Spillover effects from China and the US to global emerging markets: a dynamic analysis

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Abstract

The 2008/2009 Global Financial Crisis has accentuated the number of studies on contagion among researchers seeking to unravel the factors behind its impacts, effects and mechanisms. Several methodologies have been proposed to differentiate between contagion and other phenomenon related to the cross transmission of shocks. However, few studies distinguish between the sources of transmission of shocks and their effects on different emerging markets when analysing contagion phenomenon. This paper contributes to the literature by assessing dynamic spillover effects from two key markets (China and the U.S) to six major emerging economies from different regions making use of the wavelet analysis. The results support the presence of contagion during selected crisis periods and suggest variation in market response for each emerging market as well as shock source. The results of the paper show the heterogenous reactions of emerging markets from spillover shocks of different sources and provide useful insight to investors and asset managers seeking to diversify portfolios within the selected emerging markets as well as policy makers in establishing stronger regulations.

Keywords: *Shift Contagion, Interdependence, Wavelet Analysis, Emerging Economies, China, U.S, Maximal Overlap Discrete Wavelet Transform (MODWT), Continuous Wavelet-Transform (CWT), Wavelet Coherence, Wavelet Correlation.*

1. Introduction

In 2019, the International Monetary Fund (IMF) downgraded its projections for global economic growth in the face of mounting geopolitical tensions and indefinite trade policy (Lea, 2019; IMF, 2019). Despite these projections being revised towards a marginally improved outlook, sluggish economic growth was still anticipated for the world economy (IMF, 2020). Historically, such expectations have often stimulated a flow of capital out of emerging markets towards safe haven[1] assets in developed countries that have proven to be more reliable during times of crisis or when facing the threat of economic downturn (Calvo, 1998; Coudert & Raymond, 2011; Caldara & Iacoviello, 2018). Consequently, these movements also provoke a wave of effects across international markets, both directly and indirectly through numerous integrated channels (Prasad, Rogoff, Shang-Jin & Kose, 2003; Yeyati & Williams, 2011; Aloui, Aïssa & Nguyen, 2011; Carp, 2014). Although the idea of global crisis spillovers is by no means a contemporary notion[2], ever expanding globalisation – partly fuelled by rapid technological advancement throughout the 21st century – has strengthened the intensity and spread of these shocks to different economies around the world (Issing, 2001; Schmukler, Zoido & Halac, 2003; Yeyati & Williams, 2011; Kolb, 2018). With events such as Brexit, the United States (US) – China Trade wars, and more recently the Coronavirus pandemic, the issue of excess spillovers during times of crisis (contagion) has subsequently seen renewed interest among researchers and practitioners in a bid to better understand its behaviour–from measuring observable patterns, levels of impact, variations, and contributing factors, to finding different ways in which to mitigate its effects, and address the various challenges presented (Seth & Panda, 2018). According to Rigobon (2019), part of the growing interest in the subject could be attributed to shifting dynamics in crises over time.

Over the past three decades (early 1990s onwards), negative shocks in relatively small economies or markets have had surprisingly sizeable and persistent international effects (Fratzscher & Oh, 2002; Seth & Panda, 2018; Rigobon, 2019). From the 1997 Asian Crisis to the 2008 US subprime housing market crisis and even the 2010 Greek sovereign debt crisis, failures in comparatively smaller markets have spilled over into countries with which they had little or no direct link[3] (Tai,

[1] See https://am.jpmorgan.com/content/dam/jpm-am-aem/americas/br/en/insights/portfolio-insights/ltcma/ltcma-rethinking-safe-haven-assets-ce-en.pdf.

[2] See Bordo & Murshid (2001) and Claessens & Forbes (2001).

[3] Both the Bank of International Settlements (BIS) and IMF estimates of the size of the United States' (US) subprime housing market's securitised assets fell to less than 5% of their entire financial sector (Hellwig, 2009; Rigobon, 2019). According to Hellwig (2009), although practitioners anticipated an impending market failure, it was not expected that the crisis would hit as hard as it did across various regions. This was similar in the case of Greece in 2010 (Martin & Waller, 2012; Rigobon, 2019).

2007; Hellwig, 2009; Martin & Waller, 2012; Rigobon, 2019). Furthermore, effects appear to have been unequally spread throughout various regions, leaving some crises more contagious and some countries more affected than others (Miller, Thampanishvong & Zhang, 2003; Kaminsky, Reinhart & Vegh, 2003; Hellwig, 2009; Bein & Tuna, 2016; Hassan, Azali, Chin & Azman-Saini, 2017; Gourène, Mendy & Diomande, 2019). Each of these shifting elements has sparked a need for context-driven studies in addressing various concerns among policymakers, scholars, and investors with international portfolios (Bein & Tuna, 2016; Zhou, Lin & Li, 2018). In particular, crisis transmission between emerging markets has garnered greater attention for several reasons, including increasing economic influence, global market share, and viability of portfolio diversification opportunities (Trichet, 2007; Lagarde, 2016; Bein & Tuna, 2016; Ahmed & Huo, 2018; Zhou, Lin & Li, 2018). As such, a significant amount of literature is focused on the topic of contagion among emerging economies.

Researchers like Calvo, Leiderman, and Reinhart (1996), Dungey, Fry, González-Hermosillo, and Martin (2006), Sojli (2007), Dooley & Hutchison (2009) and Kenourgios & Padhi (2012) have studied the presence of contagion among emerging markets for different samples, crisis periods, and factors contributing to observed patterns. These and many more establish the presence of contagion between emerging markets during times of crisis or economic downturn, and acknowledge that variations across regions for a multiple of reasons. Subsequently, others have attempted to determine the underlying factors as well as channels of transmission to explain the discrepancies in crisis effects from one market to next, even among those in the same region or economic collective, such as BRICS (Roberts, Kayande & Srivastava, 2015; Das, Kannadhasan, Tiwari & Al-Yahyaee, 2018; Bonga-Bonga, 2018; Gourène, Mendy & Diomande, 2019; Ithurbide, 2019a; Rigobon, 2019). However, for much of the literature, existing distinctions can be attributed to the way in which spillovers are defined, captured, and subsequently studied over time. According to Forbes & Rigobon (2002), for instance, the way in which pure contagion and naturally occurring interdependence are defined and distinguished plays a key role in the overall accuracy of analysis for many studies. In this regard, researchers such as Ranta (2010) and Das et al. (2018) have established their work in this direction, using wavelet analysis to effectively capture separate and capture pure (shift) contagion effects from naturally occurring interdependence.

In general, irrespective of their approach, numerous studies have recognized the growing necessity in understanding the shifting dynamics of contagion among emerging markets over the last 30 years[4] as well as distinguishing this from pre-occurring interdependence. However, gaps can still be found within existing literature around the topic of 'response heterogeneity' among individual emerging markets with regards to contagious spillovers. Although many studies support the overall premise of contagion among emerging economies[5], few account for their characteristic heterogeneity[6], whereas several others focus on the contagion effect from advanced to emerging markets, emerging among themselves or emerging to the rest of the world[7]. A limited selection compares the changing impact of developed economies against that of individual emerging markets from different regions[8]. As a result, this paper seeks to lessen the divide by evaluating and comparing the changing dynamics of spillover effects (contagion) from shocks to the United States against those to China on major emerging markets across different regions. The main aim is to assess whether or not contagion from these two markets (China and the U.S) varies among individual emerging economies from different regions overtime.

