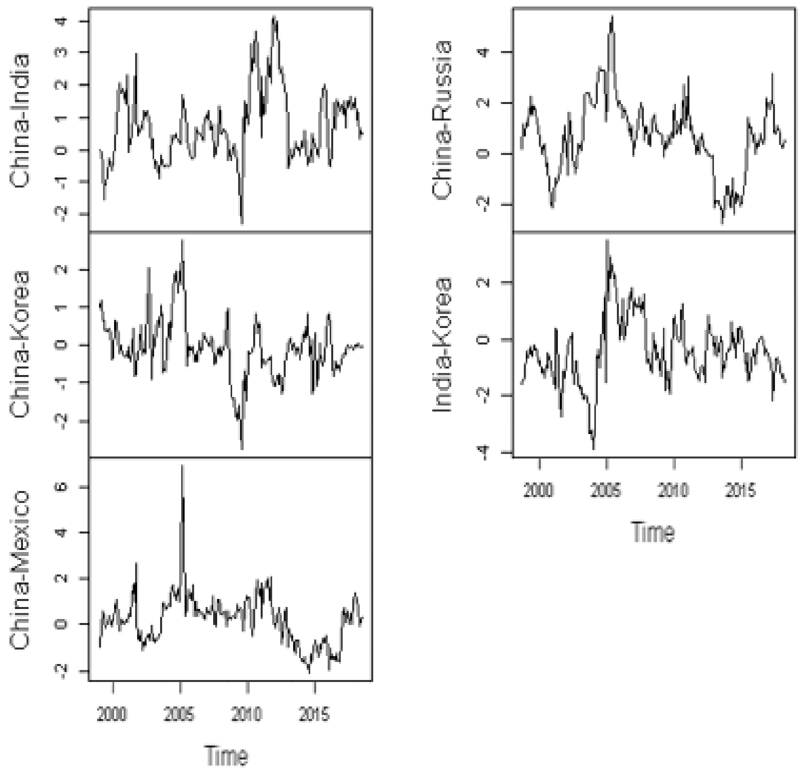
(a) Overall Rolling Spillover on Band 3.14 to 0.00 for Selected EMEs



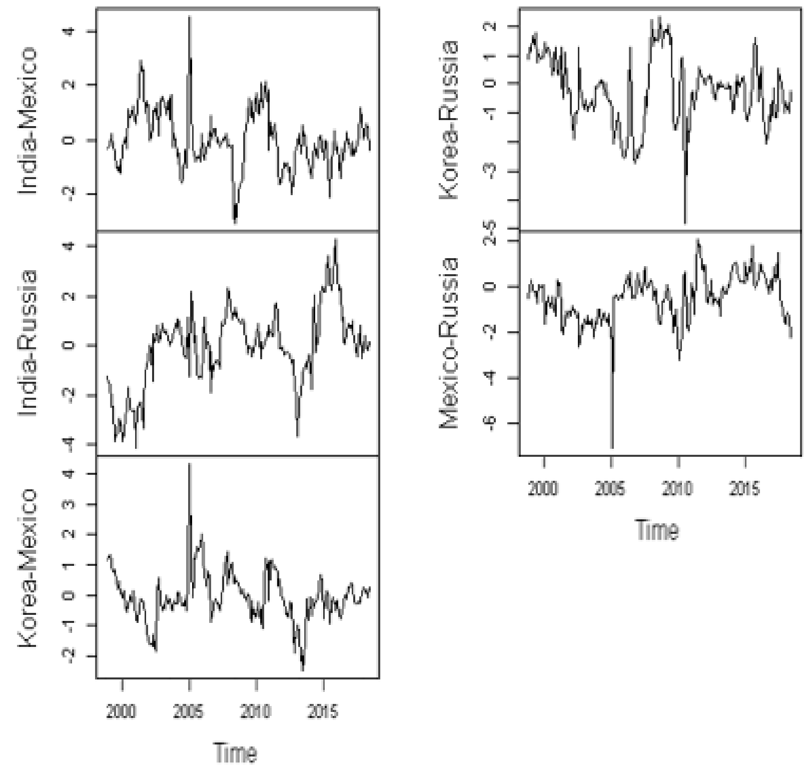
(b) i) Pairwise net rolling spillover on Band 3.14 to 0.79 for Selected EMEs.



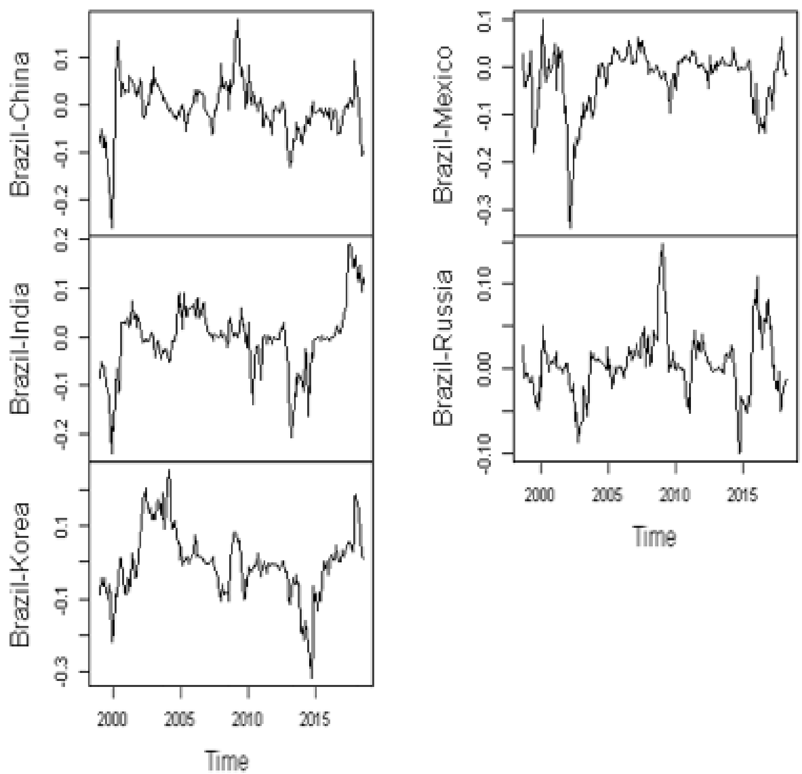
(b) ii) Pairwise net rolling spillover on Band 3.14 to 0.79 for Selected EMEs