Given that the U.S market is often used as a proxy for much of the developed world based on its level of market integration and sizable influence on overall international financial movements, this paper adopts it as a natural first choice for shock comparison (see Tai, 2000; Rothkopf, 2008; Bae, Kwon & Li, 2008). Equally, China is included as the second shock source within this study due to its rapid growth, expanding investments in various regions, greater integration of the *renminbi* currency into the world financial systems, influential trade markets and increasing global economic prominence (Ahmed & Huo, 2018; Huang, Huang & Wang, 2019; IMF, 2019). Although it is still categorized as an emerging market, China is the second-largest economy on the planet and offers various benefits as well as opportunities for international investors looking to diversify their portfolios[9](Liping, 2013; IMF, 2019). Subsequently, both the U.S and China have become key players in the global market and thus warrant a comparative study regarding spillover effects during times of crisis on emerging countries. Furthermore, leading emerging economies from five regions[10] are included in the study and selected based on their growth rate, gross domestic product

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[4] See, Seth and Panda (2018).

[5] See, Dungey et al. (2006), Tai (2007) Kenourgios & Padhi (2012) Bein & Tuna (2016) Zhou, Lin & Li (2018) and others.

[6] Ithurbide (2019a) highlights that although emerging markets at a global and even regional level may behave like a block, the difference in economic health and divergence in macro factors including policies implies that they should rather be grouped based on well-defined and precise "*homogenous subsets*".

[7] See, De Paula, Hotta & Zevallos (2008), Bonga-Bonga (2018), Kazi, Mehanaoui & Akbar (2014), Hassan et al. (2017), Huang, Huang & Wang (2019) and others.

[8] See, Das et al. (2018)

[9] In light of the ongoing trade war between the United States and China, understanding the difference in contagion effect of these two countries on major emerging markets would yield valuable information for decisions by investors and policymakers (see, Ithurbide, 2019b).

[10] Latin America, Asia, the Middle East, Africa and Europe.

(GDP) per capita as well as projected capacity within their respective regions in line with the MSCI Emerging Market Index country weights[11] and IMF classifications[12]. As such, the markets adopted are South Korea, India, Russia, Brazil, Saudi Arabia and South Africa[13]. Unlike much of previous literature[14], this paper also expands its general methodological approach by applying wavelet analysis to the study. Notably the use of this technique to evaluate changes in contagion dynamics between financial markets is similar to that of Das et al. (2018). However, the paper advances literature within this field by comparing the changes in contagion effects from the *Chinese* and *U.S.* stock markets on different key *individual* emerging economies. The contribution of this paper therefore constitutes three elements – i) distinguishing between interdependence and contagion by applying the wavelet methodology as an alternative approach to a majority of the models used within existing literature, ii) assessing whether contagious spillovers to different emerging economies vary from country to country as well as shock source and iii) evaluating whether these effects have altered over time. Daily stock market data from the Chinese Hang Seng Stock Exchange, Standard & Poor 500 Index as well as each emerging market's index is included to carry out this study.

The remainder of this paper is therefore divided as follows; *section 2* provides a review of theoretical and empirical literature, *section 3* presents the methodology, *section 4* outlines data descriptions, estimations, results and a discussion of findings, while *section 5* concludes.

2. Literature Review

The topic of contagion is one that has extensively been covered throughout present literature with no universal consensus on how to define or appropriately measure its effects (Forbes & Rigobon, 2002; Seth & Panda, 2018; Rigobon, 2019). In their seminal work, Forbes and Rigobon (2002) pointed out the significance of differentiating between *interdependence* and *shift-contagion* when modelling for excess cross-market correlations. They highlighted that, all else being equal, failing to take factors such as heteroskedasticity into consideration often establishes estimation biases and limits the effectiveness of inference (Forbes & Rigobon, 2002). With this in mind, several scholars have agreed on two key elements when distinguishing between contagious spillovers and fundamental interdependence. First, although interdependence is present throughout, contagion

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11 As of 29th March, 2019. See, https://www.msci.com/emerging-markets.

12 As of April 2020 (see https://www.imf.org/en/Publications/WEO/Issues/2020/04/14/weo-april-2020). See also https://www.imf.org/~/media/Files/Publications/WEO/2020/April/English/text.ashx?la=en.

13 Note that data availability is also considered in the selection of these countries.

14 See, Forbes& Rigobon (2002), Seth & Panda (2018) and Rigobon (2019).

tends to be more significant in times of crisis (Tran, 2018; Rigobon, 2019). Second, propagation of shocks generally intensifies during negative periods or after a specific macroeconomic event (Gravelle, Kichian, & Morley, 2006; Boako & Alagidede, 2017; Rigobon, 2019). Theoretically, these characterizations can be reflected through different '*shift-channels*' and are thus utilized across various concepts including the fundamental, financial or co-ordination views (see Boako & Alagidede, 2017; Rigobon, 2019). Empirically, however, several econometric techniques have been adopted in order to effectively separate between short-run '*excess*' effects and long-run standard spillovers while taking possible biases[15] into account.

Forbes and Rigobon (2002), for instance, applied a heteroskedasticity corrected correlation test for periods during the Asian, Mexican and 1987 U.S stock market crash. They found evidence of high levels of co-movement between the markets and concluded this to suggest interdependence rather than contagious effects in all cases (Forbes & Rigobon, 2002). Corsetti, Pericolli and Sbracia (2002), on the other hand, applied bivariate correlation analysis and found evidence of contagion (over similar periods) between most stock market pairs when the variance was fixed as *level* for country-specific shocks. For a sample of the same crisis periods, Billio and Pelizzon (2003) further compared the heteroskedasticity corrected correlation test against bivariate correlation analysis and found that the method presented by Corsetti et al. (2002) provided stronger evidence of contagion than the approach given by Forbes and Rigobon (2002). Unfortunately, both models were greatly affected by omitted variable problems and thus fell short in this regard (Corsetti et al., 2002). Bekaert, Harvey and Ng (2005) on the other hand adapted the two-factor CAPM with asymmetric GARCH over a selection of developed and emerging markets and concluded no evidence of contagion during the Mexican crisis, but significant evidence of contagion over the Asian crisis period. They accounted for market integration at different levels over non-crisis and crisis periods and noted that the asset pricing approach did not suffer from issues such as frequently unobservable shocks or increased variance during periods of financial turmoil (Bekaert, Harvey & Ng, 2005). Others such as Cappiello, Engle and Sheppard (2006) also considered regional factors as well as the challenge of heteroskedasticity and instead tested for the presence of contagion vs interdependence using a variation of the Dynamic Conditional Correlation model (an Asymmetric Generalized -DCC). They observed a significant increase in conditional correlation as well as volatility among regions during crises and found the model used to be '*well suited*' towards examining the dynamics of correlations for various asset classes (Cappiello, Engle & Sheppard, 2006). Aloui, Aïssa and Nguyen (2011) further applied copula functions to model active fat tail

[15] Including omitted variables, heteroskedasticity and misspecification (see Rigobon, 2019).

patterns along with non-linear and linear interdependencies between the U.S and BRICS countries. They found strong evidence of dynamic dependence among them and outlined the significance of fundamental economic factors when modelling these effects (Aloui, Aïssa & Nguyen, 2011). Chen, Hao, and Li (2020), however, propose a more elaborate higher-order information spatial econometric approach that combines spatial econometrics, information theory and complex network to study contagion effects of the European debt crisis to real economy sectors from the financial sector of China, Europe and the US. They find spatial effects to be widely present among financial sectors and real economy sectors, with real economy sectors in emerging markets being more susceptible to the domestic financial sector. Consequently, from a number of these works and more, scholars have since established the relevance of context-driven studies, in addition to selecting appropriate techniques, when effectively modelling contagious spillovers and distinguishing these from interdependence during crisis periods (see Dungey et al., 2006; Tai, 2007; Kenourgios & Padhi, 2012; Bein & Tuna, 2016; Zhou, Lin & Li, 2018).

The context of contagion in emerging markets is one such area that has received greater attention among researchers given the growing influence of these economies within the global financial sphere (Lagarde, 2016; Bein & Tuna, 2016; Ahmed & Huo, 2018; Zhou, Lin & Li, 2018). For example, Yiu, Ho and Choi (2010) combined Principal Component Analysis (PCA) with Asymmetric DCC to evaluate the correlation between the U.S and emerging Asian markets and found evidence of contagion from the U.S to Asia during the Global Financial Crisis, but no such effect during the Asian crisis. Chudik and Fratzscher (2011), however, adopted the Global Vector Autoregressive (GVAR) model to their study on transmission of contagion effects from the U.S to other world economies. They noted evidence of contagion among advanced and emerging economies, highlighting that liquidity conditions along with investor risk attitudes have played a vital role in the varying nature of contagion effect, particularly among emerging markets (Chudik & Fratzscher, 2011). Bonga-Bonga (2018) further streamlines the literature by focusing on co-movements among BRICS countries using a VAR-DCC-GARCH method with a t-test to differentiate between calm and turbulent periods. He finds cross-transmission and interdependence between the Brazilian and South African equity markets and observes that the South African market is mainly a recipient of contagion effects when it comes to the other three countries (RIC) (Bonga-Bonga, 2018). Although there are various works in the area of contagion vs interdependence among emerging markets, the mixed results reported throughout present literature are largely influenced by definitions and choice of empirical methodology (Albulescu, Goyeau & Tiwari, 2017; Seth & Panda, 2018; Rigobon, 2019). Moreover, several of the above-listed works[16] focus only on the time-domain, overlooking the notion that co-movement strength and direction may fluctuate over different frequencies (Benhmad, 2013; Albulescu, Goyeau & Tiwari, 2017; Das et al., 2018). Subsequently, some authors have adopted the alternative *wavelet* approach that combines both the time and frequency domains in a bid to better assess the dynamics of cross-market correlations and capture a '*pure*' form of contagion within emerging financial markets.

Among these are academics such as Albulescu, Goyeau and Tiwari (2017) who adopt the wavelet method to test for contagion among six international equity futures markets. They find that co-movements often manifest themselves in the long-run, while contagion typically occurs within the very short-run especially among the European markets within their study due to high levels of integration (Albulescu, Goyeau & Tiwari, 2017). More recently, as global factors shift[17], researchers have applied this technique to evaluating whether cross-market correlation structures have been altered since the 2008 global financial crisis particularly between emerging markets and developed economies. Das et al. (2018), for instance, applies this alternative wavelet analysis to one such study on the changing dynamics of emerging equity market correlations after the GFC and present evidence of variations in co-movement over different regions. That is, their findings suggest weaker contagion for emerging Latin American markets during the crisis, stronger contagion among emerging European as well as Middle Eastern markets and overall lower long-run interdependence after the GFC (Das et al., 2018).

Like Das et al. (2018), this paper equally attempts to evaluate the variation in contagion effects among emerging equity markets using a time-frequency domain wavelet approach. However, unlike Das et al. (2018), the study applies this alternative wavelet methodology to a selection of *individual* leading emerging markets from five different regions. Furthermore, the study contributes to current literature by assessing the effects of shocks emanating from both a developed (the U.S) and emerging economy (China) to compare variations in co-movement dynamics over time. Although the wide range of methodologies used in contagion studies presents a challenge in appraising evidence for or against '*pure contagion*' and its transmission, distinguishing between the sources of shocks (such as China and US) as well as disaggregating the emerging economies is

[16] See also Dimitriou, Kenourgios and Simos (2013), Mighri and Mansouri (2014), Rotta and Valls Pereira (2016), Jin and An (2016), Ye et al. (2016), Ahmed and Huo (2018), Zhou, Lin and Li (2018) and others.

[17] The surge of populism, China emerging as a superpower, Brexit, the China-US trade war and the now novel coronavirus pandemic that has brought the world to a standstill are all factors that are leading to growing uncertainty around the future state of the global economy (Hu, 2011; Brooks & Wohlforth, 2016; Caldara & Iacoviello, 2018; OECD, 2020).

more likely to provide useful, context-driven information to international investors and policymakers in the long-run.

3. METHODOLOGY

This paper makes use of the wavelet-based framework adopted by Das et al. (2018) and adapts it to the case of two shock sources for six key emerging markets from various regions. Given that financial data (i.e. stock price) is generally high-frequency in nature, this technique allows for correlation patterns to be observed across both frequency and time domains, while establishing an effective means of capturing contagion effects with greater accuracy (Ranta, 2010; Afshan et al., 2018; Das et al., 2018). The distinct ability of wavelets to decompose a signal or time series into its time-scale elements offers the unique opportunity to evaluate dynamic cross-market linkages over different time frames, providing a broader perspective than most time domain approaches that aggregate all time horizons (Ferrer et al., 2018). Additionally, since shock transmission resulting from contagion is typically swift and quick to diminish, this time-localized method has proven to be very useful in distinguishing contagious behaviour from interdependence within heteroskedastic stock market data[18] (Ranta, 2010; Rigobon, 2019). Therefore, in a bid to harness these benefits towards studies of contagion among emerging markets, the paper applies this method to the evaluation of whether contagion effects from two sources vary over different emerging markets. The paper borrows elements of its overall approach from various authors and briefly highlights some of the basic concepts around the wavelet framework within this section[19].

3.1 Wavelets

The term wavelet simply refers to '*small waves*' or a small "wave packet" that expands and declines over a limited time period (Ferrer et al., 2018). Mathematically, the fundamental definition of wavelets falls under two main categories – a) father wavelets φ (scaling function) and b) mother wavelets ψ (wavelet function), as presented below[20];

[18] Stock market data has typically been used in various studies when to analyze contagion as it has been observed that shocks may easily be spread through this channel to other financial markets (see, Seth & Panda, 2018).

[19] For more detailed descriptions, see Torrence and Compo (1998), Torrence and Webster (1999), Percival and Walden (2000), Gençay, Selçuk and Whitcher (2001), Grinsted et al. (2004), Aguiar-Conraria et al. (2008), Aguiar-Conraria and Soares (2011), Bultheel and Huybrechs (2014), Fernández-Macho (2018) and others highlighted in this section.

[20] Note that, there are several different forms or families of wavelets that fall under these categories, the mother and father wavelets simply present the general form.

$$\int \varphi(t)\, dt = 1, \tag{1}$$

$$\int \psi(t)\, dt = 0 \tag{2}$$

Where father wavelets, φ, denote the *smooth low-frequency* component or trend structure of the signal and mother wavelets, ψ, denote the *detailed high-frequency* aspects or trend variation (Crowley, 2005; Sharif, Saha & Loganathan, 2017). Graphically, this can be illustrated as in figure 1 below[21].