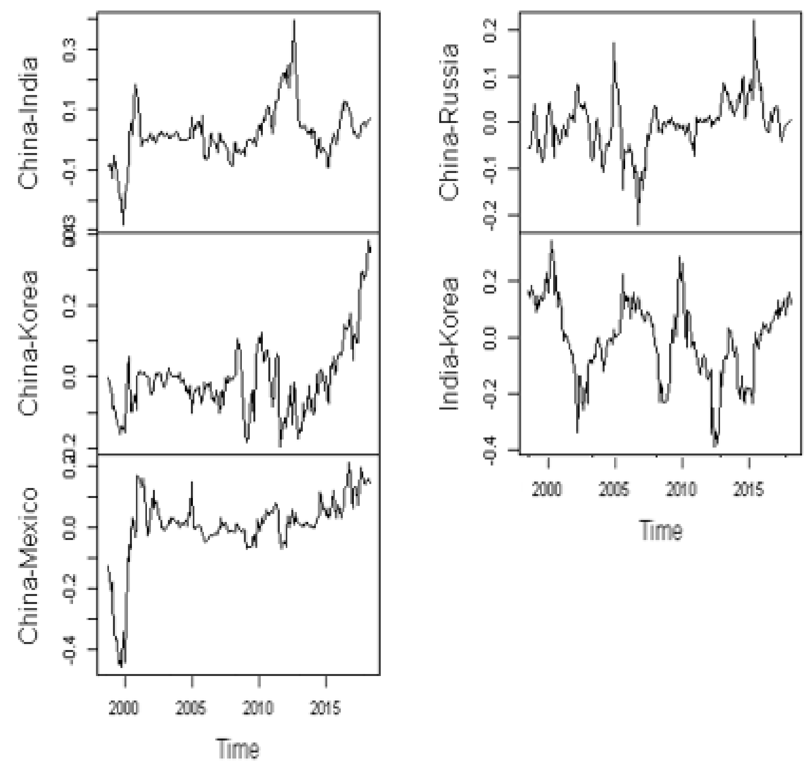
(c) iii) Pairwise net rolling spillover on Band 3.14 to 0.79 for Selected EMEs



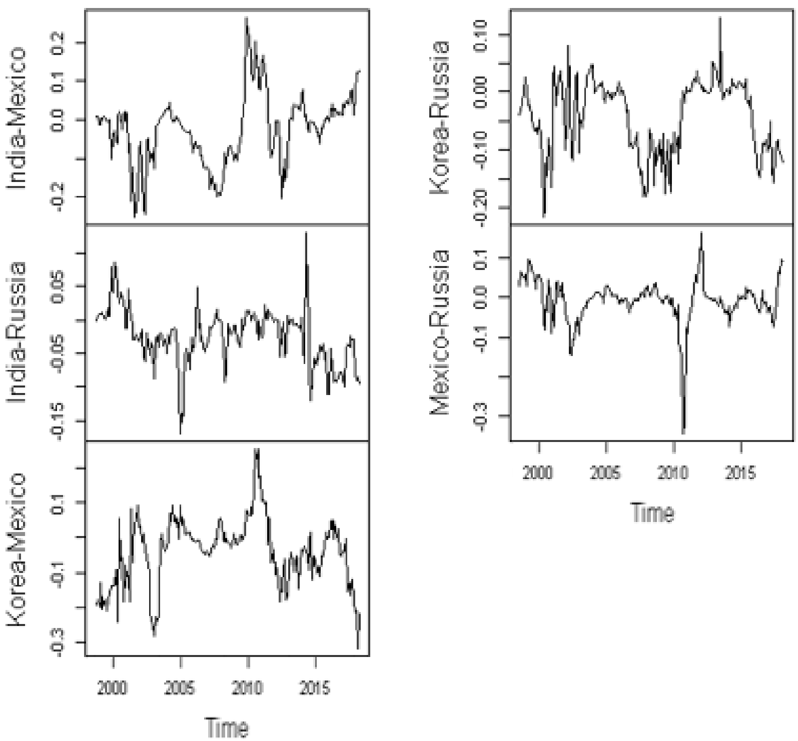
(c) i) Pairwise net rolling spillover on Band 0.79 to 0.26 for Selected EMEs



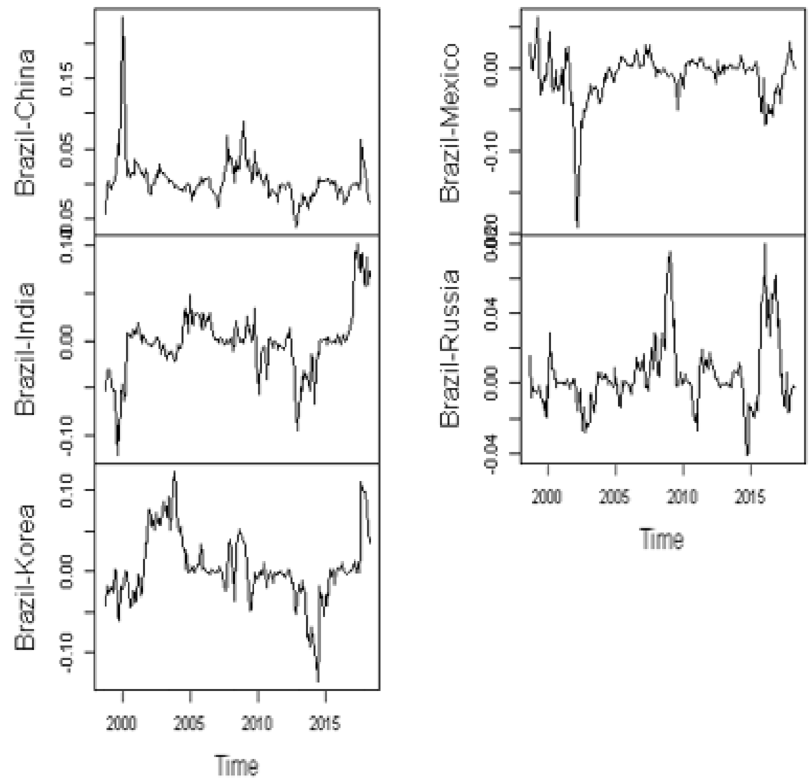
(c) ii) Pairwise net rolling spillover on Band 0.79 to 0.26 for Selected EMEs