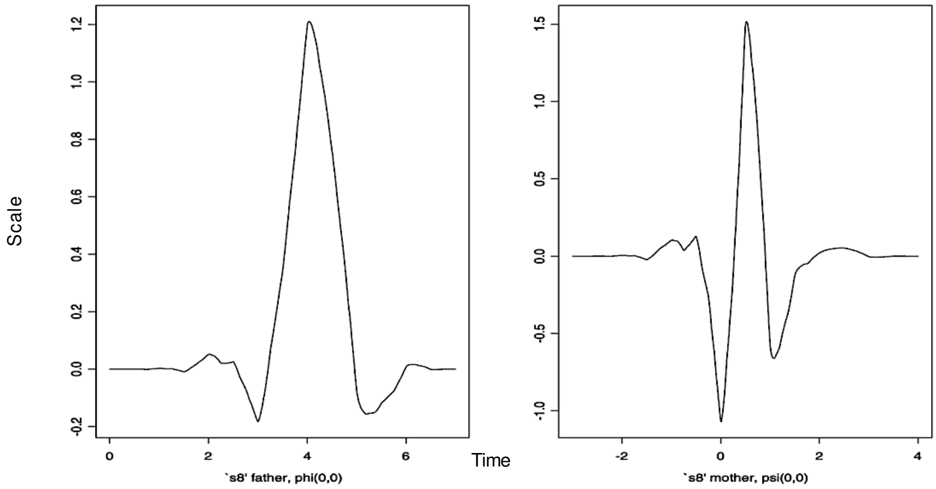

Figure 1: Father and Mother wavelet for Daubechies wavelet

The diagram (*figure 1*) shows that the scaling function (father wavelet) covers wider time-range, but smaller frequency-range than the wavelet function (mother wavelet) which instead covers a wider frequency-range and narrower time-range. The variation in '*stretch*' on both frequency and time planes allows the two functions to each capture different aspects of the signal, thereby offering broader view of its principal components (Crowley, 2005). In this way, the father wavelet captures the smoother trends or low frequency attributes while the mother wavelet captures the more detailed patterns or high frequency attributes of the signal as earlier mentioned.

Father and mother wavelets can also further be defined as (Sharif & Afshan, 2016),

$$\varphi_{j,k} = 2^{j/2}\varphi\left(2^j t - K\right), \tag{3}$$

$$\psi_{j,k} = 2^{j/2}\psi\left(2^j t - K\right), \tag{4}$$

[21] Image obtained from https://core.ac.uk/download/pdf/6603887.pdf.

Where $j = 1, \dots, J$ denotes the measure or the wave function's factor of expansion and $k = 1, \dots, 2^j, T \geq 2^j$ denotes the transformation or '*positioning*' factor for T number of observations[22].

In essence, by striking a balance between time (x-axis) and frequency (y-axis) analysis, wavelet methods account for changes in volatility while further decomposing series into their inherent building blocks and offering greater insight into observed patterns or behaviour[23] (Ranta, 2010; Das et al., 2018). As such, for the purpose of running a comprehensive wavelet analysis this paper applies the following steps in its approach[24];

a) a maximal overlap discrete wavelet transform (MODWT) to dissect and analyse multi-resolution properties of each market series for specific time scales without loss of information;

b) a continuous wavelet-transform (CWT) to discretise the individual series more finely on different scales and to better map its changing properties; and

c) a wavelet coherence (WTC) to capture the bivariate relationships between markets (degree of interdependence)[25].

Finally, to test the strength of the results, this research study also carried out a wavelet correlation (WC) analysis and compared observed correlations between selected markets over the last two decades (2000-2020).

3.1.1 *Maximal Overlap Discrete Wavelet Transform (MODWT)*

The maximal overlap discrete wavelet transform (MODWT) is an extended version of the discrete wavelet transform (DWT) that behaves much in the same way as DWT, but does not suffer from its sensitivity towards selecting a starting point for the signal (Percival & Walden, 2000)[26].

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[22] See, Sharif and Afshan (2016) for more detail.

[23] According to Afshan et al. (2018), several researchers have found the wavelet methodology to be an appropriate tool for "denoising" financial data and capturing numerous "irregularities" within said data over different scales in a manner that circumvents the current lack of consensus in the area of contagion study methodologies and offers greater flexibility of application.

[24] See Das et al. (2018). See also, Fernández-Macho, J., 2018. Time-localized wavelet multiple regression and correlation. *Physica A: Statistical Mechanics and its Applications*, *492*, pp.1226-1238.

[25] See Sleziak, Hlavčová and Szolgay (2015).

[26] According to Percival and Walden (2000) this sensitivity often occurs as a result of subsampling of outputs from scaling and wavelet filters at each '*pyramid algorithm*' stage. See Percival and Walden (2000) for more in-depth description.

According to Ismail, Audu, and Tumala (2016), some advantages of using MODWT in financial and economic data are not only that it breaks down the correlation structures between markets, but that it can also detect structural breaks and extreme volatility clusters inherent in high-frequency series. Essentially it allows for multi-resolution analysis (MRA) as an additive scale-based decomposition, without being shift-variant, that is, without being affected by the starting point choice (Bradley, 2003; Alessio, 2015). Additionally, MODWT provides coefficients (wavelet coefficients) that can be used to generate a more efficient estimation of the wavelet variance described as the variance of a process after being subjected to an '*approximate band-pass filter*' (Percival & Guttorp, 1994; Guerrier et al., 2013; Gallegati & Semmler, 2014)[27]. In the context of this study, MODWT is applied as a means of decomposing selected market series into their primary elements through a univariate MRA of each market's correlation structure.

Alarcon-Aquino & Barria (2009) propose that generally the idea behind MRA is to decompose a signal or time series into its base elements at specific scales, such that any signal $x(t) \in L^2(\mathbb{R})$ can be expressed as;

$$x(t) = \sum_{n\in\mathbb{Z}} c_{J,n}\varphi_{J,n}(t) + \sum_{j=J}^{\infty}\sum_{n\in\mathbb{Z}} d_{J,n}\psi_{J,n}(t), \tag{5}$$

Where $(\varphi(t))$ represents the scaling function, and $(\psi(t))$ the wavelet function as in equation (1) and (2) above, while $c_{J,n}$ and $d_{J,n}$ denote the scaling (approximation) and wavelet (detail) coefficients respectively. $x(t) \in L^2(\mathbb{R})$ roughly implies that under MRA the signal $x(t)$ can be written as a limit of successive estimates that correspond to different resolutions in a closed and complete sequence of subspaces that represent these resolutions or scales (Alarcon-Aquino & Barria, 2009). Given the drawbacks of DWT (particularly the lack of shift-invariance), the defining filters, $c_{J,n}$ and $d_{J,n}$, are modified for MODWT to 'conserve energy' through shift invariance (Alarcon-Aquino & Barria, 2009) and can be expressed as below,

$$c_{j,n}^{(M)} = \sum_{l=0}^{L-1} \tilde{g}_l \, c_{j-1,(n-2^{j-1}l) \bmod N}^{(M)} \tag{6}$$

$$d_{j,n}^{(M)} = \sum_{l=0}^{L-1} \tilde{h}_l \, d_{j-1,(n-2^{j-1}l) \bmod N}^{(M)} \tag{7}$$

[27] See Gallegati and Semmler (2014) for more advantages of MODWT over DWT along with a few examples.