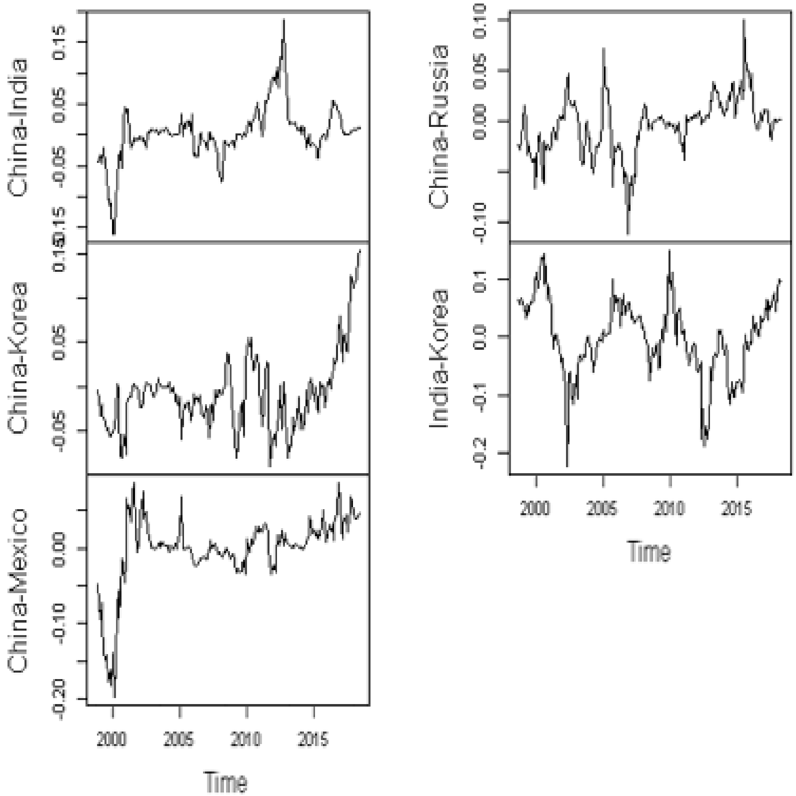
(c) iii)Pairwise net rolling spillover on Band 0.79 to 0.26 for Selected EMEs



(d) i)Pairwise net rolling spillover on Band 0.26 to 0.00 for Selected EMEs



(d) ii) Pairwise net rolling spillover on Band 0.26 to 0.00 for Russia (Long-term Frequency)



(d) iii) Pairwise net rolling spillover on Band 0.26 to 0.00 for Russia (Long-term Frequency)

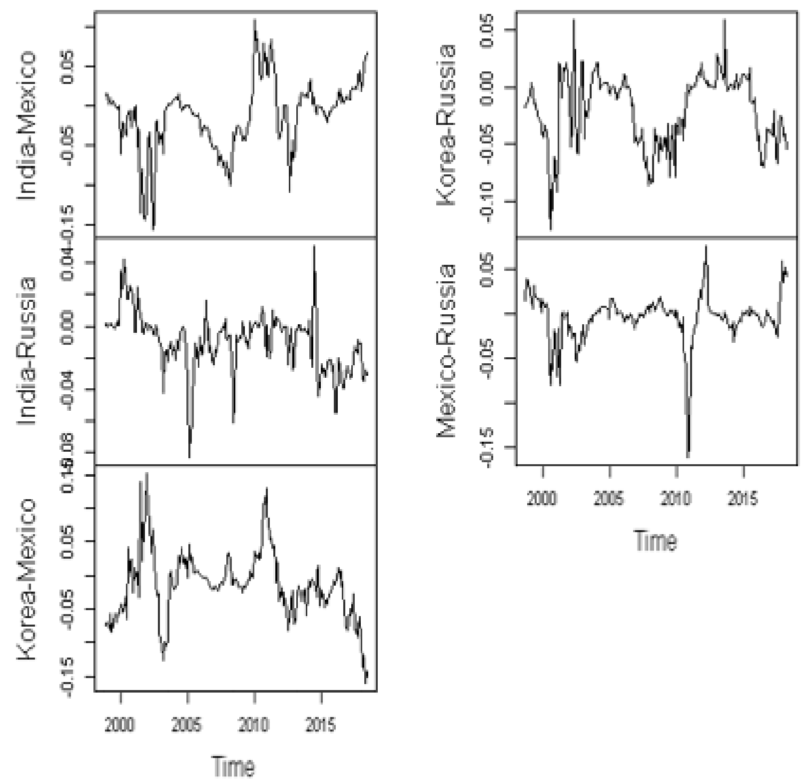
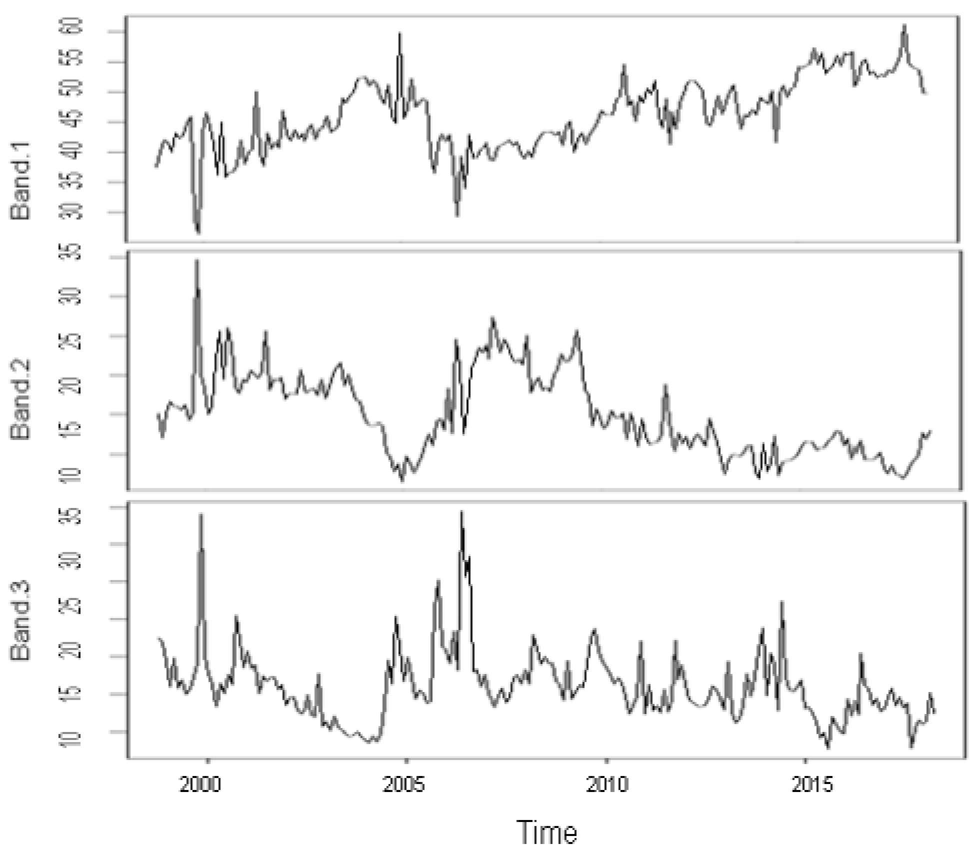


Figure 5.7: Overall rolling and Pairwise net rolling spillovers between EPU of selected EMEs

5.4.4.2 Time-varying spillover index with rolling window analysis between the EPU, GDP and SPX of selected EMEs.

The evidence of overall connectedness for EPU, GDP and SPX across the selected EMEs is displayed in Figure 5.8. We see that the overall connectedness is highest in the short-term and lowest in the medium-term. In other words, in the short-term (frequency band 1) we record fluctuations from 25% to 60%, followed by fluctuations ranging from 5% to 35% in the medium-term and finally recording a value range of 5% to 40% in the long-term. We record evidence of high connectedness in all three frequencies. In other words, although we find significant evidence of spillover variations in the whole system, spillover shocks in the short-term drive “high” connectedness in 2000 and 2005. In 2000, we experience a sudden rise from 25% to 45% after a sudden drop in spillover connectedness. In 2005 we record a sudden rise from 45% to 58% which is immediately followed by a sudden drop to 45% then spillover connectedness consistently rises till it reaches a peak of 60% in 2018. The medium-term shocks transmission implies that spillover shocks are been transmitted for longer periods and the responses to these shocks are in the medium-term (medium frequencies). Highlights of spillover shocks in the medium-term drive “high” connectedness around 2000, and from 2006 to 2010. In 2000 the spillover connectedness rises from15% to 35%. However, we identify multiple fluctuations from 2006 through to 2010 which afterwards reduces over the years to a value of 10% in 2018. Lastly, the long-term (low frequency) also implies that spillover shocks are been transmitted for longer periods and the responses to these shocks happen in the long-term. We record the first heightened value in the long-term in 2000 with a spillover value of 38%. We also record consistent fluctuations from 2005 (25% to 30%) reaching a peak of 38% in 2006.

Once again, the high levels of connectedness relate to the 1997 -1999 Asian financial crisis, 2005 oil crises, and 2007-2009 Global Financial Crisis. This implies that global economic and financial events that happens across the globe influences the EPU, GDP and SPX in all the selected EMEs which intensifies the total spillovers between the EMEs during the period of these global events. The high valued connectedness can also be attributed to further uncertainty transmission resulting from the insecurities about the effect of the shock on other economic situations. These variations are largely expected because 1999 to 2018 includes both calm and turbulent periods where shocks of different magnitudes are transferred within and across economies.



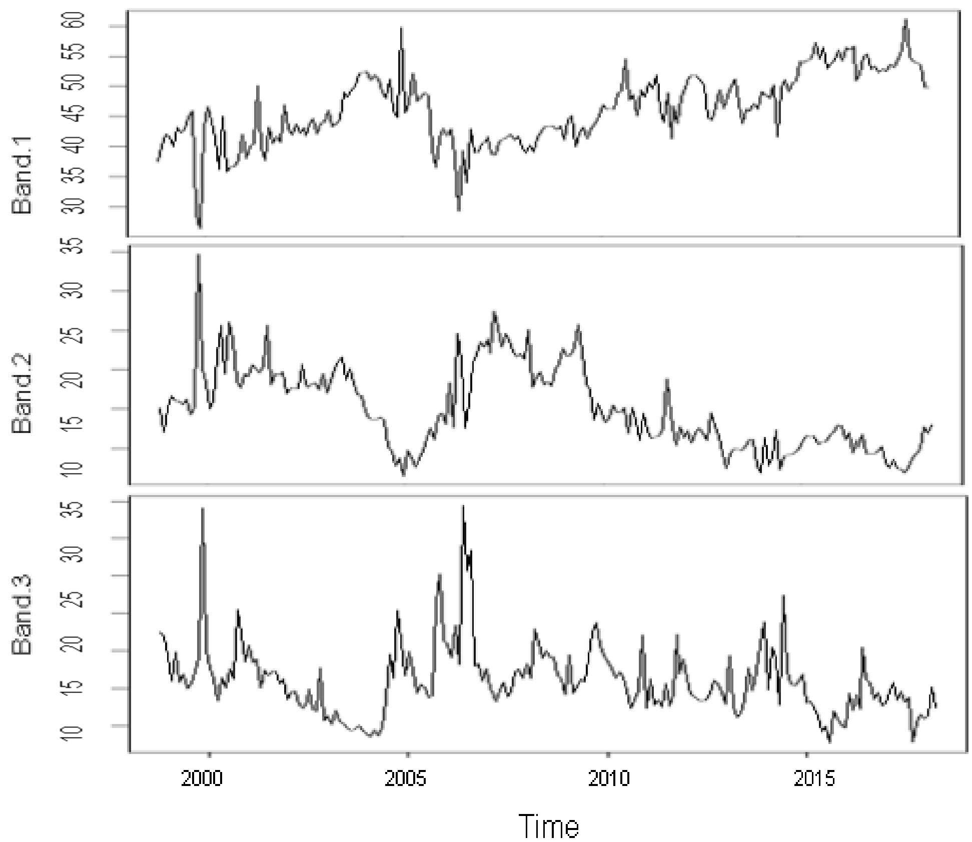


Figure 5.8: Overall rolling spillovers between EPU, GDP and SPX of selected EMEs

5.5 Conclusion

In this Chapter, we investigate the total, net and pairwise spillover connectedness between EPU and macroeconomic variables in EMEs as well as across selected EMEs. Based on our research objective and questions we made the following contributions.

Under the static spillover analysis, we provided useful information to investors and portfolio managers that can help them achieve the best portfolio diversification benefits. Specifically, we identified the net transmitters and recipients within each EME and across EMEs for EPU and selected macroeconomic variables. The intra-counrty analysis showed that GDP and SPX are major spillover shock transmitters across all the selected EMEs while GDP and SPX are the main recipients of EPU spillover shocks across the selected EMEs. We were therefore able to show evidence to literature that argued that EMEs transmit spillover shocks (see for example, Dizioli, Guajardo, Klyuev, Mano, & Raissi, 2016; and Russel, 2016). Also from a regulator's point of view, policies targeted at moderating spillover in EMEs should focus on GDP and SPX. We also discovered that the higher the frequency (short-term) the higher the magnitude of the total spillover effect. In other words, except for Korea and Russia overall connectedness is highest in the short-term (high frequency) which creates diversification benefits in the long-term.