Where (M) denotes MODWT, (N) the length of time series to be evaluated and $n = 0, 1, \dots, N-1$ (Alarcon-Aquino & Barria, 2009), with $\tilde{g}_l$ and $\tilde{h}_l$ further expressed as,

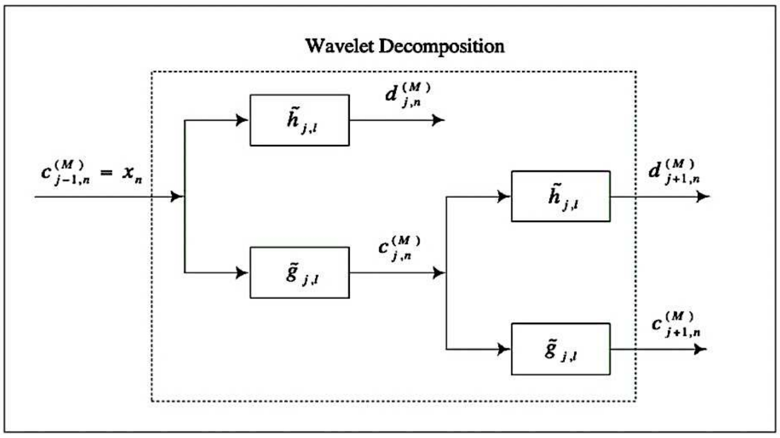
$$\tilde{g}_l = \frac{g_l}{\sqrt{2}} \tag{8}$$

and

$$\tilde{h}_l = \frac{h_l}{\sqrt{2}} \tag{9}$$

Graphically, the wavelet decomposition of MODWT can be illustrated as in Figure 2 below, which shows the wavelet decomposition of a signal or time series (x_n) into scaling ($c_{j,n}^{(M)}$) and wavelet ($d_{j,n}^{(M)}$) features (coefficients), using the corresponding scaling ($\tilde{g}_{j,l}$) and wavelet ($\tilde{h}_{j,l}$) filters[28] (Alarcon-Aquino & Barria, 2009).

Figure 1: MODWT Wavelet Decomposition



Source: Alarcon-Aquino & Barria (2009).

Given the desirable properties of MODWT, particularly towards analysing financial series using the wavelet approach[29], this paper applies it as a first step in the overall methodological process in order to gain some insight on the data patterns and behaviour at various resolutions. More precisely, this paper applies the Daubechies Least Asymmetric filter with length 8 (LA8) as noted in Zhang et al. (2016) as well as Dajcman, Festic and Kavkler (2012) this approach and data[30].

[28] Note that, in this instance, $c_{j,n}^{(M)}$ and $d_{j,n}^{(M)}$ are generated through cascading convolutions with modified $\tilde{g}_{j,l}$ and $\tilde{h}_{j,l}$ filters. See Alarcon-Aquino & Barria (2009) for additional elucidation.

[29] See, Ismail, Audu & Tumala (2016).

[30] Zhang et al. (2016) highlight that this precise filter with length 8 generally demonstrates high reliability, decreased variability and lesser sensitivity to artifacts of rough edges in the wavelet, while Dajcman, Festic and Kavkler (2012) point out that LA8 has typically been used in various empirical studies on interdependence among financial markets for some such theoretical properties. See also, Ranta (2010).

3.1.2 Continuous Wavelet-Transform (CWT)

As a process, continuous wavelet transform (CWT) breaks down a one-dimension signal (time series) into two-dimension wavelets on a time-frequency plane by projecting a big wave (mother wavelet) onto a time series and breaking it down into smaller waves (wavelets) that express the different time positions as well as scales (frequency) of each series' variance (Saiti et al., 2016; Albulescu et al., 2017; Bultheel & Huybrechs, 2014; Fernández-Macho, 2018). This paper exploits this attribute to determine the strength and nature of spillover effects present in each market prior to establishing any causal links. Unlike MODWT which focuses on component variation at different timescales, CWT draws attention to finer details and highlights the variation types or strengths. However, given that financial data is typically high frequency in nature and could be influenced by a variety of factors, the study applies both MODWT and CWT to its preliminary analysis to provide a more in-depth investigation into market behaviour[31].

Mathematically, CWT is defined as the correlation between a signal $x(t)$ and a wavelet function, expressed as (Komorowski & Pietraszek, 2016),

$$Cw(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\, \psi^{*}\left(\frac{t-b}{a}\right) dt \tag{10}$$

where a is the dilation (or scale) of the wavelet which indicates how much the wavelet has been 'stretched', b highlights the translation of the wavelet or time location and $\psi^{*}(t)$ represents a complex conjugation of the analysing mother wavelet $\psi(t)$ (Addison, Walker & Guido, 2009; Komorowski & Pietraszek, 2016). $x(t)$ is the continuous time signal (or time series) that is analysed, while $\frac{1}{\sqrt{a}}$ denotes an energy normalised factor[32] (Komorowski & Pietraszek, 2016). It also follows that for $\psi(t)$ to be classified as a wavelet, it must satifisy the criteria below (Addison et al., 2009).

a) Its energy must be finite;

$$E = \int_{-\infty}^{\infty} |\psi(t)|^{2}\, dt < \infty \tag{11}$$

[31] See Percival & Walden (2000, pp. 12 - 19), Fedi, Primiceri, Quarta, and Villani. (2004), Masset (2015) and Zhang et al. (2016).

[32] For different scale values, a, the wavelet energy must be the same (Komorowski & Pietraszek, 2016). Recall shift invariance.

b) If $\psi(t)$ has the Fourier transform,

$$\hat{\psi}(t) = \int_{-\infty}^{\infty} \psi(t) e^{-i(2\pi f)t}\, dt, \tag{12}$$

then the admissibility condition,

$$C_g = \int_{0}^{\infty} \frac{\left|\hat{\psi}(t)\right|^2}{f} dt < \infty \tag{13}$$

must hold for $\hat{\psi}(t)$. This suggests that the wavelet must have a zero-mean ($\hat{\psi}(0) = 0$), that is, contain no zero-frequency component (Addison et al., 2009).

c) In the case of analytic (complex) wavelets, the Fourier transform should have both a zero value (for negative frequencies) and a real component (Komorowski & Pietraszek, 2016).

Altogether, a two-dimensional energy density function,

$$E(a, b) = |Cw(a, b)|^2, \tag{14}$$

known as a scalogram is obtained, which presents the energy distribution of signals for employed scales, a, and time locations, b (Addison et al., 2009; Komorowski & Pietraszek, 2016). This is depicted in Figures 6a-h in section five.

To implement its CWT, this research study used the popular Morlet wavelet described as,

$$\psi(t) = \frac{1}{\sqrt[4]{\pi}} \left(e^{i\omega_0 t} - e^{-\frac{\omega_0^2}{2}} \right) e^{-\frac{t^2}{2}}, \tag{15}$$

where $e^{-\frac{t^2}{2}}$ is essentially a Gaussian envelope (added to fulfil the admissibility condition)[33] and $e^{i\omega_0 t}$ a *complex sinusoid*, with $e^{-\frac{\omega_0^2}{2}}$ as the correction term, which becomes negligible for values of $\omega_0 > 5$ (Aguiar-Conraria et al., 2008; Addison et al., 2009). ω_0 is the mother wavelet's central frequency (the frequency at the centre of a Gaussian envelope) and $\frac{1}{\sqrt[4]{\pi}}$ the normalisation factor (Addison, 2018).

[33] See Aguiar-Conraria et al. (2008) for more detail.

To implement the CWT for this study, the *Morlet* wavelet is adopted because of its ability to be decomposed into both real and imaginary parts which allows for broader analysis of the dynamic movements between two signals or time series (Ferrer et al., 2018). Equally, an appropriate value of $\omega_0 = 6$ is employed as it provides a good balance between frequency and time localization, while simplifying interpretation given that the wavelet scale and frequency are inversely related (see Grinsted et al., 2004; Aguiar-Conraria et al., 2008; González-Concepción, Gil-Fariña & Pestano-Gabino, 2012; Aloui & Hkiri, 2014 for more detail). Subsequently, the *Morlet* wavelet used within this study is a truncated version expressed below.

$$\psi(t) = \frac{1}{\sqrt[4]{\pi}} e^{i\omega_0 t} e^{-\frac{t^2}{2}} \tag{16}$$

3.1.3 Wavelet Coherence (WC)

Wavelet-*squared* coherence (WC) can be described as a bivariate structure used to evaluate the joint-behaviour or cross-correlation between two signals (time series) over a time-frequency plane (Aloui & Hkiri, 2014; Sharif & Afshan, 2016; L. Yang et al., 2016). To understand as well as apply WC effectively, the *cross-wavelet transform* (XWT) and *phase patterns* should be considered.

According to Torrence and Compo (1998), for two signals $x(t)$ and $y(t)$, the ***cross-wavelet transform*** is defined as,

$$W_{xy}(m,n) = W_x(m,n)W_y^*(m,n) \tag{17}$$

Where $W_x(m,n)$ and $W_y(m,n)$ are the continuous wavelet transforms of $x(t)$ and $y(t)$, respectively. m indicates the location, n the scale and $*$ the complex conjugate. Aloui and Hkiri (2014) note that the *cross-wavelet power spectra*, $|W_{xy}(m,n)|$, highlights regions in the time-frequency space where the signals demonstrate high mutual power. That is, it shows the '*local covariance*' between two series (in this case stock market indices) at each scale (Aloui & Hkiri, 2014; Afshan et al., 2018). This feature has proven useful when evaluating *contagious effects* or stock market co-movement as it enables researchers to focus on regions where the two selected time series change simultaneously within a time-frequency space, but do not necessarily display high mutual power (Afshan et al., 2018). It is through this that wavelet coherence becomes beneficial - as a measure of local correlation through which the extent of interdependence among signals can be compared across timescales (Aloui & Hkiri, 2014; L. Yang et al., 2016). Thus, following Torrence and Webster (1999), wavelet-squared coherence is adequately defined as the squared *absolute value of the* *smoothed cross-wavelet power spectra* adjusted by the product of *the smoothed individual wavelet power spectra of each chosen signal*. That is,

$$R^2(m,n) = \frac{\left|N\left(n^{-1}W_{xy}(m,n)\right)\right|^2}{N(n^{-1}|W_x(m,n)|^2)N\left(n^{-1}\left|W_y(m,n)\right|^2\right)} \tag{18}$$

Where n is the smoothing factor and the squared wavelet coherence coefficient sits within the range $0 \leq R^2(m,n) \leq 1$. If $R^2(m,n)$ is close to zero, then weak interdependence is recognized and if $R^2(m,n)$ is close to one, then the opposite holds. To this effect, contagion can further be investigated across markets by comparing low-frequency interdependence with high-frequency interdependence. That is, if the latter *increases sharply* during a given period and the former *does not*, then it can be concluded that contagion occurred during that time (L. Yang et al., 2016).

In addition, because the wavelet coherence coefficient is squared, applying the ***phase difference*** is needed to enhance the analysis and distinguish between both positive and negative dependence (L. Yang et al., 2016). Essentially *phase difference* or *phase pattern* outlines the relative positions of $x(t)$ and $y(t)$ and can be expressed as (Aguiar-Conraria & Soares, 2011)[34],

$$\phi_{x,y} = \left(\frac{\Im\{W_n^{xy}\}}{\Re\{W_n^{xy}\}}\right), \qquad \text{with } \phi_{x,y} \in [-\pi, \pi] \tag{24}$$

Where, $\Im$ and $\Re$ represent the imaginary and real parts of the smoothed cross-wavelet transform, respectively (L. Yang et al., 2016). A phase-pattern or difference of zero suggests that the series $x(t)$ and $y(t)$ move together at a given frequency (L. Yang et al., 2016). According to Aguiar-Conraria & Soares (2011), if $\phi_{x,y} \in \left(0, \frac{\pi}{2}\right)$ or $\phi_{x,y} \in \left(-\pi, -\frac{\pi}{2}\right)$ then the $y(t)$ series is leads, but if $\phi_{x,y} \in \left(0, -\frac{\pi}{2}\right)$ or $\phi_{x,y} \in \left(\pi, \frac{\pi}{2}\right)$ then the $x(t)$ series is leads. Additionally, in the case where $\phi_{x,y} \in \left(\pi, \frac{\pi}{2}\right)$ or $\phi_{x,y} \in \left(-\pi, -\frac{\pi}{2}\right)$, the term 'in-phase' is applied and indicates a positive relationship between $x(t)$ and $y(t)$ (Yang et al. 2016a). However, if $\phi_{x,y} \in \left(0, \frac{\pi}{2}\right)$ or $\phi_{x,y} \in \left(0, -\frac{\pi}{2}\right)$, then the term 'out-of-phase' is adopted and suggests a negative relationship between the series (Yang et al. 2016a).

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[34] Note that $W_n^{xy} = N\left(n^{-1}W_{xy}(m,n)\right)$ from equation (23). See Bloomfield et al. (2004) and L. Yang et al. (2016) for more detail.

Visually, these patterns are more simply represented by the quadrants and direction of arrows on the WTC plot that highlights the nature of causality between two series or selected market indices summarised in Figure 2[35].

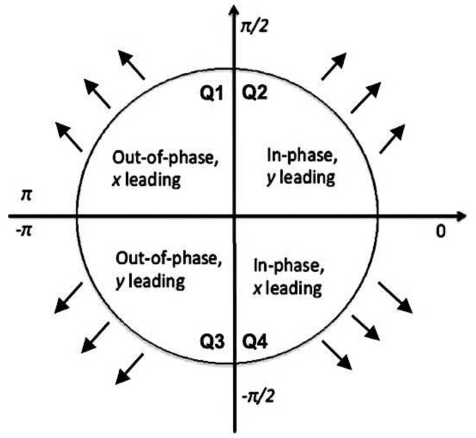


Figure 3: Phase Difference Circle. Quadrants highlight significance of phase pattern (arrow) direction.

Ultimately, wavelet coherence works as an appropriate tool for capturing and analysing stock market co-movements overtime and is thus equally applied to this study's methodological framework.

3.2 Wavelet Correlation (Robustness Test)

Much like the standard correlation measure, wavelet correlation (WC) is used to provide insight on the strength and direction of co-movements between two signals (In & Kim, 2012). Generally, wavelet correlation provides an alternative means of assessing bi-variate signal characteristics through wavelet analysis and is as such included in this study to test the robustness of results obtained through the main framework (Gençay, Selçuk & Whitcher, 2001; Gallegati & Gallegati, 2005; In & Kim, 2012; Das et al., 2018). Although some authors apply both wavelet covariance and correlation as complimentary methods within their studies, this paper applies only the correlation aspect of the analysis given that correlation typically provides a better measure for inference[36] (Whitcher, Guttorp & Percival, 2000; Gallegati & Gallegati, 2005; Crowley, 2005; In & Kim, 2012).

[35] Quadrants highlight significance of phase pattern (arrow) direction.

[36] According to In and Kim (2012), because covariance (wavelet covariance) does not take into account the variation of the individual series, wavelet correlation is introduced to provide a normalized measure that combines both the covariance and individual variances of bi-variate series.