We document that country specific as well as global economic and financial events intensify the volatility of the total spillover within and across the selected EMEs. Although previous studies found evidence on high transmission during 2007-2009 great recession (Fernandez-Villaverde, Guerrón-Quintana, Rubio-Ramírez, & Uribe, 2011; Bloom, 2014), we find further evidence of high transmission during the 1997 -1999 Asian financial crisis, 2005 oil crises, 2012 Eurozone Crises, 2012 US Fiscal Fights, 2012 China Leadership Transition, 2016 Brexit Referendum, 2016 US presidential elections and 2016 European immigration crisis. We finally conclude that, since the magnitudes of spillover between each EME and across the selected EMEs at the various time horizons are different, applications of these outputs (including policy and investment related approaches) should be done on a case by case basis.

The second session focused on time-varying and pairwise net spillover index with rolling window analysis to determine whether the spillover shocks that create the various sharp increases (large connectedness) in the system occur (or impact) in the short-, medium-, or long-term. This is important because investors make investment decisions at different frequencies (Bandi & Tamoni, 2016). It also helps in the investigation of the sources of the shocks as well as the different responses these shocks create short-, medium-, and long-term spillover effects. The study finds evidence of overall connectedness and pairwise net directional spillover within each of the selected EMEs as well as for the inter-country analysis across the selected EMEs. We also discover that the pattern of connectedness is unique for each of the pairwise net directional spillover analysis. The implementations of policies to reduce the spillover transmissions of EPU "within" and "to" other economies should be handled on a pairwise bases rather than the implementation of general policies that have the tendency to affect only the outcome of a fraction of economies. This chapter is a novel study in the network connectedness literature with respect to EPU in EMEs. As the focus has primarily been on spillover dynamics and net transmissions, extension of this work would like to explore EPU transmissions between advanced economies and EMEs that are members of the G20.

CHAPTER SIX

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

6.1 Introduction

This last chapter comprises the summary, conclusions, and recommendations from the study. The summary of the main findings briefly delineates the justification of the research area. The summary is followed by an overview of the significant findings and contributions to knowledge for each research objective and its corresponding research question. Next, we provide implication and recommendations for the general conclusions. Lastly, we suggest directions for future research.

6.2 Summary

Based on the review of EPU literature, this study focus on three main aspects of EPU in selected EMEs as it aims at addressing three problems. First, the relationship between EPU and business cycle fluctuations is investigated. This study tries to investigate if uncertainty is what causes business cycles fluctuations. Second, the importance of distance in relation to EPU is examined since no study has investigated the relationship between distance and EPU. Third, the study investigates the directional spillover effects of EPU in EMEs since previous literature that have provided evidence of uncertainty shock spillover within and beyond an economy have not been able to show the direction of these spillovers. In the analysis, we added selected macroeconomic variables because literature proved that macroeconomic variables respond significantly to fluctuations in uncertainty. The variables selected are CPI, broad money, GDP, SPX and trade (thus export and import). Knowledge on how EPU relates with key macroeconomic indicators in EMEs helps policy makers to further understand the impact of EPU as well as what influences

EPU to help control the level of EPU in an economy. Following the above arguments, the study focuses on three main questions to fill the research gap. This thesis seeks to find answers to the following questions:

i. Are the fluctuations of the business cycles in emerging market economies interdependent and does uncertainty indicate such interconnections?
ii. Can the differences and similarities of economic policy uncertainty among emerging market economies be influenced by the distance between these emerging market economies?
iii. What are the effect of uncertainty shocks on the economic activities of an emerging market economy and the spillover effect on neighbouring countries?

6.3 Contributions, conclusions and findings

6.3.1 Non-Linear Interdependence and Causality Test

The objective of this session was to research on the non-linear interdependence and causality between economic policy uncertainty and macroeconomic indicators in emerging market economies. For this session, we sought to find an answer to the following question: are the fluctuations of the business cycles in emerging market economies interdependent and does uncertainty indicate such interconnections? The study makes an important contribution by finding answers to why business cycles fluctuate. The theoretical contribution is unique because, it deviates from traditional sources of fluctuations such as production technology and labour supply shocks and focus on uncertainty as a potential cause or effect of business cycle fluctuations. We also contribute to the role EPU plays in the comovement of variables (GDP, CPI. SPX, import, export and broad money) by investigating if EPU has the potential to lead or follow the other variables within the selected EMEs. The inclusion of CPI, SPX, import, export and broad money is novel to the scope of study and has significantly altered the understanding on the relationship between EPU and business cycle fluctuations. The theory that formed the foundation for the study on economic distance is) is the real business cycle theory views the fluctuations of the business cycle as the consequence of real external shocks, where production technology argues that real exogenous shocks to productivity leads to adjustments that cause the expansions and recessions in the business cycle. This theory therefore classifies the ups and downs of the business cycle to be an efficient response to the exogenous changes to real economic activities (that is, the level of national output) (Plosser 1989). This study adopts the wavelet methodology proposed by Fernandez-Macho (2012) to examine the independence between EPU and selected macroeconomic indicators, and the Diks and Panchenko (2005, 2006) nonparametric causality test to answer the question of whether EPU is a cause or effect (or both) of business cycles fluctuations in selected EMEs. The study elected to use the bivariate correlation, wavelet multiple correlation and cross-correlation to measure the overall statistical relationship that might exist at differing scales. We find evidence of interdependence for both intra-country and inter-country analysis which proves Lucas's (1979) argument that business cycles comove. However the scale by scale analysis has further proved that the level of integration is strongest in the long-term. For the intra-country analysis, we record evidence of both positive and negative comovement between EPU and the macroeconomic variables within each EME. Evidence of positive correlation was generally recorded between EPU and CPI within each EME while evidence of negative correlation was recorded between EPU and SPX within all EMEs. The positive relationship recorded are supported by studies that show EPU has a positive association with economic activity (Segal et al., 2015; Kido, 2016; Kung and Schmid, 2010; Gilchrist and Williams, 2005; Kraft et al., 2018). Also, other studies buttress arguments that EPU negatively correlates with the economic activities in an economy (see for example Friedman, 1968; Rodrik, 1991; Higgs, 1997; Hassett & Metcalf, 1999; Rafiq & Mallick, 2008; Gupta, Jurgilas, & Kabundi, 2010; Frankel, 2006; Xu & Chen, 2012; Handley & Limao, 2015; Brogaard & Detzel, 2015). We futher discovered that China's GDP has a negative correlation with Chna'import. This finding contradicts earlier research that claims imports are positively associated to GDP (Hye, 2012; etintas and Barisik, 2009; Herrerias and Orts, 2011). Although there is strong evidence of comovement between EPU and the macroeconomic variables, EPU does not pose any leading or lagging power in all the six EMEs, but import had records of dominance within each EME. We further investigate the role EPU plays in inter-country comovement. We find evidence that China's EPU and Korea's EPU have the strongest positive relationship while Brazil and China have the strongest negative association. The wavelet multiple cross-correlation shows that Korea's EPU dominates the whole system across all the scales. We also observe that, while EPU correlates with business cycles, EPU is not an indicator of EPU-business cycle comovement; rather, business cycles drive EPU-business cycle comovement. As a result, our paper is consistent with classical theory and empirical literature, which acknowledge that uncertainty can be endogenous and driven by the business cycle (Ludvigson et al., 2015; Van Nieuwerburgh and Veldkamp, 2006; Fajgelbaum et al., 2017). Based on our research question we find that the fluctuations of the business cycles in emerging market economies are interdependent.

Second, we investigate if uncertainty dictates the interconnections between the business cycles in the selected EMEs. We discover that EPU is both a cause and effect of business cycles fluctuations in the selected EMEs except for India where business cycle fluctuations rather cause EPU fluctuations. Although, we have just a handful of evidence to prove that EPU causes business cycle fluctuation and vice versa it has been made clear that the indicator of business cycle plays a significant role. It is also evident that the selected macroeconomic variables respond differently to EPU in each EME. Thus, causality with respect to the economic indicator of business cycles is specific to each EME. The causality results for all the selected EMEs are positive which implies that, an increase (decrease) in EPU leads to an increase (decrease) in business cycles. Likewise, an increase (decrease) in business cycles movements leads to an increase (decrease) in EPU. The reason for the positive causality between EPU and business cycles can be attributed to good uncertainty. Good uncertainties are uncertainties that trigger a rise in economic growth through trade, investment and consumption. This implies that, investors can gain revenues when uncertainty is high. This is because an increase in uncertainty leads to an increase in GDP, SPX, import, export and broad money. Forth, the findings clearly demonstrate that EPU causes business cycles and business cycles also cause EPU. These findings could explain the inconsistent findings in literature, since some studies argue that EPU causes business cycles while others argue that business cycles cause EPU. It can be argued that studies who found EPU to be the cause of business cycle fluctuations and studies who also argued that business cycles cause changes in EPU are both making robust arguments. This is because the findings of this study show evidence of the two sides of the argument.

6.3.2 Economic and spatial dimension of distance

The objective of this session was to examine the relationship between distance and economic policy uncertainties in emerging market economies. Can the differences and similarities of EPU among emerging market economies be influenced by the distance between these emerging market economies? This section's first contribution is to investigate and quantify the empirical association between economic distance and EPU in the selected EMEs. The findings will help policymakers recognize the differences and similarities that exist between EMEs as a result of their distinct and similar economic characteristics. The study on distance makes a second contribution by employing a non-parametric geospatial analysis to investigate the spatial dependence between EMEs (with respect to their EPU measures). The analysis of spatial autocorrelations between EMEs provides robust information for policy makes and investors for international portfolio management, policy decision processes and international trade. The theoretical argument for the study of distance is founded on Ghamawat's (2001) argument that "distance still matters". Ghamawat (2001) used this statement (distance still matters) to dispute literature that argued that globalisation has turned the world into a small place, hence, the world was dead to distance. In order to assess the relationship between economic distance and EPU, this study employs the dynamic linear regression method, where difference in the GDP of EMEs is the proxy for economic distance. Secondly, to investigate if geographical proximity can influence the similarities or dissimilarities between EPU among EMEs, the study deploy the local Moran's I (Moran, 1984) as the measure of spatial autocorrelation. The finding on the analysis of distance in this study supports Ghemawat's (2001) argument that "distance still matters". For the dynamic linear regression analysis we discover that macroeconomic variables were largely statistically significant and have explanatory power to explain the economic distance between the EMEs. The hypothesis for the test is stated below:

H_o: There is no relationship relation economic distance and the explanatory variables.

H_1: There is a relationship between economic distance and the explanatory variables.

We find limited evidence of EPU effects on the economic distance between EMEs. We also discover that changes in the values of import, CPI and broad money in most EMEs are statistically relevant and significantly drive the changes in the values of economic distance between the selected EMEs. These findings also support studies that argue that the trade and economic policies between countries reduces the dictance between them, thereby increasing the investment level and business development between the two economies (IMF, 1997, Harrison, 1996; Novy & Taylor, 2014). This confirms the theoritcal expectation that trade and institutional distance (CPI and broad money) has an explanatory power in explaining economic distance between economies Malhotra, Lin and Farrell's (2016) and Ghemawat (2001). We therefore conclude that the similarities and dissimilarities between the selected EMEs are significantly influenced by the distance between them.

The second session focused on the spatial dimension of distance. Tobler's first law of geography forms the theoretical foundation of this investigation. The law states that "everything is related to everything else, but nearer things are more related than distant things" (Tobler, 1970, p.236). . The results showed evidence of spatial autocorrelation across all the EMEs which support Tobler's first law of geography. Hence, the similarities and dissimilarities between the selected EMEs are significantly influenced by the distance between them. It was observed that for each of the Moran's I scatter plots the six EMEs were independently positioned within the quardrants. This implies that, country and geographical specific features (or characteristics) affect the outcome of the results. We discover that, country specific features, international policies (for example trade policies), terms of trade, spillover effects, monetary and fiscal policies are some of the factors that influence EPU spatial autocorrelation in EMEs. The sub-sectioned (regionalised) analysis of the selected EMEs recorded evidence of heterogeneity. This study provides information on safe zones for portfolio diversification and risk minimisation for investors who intend to invest in stock markets, financial institutions, international trade and sales of commodities. Policy makers and regulators also have access to findings on a broad field of macroeconomic variables and their relationship with EPU.

6.3.3 Spillover effects

The objective of this session is to identify dynamic and network spillover between EPU and major macroeconomic indicators with a major focus on focus on the directional spillover effects. The study finds answers to the effects of uncertainty shocks on the economic activities of EMEs and what the spillover effect on neighbouring countries. This study contributes to existing literature through an empirical research on the spillover effect of EPU within each of the EMEs and across the EMEs. We investigate the amount and direction of EPU spillover in the selected EMEs. We further investigate the spillover effect pattern between EPU and key macroeconomic indicators. This discovery sheds new light on the levels and patterns of spillover "to" and "from" the selected EMEs. The findings include time-frequency dynamics as well as frequency domain dynamics. This investigation adopts Baruník and Křehlík’s (2018) methodology to measure total spillover, total directional spillover and pairwise directional spillover. The study conducts a country specific and cross border events analysis to examine the nature of spillover within and across EMEs. The intra-counrty static analysis showed that GDP and SPX are major spillover shock transmitters within each of the selected EMEs while GDP and SPX are the main recipients of EPU spillover shocks within each of the selected EMEs. It is clear from the findings that although EPU transmits and recives spillover shocks, EPUdoes not dominate in the transition or receiving of spillover shocks within the selected EMEs. We were therefore able to show evidence to literature that argued that EMEs transmit spillover shocks (see for example, Dizioli, Guajardo, Klyuev, Mano, & Raissi, 2016; and Russel, 2016). The time-varying intra-country analysis also show that the higher the frequency, the higher the magnitude of the total spillover effect. We document that country specific as well as global economic and financial events intensify the volatility of the total spillover within and across the selected EMEs. Although previous studies found evidence on high transmission during 2007-2009 great recession (Fernandez-Villaverde, Guerrón-Quintana, Rubio-Ramírez, & Uribe, 2011; Bloom, 2014), we find further evidence of high transmission during the 1997 -1999 Asian financial crisis, 2005 oil crises, 2012 Eurozone Crises, 2012 US Fiscal Fights, 2012 China Leadership Transition, 2016 Brexit Referendum, 2016 US presidential elections and 2016 European immigration crisis. The study finds evidence of overall connectedness and pairwise net directional spillover within each of the selected EMEs