Mathematically, wavelet correlation is simply defined as the interaction between the wavelet covariance of two signals [$x(t)$,$y(t)$] and their individual wavelet variances, typically expressed using the MODWT estimator as (In & Kim, 2012),

$$\tilde{\rho}_{xy}(\lambda_j) = \frac{Cov_{xy}(\lambda_j)}{\hat{\sigma}^2{}_x(\lambda_j)\hat{\sigma}^2{}_y(\lambda_j)} \tag{25}$$

Where $\hat{\sigma}^2{}_x(\lambda_j)$ and $\hat{\sigma}^2{}_y(\lambda_j)$ are the wavelet variances associated with scale λ_j for $x(t)$ and $y(t)$, respectively, and WC is expressed as $|\tilde{\rho}_{xy}(\lambda_j)| < 1$ as with the standard correlation coefficient (In & Kim, 2012; Das et al., 2018). In accordance with the reasoning previously highlighted (see *sub-section 3.1.1*) the MODWT estimator is employed to decompose the time series using LA filter of length 8 to obtain correlation coefficients. The time series are also decomposed into eight details (W_{i1} … W_{i8}) (interpreted as in table 1 below), with frequencies denoted in terms of days to simplify interpretation (Das et al., 2018).

***Table 1*: CWT Time interpretation of various frequencies.**

W_{i1}	2-4 days	Semi-Weekly scale
W_{i2}	4-8 days	Weekly scale
W_{i3}	8-16 days	Fortnightly scale
W_{i4}	16-32 days	Monthly scale
W_{i5}	32-64 days	Monthly to Quarterly scale
W_{i6}	64-128 days	Quarterly to Biannual scale
W_{i7}	128-256 days	Biannual to Annual scale
W_{i8}	256-512 days	1 to 2 years scale

4. DATA, ESTIMATION AND RESULTS

The first part of this section briefly outlines a description of the selected data, including transformations applied, variables used and the preliminary analysis. The second part presents the estimations and discussion of results.

4.1 Data, Transformations and Descriptive Stati

This research study used daily stock price data of eight different indices, from January 2000 until April 2020. This sample period was purposefully selected over other periods on the basis that it covers an expansive array of events and unexpected changes in global dynamics, such as the GFC in 2008, that had the potential of providing a wealth of information. The sample also provided a more current, yet still wide selection of observations from which suitable inferences could be made. The data used was collectively sourced from *Yahoo! Finance*, *Google Finance,* and *Bloomberg* websites. The variables (markets) included in this study are shown in Table 1. Note that based on the Asian region's size and distinct nature (in terms of various emerging markets) two market indices are included under the Asian Emerging heading to provide a greater perspective regarding the dynamics of market behaviour and co-movements.

***Table 1**:* Market Variables and Classification

Market Variable[37]	***Country***	***Classification***
Standard and Poor 500 Index	United States	Source Market (Advanced)

The emerging markets included in this list were randomly selected based on their MSCI Emerging Market Index country weight and IMF classification as well as overall data availability. Given the size of the region and distinctions between its markets, two market indices are included under the Asian Emerging heading to provide a broader perspective regarding market behaviour and co-movements.

[37] See **Acronyms and Abbreviations** for market abbreviations.

(S&P 500)[38]		
Hang Seng Index (HSI)[39]	China	Source Market (Emerging)
Bombay Stock Exchange (BSE)	India	Asian Emerging (Response Market)
Korea Composite Stock Price Index (KOSPI)	South Korea	Asian Emerging (Response Market)
Moscow Exchange (MOEX)	Russia	European Emerging (Response Market)
Johannesburg All Share Index (JALSH)	South Africa	African Emerging (Response Market)
Índice Bolsa de Valores de Sao Paulo (IBOVESPA)	Brazil	Latin America Emerging (Response Market)
Borsa Istanbul 100 Index (BIST)	Turkey	Middle East Emerging (Response Market)

4.1 Transformations and Descriptive Statistics

To maintain analysis uniformity, as well as ease of interpretation, the stock price data is first transformed into returns for each market using the following equation,

$$R_t = \left[\ln\left(\frac{P_t}{P_{t-1}}\right)\right] \times 100 \tag{26}$$

where R_t represents the market return, and P_t the market price at a given time t. P_{t-1} denotes the market price the day before or a previous time $t-1$.

Next, the data is tested for stationarity using the Augmented Dickey-Fuller (ADF) test (Hochreuther, Wernicke, Grießinger & Bräuning, 2017). Although wavelet analysis is free from the assumption of stationarity and is particularly useful in analysing and capturing trend behaviour in non-stationary time series data, the test for stationarity is included in this study for the purpose

[38] The S&P 500 index was chosen above over other national indices as it accounts for roughly 80% of total market capitalisation in the US (CFA Institute, 2016).

[39] The Hang Seng Index (HSI) was used on the basis that a quarter of its listings comprise the largest mainland Chinese and Hong Kong firms, making it an important benchmark for domestic investors as well as a suitable index for this study (Girardin & Zhenya, 2007).

of coherency (Cazelles, Chavez, Berteaux, Ménard, Vik, Jenouvrier & Stenseth., 2008; Chen, 2008; Schmitt, Chetalova, Schäfer & Guhr, 2013; Rhif, Ben Abbes, Farah, Martínez & Sang., 2019). Results of these tests are presented in Table 2 along with a summary of descriptive statistics for the data set.

Table 2: Descriptive Statistics

This table shows a summary of the descriptive statistics for each market index including the results obtained from the ADF test for stationarity. * denotes 10% significance level, ** represents 5% and *** marks 1% significance level.

Source: Author's own calculations using selected data.

Variable	*Mean*	*Max.*	*Min.*	*Std Dev.*	*Skewness*	*Kurtosis*	*ADF*	*Obs.*
S&P500 (US)	0.01466	10.95720	-9.46951	1.21218	-0.17601	12.72726	-16.818***	5031
HSI (CHINA)	0.00878	13.40681	-13.58202	1.45530	-0.03547	11.08561	-16.12***	5031
BIST (TUR)	0.03552	17.82204	-20.00374	2.06232	-0.16187	11.25850	-16.103***	5031
BSE (IND)	0.03657	15.98998	-14.10174	1.47741	-0.36193	12.33721	-15.368***	5031
MOEX (RUS)	0.05366	25.22612	-20.65708	1.98665	-0.28246	19.46964	-17.428***	5031

KOSPI (S. KOREA)	0.01352	13.86347	-12.80470	1.48422	-0.40338	10.51375	-16.305***	5031
JALSH (S. AFRICA)	0.03559	7.26147	-11.10370	1.23542	-0.37725	9.38819	-17.969***	5031
IBOVESPA (BRAZIL)	0.03181	13.67942	-15.99383	1.82572	-0.38960	10.06086	-15.848***	5031

Firstly, the table indicates that the mean returns for most of the selected emerging markets (Turkey, India, Russia, South Africa, and Brazil) were significantly higher than that of the developed market proxy (the US). Theory and evidence suggest that this observation can be attributed to factors such as higher growth rates among emerging markets as well as their volatile nature, which produce greater risks and thus require greater average returns to compensate the standard risk-averse investor (Kohers, Kohers & Kohers, 2006; Ward, 2019). As such it can be expected that emerging markets will have higher mean returns than their advanced market counterpart. China (HSI) on the other hand showed the lowest average market returns (0.00878), while Russia showed the highest (0.05366). Wang, Lai, and Yen (2014) highlight several challenges that could explain the lower average return (particularly after 2007) on the Chinese index, including, inter alia, political and economic issues, the GFC, limited local diversification opportunities, and a tendency to underperform over the long term[40]. However, for Russia, declining market sensitivity to political factors (and a simultaneous increase in sensitivity to macroeconomic factors), generally favourable oil prices, greater diversification opportunities, risk mitigation, exchange rate, and overall market performance added to the high average returns over time and could explain the mean result observed above (Goriaev & Zabotkin, 2006; Gaddy & Ickes, 2010).