The static analysis for the inter-country analysis shows that, The EME that receives the highest spillover from the rest of the five (5) EMEs in the short-term is Korea-EPU. In the medium-term, China-EPU and Mexico-EPU receives the highest spillover shocks, while Mexico-EPU receives the highest transmission in the long-term. Clearly, India as an economy is the main transmitter of spillover shocks to Brazil-EPU. Also, the main transmitter of spillover shocks to India-EPU is Korea- EPU across all the frequency bands. We conclude that the main transmitters of spillover shocks to China-EPU are Korea-EPU, Brazil -SPX and Korea- EPU in frequency band 1, 2, and 3 respectively. Likewise, the main transmitter of spillover shocks to Korea-EPU is China-EPU, Mexico-SPX and Mexico-SPX in frequency bands 1, 2, and 3 respectively. Further, the main transmitter of spillover shocks to Mexico-EPU is Korea-EPU across all the frequency bands. Last, Korea-EPU is main transmitter of spillover shocks to Russia EPU across all frequency bands. The time-varying analysis show evidence of overall connectedness and pairwise net directional spillover across all the economies. Likewise for the intr-country time-varying analysis, the inter-country time-varying analysis also show heightened spillover values that overlap with some global incidents such as 1997-1999 Asian crises, Eurozone Crises (2012), US Fiscal Fights (2012), China Leadership Transition (2012), 2016 Brexit Referendum, 2016 US presidential elections and 2016 European immigration crisis. This also confirms previous studies that argue that economic and financial crises intensify the levels of uncertainties in an economy. We also argue that economic and financial occurrences heighten the volatility spillover of EPU as well as key macroeconomic variables. We also discover that the pattern of connectedness is unique for each of the pairwise net directional spillover analysis. Hence, policy implementations and investment decisions should be handled on pairwise bases.

6.4 Concluding remarks and recommendations

This study makes relevant findings and contributions that has resulted in a significant number of recommendations that are important to literature, policy makers, regulators, and investors. It is evident in literature that policy makers, regulators, and investors are reluctant to make decisions in the presence of heighten uncertainty. The results of the delay in decision making (as a result of uncertainty) are known to lead to a reduction in investment and delay in economic activities but this study has been able to clear a significant level of misunderstandings on EPU.

Seeking answers to the question, "*are the fluctuations of the business cycles in emerging market economies interdependent and does uncertainty dictate such interconnections?*" revealed some findings. First, the study supports Lucas's (1997) argument that business cycles comove together. It was discovered that the level of integration within and across EMEs is strongest in the long-term. This means that in the long-term (8 ~ 16 months) the outcome of one variable is significantly determined by the overall performance of the other variables. The "variables" referred to are EPU, GDP, trade (import and export), SPX, CPI and broad money. In other words, all the seven variables collectively influence each other. Also, the weakest integration of the overall correlation of the set of seven variables was recorded in the short-term for each of the selected EMEs. This implies that the seven variables are less dependent in the short-term which is the best period for investors to hedge their portfolio, trade and reduce market risk. Second, it was also observed that EPU has no lead or lag potential across all the scales (short-, medium-, and long-terms) within and across all the selected EMEs under study. We identify import as the variable that dominants all the selected variables in each EME. Investors and policy makers are rather advised to focus on imports and trends within the selected EMEs rather than EPU (as initially speculated) since import has power to lead/follow all the other variables. The inter-country analysis shows that Korea's EPU dominates the whole system across all the scales. The also study brings clarity to the wide range of inconsistencies on the directional sign of the relationship between uncertainty and the business cycle. We discover that EPU is both a cause and effect of business cycles fluctuations in the selected EMEs except for India where business cycle fluctuations rather cause EPU fluctuations. It is also evident that the selected macroeconomic variables respond differently to EPU in each EME. This implies that, causality with respect to the economic indicator of business cycles is specific to each EME.

The study makes the following recommendations based the research findings on the interdependence of business cycles in emerging market economies as well as the causal relationsip bewteen EPU and business cycles. The study recommends that investors should note that portfolio diversification will be less profitable in the long- term and should not risk investments exceeding 6 months. Although the study identified general similarities across the EMEs, there were also specific features of comovement to each EME (especially for the pairwise analysis of variables within each EME). For example in China, import and GDP have a negative correlation in the medium- term but recorded a positive correlation in the long- term. This implies that an increase in import is associated with a decrease in GDP (vice versa). We also note that the findings of China are in contrast to previous literature that argues that import positively relates to GDP. Hence we advise careful consideration of these EME specific features for effective decision making (see comovement intra-country analysis for specific findings of each EME). We also recommend that policy makers should work on reducing the interdependence they have with Korea; especially Korea's EPU bearing in mind that EPU negatively impacts an economy. Investors on the other hand must follow Korea's EPU trends since it movements can predict the potential movement of the variables across all the selected EMEs. With respect to the findings on the causal relationship between EPU and business cycles, policy makers can now implement and amend predictable fiscal and monetary policies that will prevent or reduce the occurrence of uncertainty and business cycle fluctuations, which will make investors, feel more secure to invest in the economy. Policy makers and regulators are advised not to generalise policy formulations, amendments and regulations but should rather be focused on each EME.

In an attempt to answer the question, *"can the differences and similarities of economic policy uncertainty among emerging market economies be influenced by the distance between these emerging market economies?"* we draw important conclusions. The results showed evidence that import, export, broadmoney, SPX and CPI have significant explanatory to explain the economic distance between the selected economies. The spatial autocorrelation analysis across all the EMEs supports Tobler's first law of geography. One of the situations that lead to spatial autocorrelation is spillover of shocks which frequently occur through the trade openness a country shares with other countries. Thus, an economy carries information not only about itself but also about neighbouring site values. This finding implies that the way information is disseminated across EMEs is very important because, it can alter or delay decision making thereby creating more uncertainty.

The study makes the following recommendations. We advise policy makers to communicate clearly and in a timely manner all policy decisions since it has an impact on neighbouring economies. To help reduce the wait-and-see (delay) approach of investors and agents as a result of the uncertainty of future happenings, policy makes should provide sound and detailed implementation framework that will ensure transparency and credibility. Although economic and geographical ties foster trade, investment and economic growth, uncertainty shock transmissions on the other hand can cause negative impacts on economies as a result of these links. We, therefore, advise policy makers and regulators to moderate the levels of interdependence with other economies to help regulate the transmission and impact of spillover shocks. Likewise, economies at the receiving end of these shocks should also develop policies and strong fundamentals that can buffer the impact of the uncertainty transmissions. It is safer for investors to invest in the regions that record negative spatial autocorrelation since they can avoid the risk of losing all their investment in case of heightened EPU across all EMEs, thus avoiding the risk of losing all their investments. However, investors must take caution to avoid investment when EPU is high in an economy because EPU volatilities correlate with economic activities in neighbouring economies.

Last, the time domain analysis of spillover effects showed that GDP and SPX are major spillover shock transmitters across all the selected EMEs while GDP and SPX are the main recipients of EPU spillover shocks across the selected EMEs. We recommend that policy implementations and investment decisions should be handled on pairwise bases. With knowledge about the amount of shocks been transmitted and received by each EME, policy makers know the specific countries to monitor during the early signs of uncertainty fluctuations to decide their next point of action and adequately regulate these variables in the economy to curtail internal and external shock transmissions. Investors can also intelligently plan their portfolio diversification strategies as there is detailed knowledge on the main transmitters and recipients of shocks at different frequencies. Investors are safe to diversify their portfolio in the event of weak interactions for maximum return on investment. With the detailed information about the short-, medium-, and long-term net spillover received from and contributed by the EMEs, policy makers are well equipped to efficiently forecast global and country specific uncertainty fluctuations, make well informed predictions and implement policies that can significantly reduce uncertainty in the economy. Investors should apply findings in the study to make precise investment decisions and intelligently plan their portfolio diversification strategies.

6.5 Limitations of the study and areas for further research

The thesis argues for the need to further understand the trend and behaviour of EPU as well as the relationship between EPU and key macroeconomic variables in selected EMEs. The findings of this study have clearly proved the importance of EPU in relation to macroeconomics, financial markets, investment, and trade.

However, the study had some limitations. First, it is evident that, just a handful of the results proved that EPU causes business cycle fluctuation and vice versa. We therefore need to explore if other variables can explain the causal link between EPU and business cycles. Second, the authors were hoping to conduct the research for all EMEs that are members of the G20. However, the authors had a limitation with respect to the EPU index data for some of the EMEs. Although Baker et al. (2013) EPU index is the most robust and universal according to literature, there was no EPU index for South Africa, Turkey, Argentina and Indonesia. For the purpose of a robust comparison of the EMEs with the same measure of EPU, we had to limit the analysis to Brazil, China, India, Mexico, Korea and Russia. Hence this study was not able to provide findings on the causal relationship between EPU and business cycles for South Africa, Turkey, Argentina and Indonesia. In the selected economies, the authors wanted to conduct a comparison test between Baker et al. (2013) EPU index and other measures of EPU. However, most of these alternative measures mostly focused on advanced economies and have limited data periods, which often start in the early 2000s. As a result, data from the early 1990s were excluded for the alternative measures of EPU. The authors were unable to compare different EPU measurements due to these factors.

Bearing in mind that EPU is a less researched area, the findings has highlighted the need for further research in some areas of uncertainty and macroeconomic indicators. The study discovers that EPU is both a cause and effect of business cycles fluctuations in the selected EMEs (Brazil, China, India, Korea, Mexico and Russia) except for India where business cycle fluctuations rather cause EPU fluctuations. However, the evidence recorded was a handful. The findings also show that some (but not all) of the explanatory variables (GDP, export, import, SPX, CPI and broad money) cause EPU (vice versa). We also recorded that for each EME more than one variable causes EPU in the country. We, therefore, infer that there are other indicators of business cycles (economic activities) that could explain the relationship between business cycles and EPU business cycles fluctuations. For this reason, further studies should be conducted. Knowing all or most of the significant causes of EPU helps mitigate EPU fluctuations.

This study introduced the concept of economic distance into the study of EPU. This novle study creates a new research path. We discover that EPU and macroeconomic variables were largely statistically significant and have explanatory power to explain the economic distance between the EMEs. We find limited evidence of EPU effects on the economic distance between EMEs. It is important for policy makers, regulators and investors to note that economic differences (termed economic distance) between the selected EMEs have a relationship with EPU, import, export, SPX, CPI and broad money across the selected EMEs. However, the findings are specific to each EME. These findings serve as a means for investors to understand how the economic differences between the economies are influenced by trade (export and import), investment (CPI and SPX) and economic policy actions (EPU and broad money). Although this study focused on the economic dimension of the CAGE distance framework, it was observe in the review of literature that, the other dimensions of the CAGE distance framework remain unexploited. Studying the similarities and differences between EMEs using the other dimensions of distance can broaden the understanding of the role EPU plays in economies. Further, a comparative study can conducted on the various dimensions of distance and how they respond to EPU and the microeconomic as well as macroeconomic environment. Although we discovered that international policies (for example trade policies), terms of trade, spillover effects, monetary and fiscal policies are some of the factors that influence EPU spatial autocorrelation, a more robust study should be conducted to investigate the factors leading to spatial autocorrelation in EMEs since this will help curtail incidences of spatial autocorrelation. The different outputs generated when the EMEs were regionalised (in the spatial analysis) indicate that acquiring knowledge on the specific characteristics of each economy and how it integrates with other economies is very necessary. An obvious way to go is to conduct more country-specific studies. What are the factors or causes of the different impact of EPU and macroeconomic variables in each of the selected EME?

We also discovered that global economic and financial events have a significant impact on EPU, GDP, and SPX in each of the selected EMEs. During the length of these global economic and financial crises, total spillovers between EMEs were intensified. The high valued connectedness has been attributed to further uncertainty transmission resulting from the insecurities about the effect of the shock on other economic situations. Now that we know the sources and recipients of uncertainty shocks, a more detailed investigation of how EPU responds during country specific and global events (both fortunate and unfortunate), how uncertainty is transmitted, and how the various sectors of an economy respond to the uncertainty shock, will better inform policy decision to forecast uncertainty fluctuations and its effects.

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