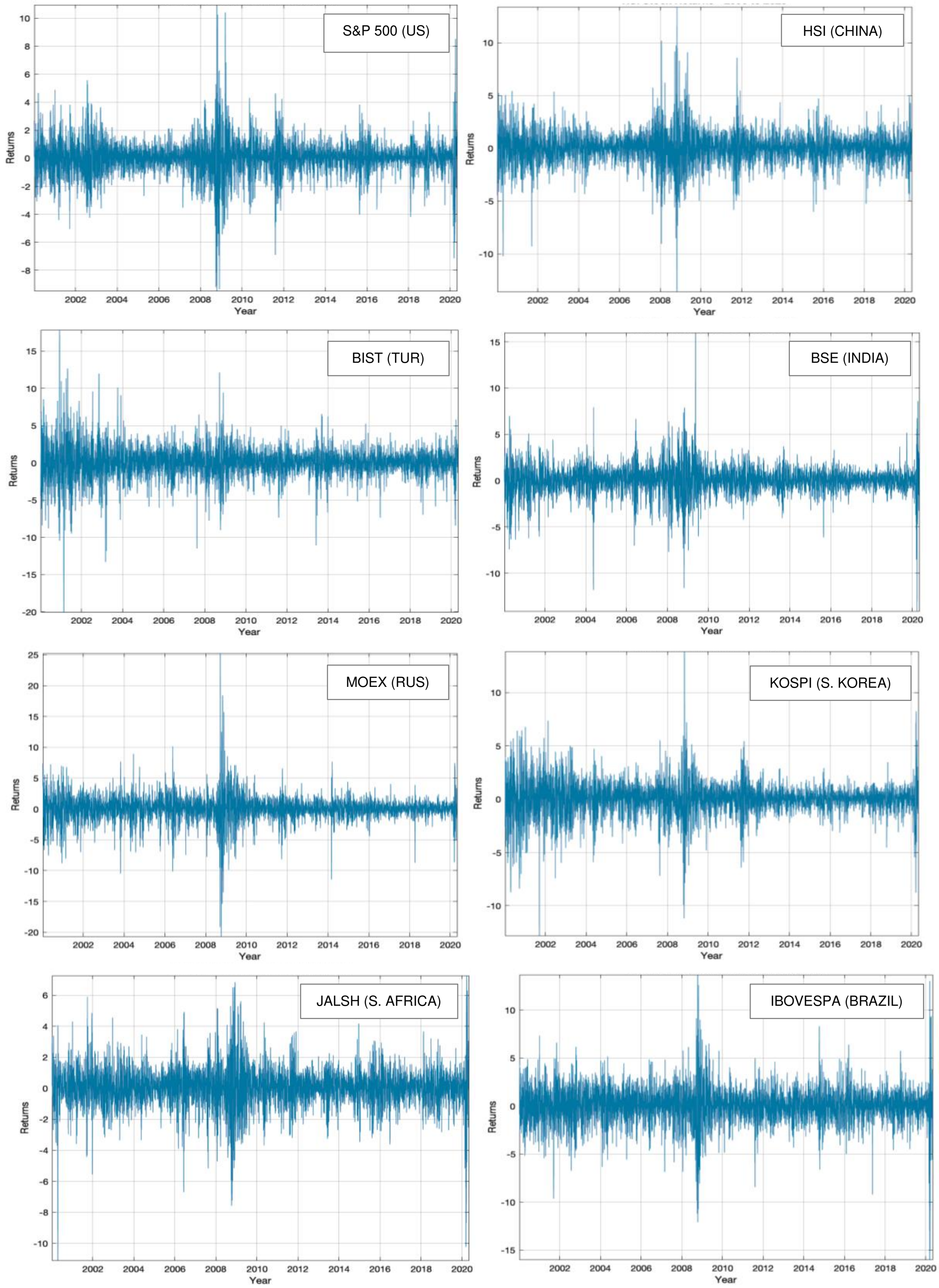
Secondly, market return volatility in terms of standard deviation indicated similar volatility in all included Asian emerging markets (China, South Korea, and India), high volatility for Turkey, Russia, and South Africa, and slightly lower volatility for the US. Once again it is noted that most emerging economies typically have comparatively higher market volatility than their developed counterparts for various reasons, such as uncertainty fuelled by political or socio-economic instability (De Santis, 1997; Aggarwal, Inclan & Leal, 1999; Chaudhuri & Koo, 2001; Cakan,

[40] See also, Lipschitz, Rochon and Verdier (2009).

Doytch & Upadhyaya, 2015). This is also true in the case of South Africa and Russia where macroeconomic risk factors, political variability, and socio-economic issues (among other aspects) have played a role in the relatively high levels of volatility over time (Goriaev & Zabotkin, 2006; Fedderke & Luiz, 2008; Lebedeva, 2015). Additionally, because changes in the US economy typically influence market performance among a number of emerging markets, it is more than likely that volatility movements in the US market would correspond to slightly higher volatility in its emerging counterparts (Cakan et al., 2015). In the case of Turkey, although the influence of political risk has seen a downward trend in recent years, it has continued to negatively affect Turkish market return stability, and could explain some of the higher volatility (standard deviation) observed in Table 2 above (Günay, 2016).

Thirdly, the skewness coefficient indicated a negative result for all the listed aggregate markets and suggested a left-skewed distribution for returns, as expected of volatile stock markets that are typically heavily influenced by negative news (or price drops) in real life (Charoenrook & Daouk, 2009; Albuquerque, 2012; Kelly & Jiang, 2014; Das et al., 2018). Conversely, the Kurtosis showed a positive result for all markets and implied a high probability of achieving positive returns (Arouri, Jawadi & Nguyen, 2010).

Figure 2: Market Returns (2000-2020)



Source: Yahoo! Finance, Google Finance and Bloomberg.

In terms of the ADF test, at a one percent level of significance, the null hypothesis of no stationarity was rejected for all the tested markets based on the results obtained at a lag order of 17 and p-value of ≤0.01 across the board. Given that the data was found to be stationary, the standard cointegration analysis was not included in this research. However, even in the instance of serial correlation, the MODWT approach was still effective in analysing the series as it has been shown to provide unbiased estimates for various regression models and produce robust results that increased in precision with every increase in level of decomposition (Gençay & Gradojevic, 2011).

Lastly, market return movements for each selected index were plotted and are presented in Figure 4 above. The figure suggests some common trends between markets, particularly in 2008-2009 (during the GFC), with South Africa and Turkey's response appearing to be of a lesser degree. According to Rena & Msoni (2014), for South Africa, much of the initial impact of the GFC was absorbed by efficient market regulations as well as comparatively reduced levels of global financial integration and could explain the behaviour observed below. Whereas in Turkey, the years of crises prior to the GFC may have left the country better prepared to manage the crisis fallout, contributing to the noted delayed response (Terzi, 2010; Irem, 2013). Generally, each market shows some kind of excess movement (spikes) around the time of the GFC and visually attests to possible contagion effects. A more thorough investigation of market patterns is presented in the next chapter.

CHAPTER FIVE - ESTIMATION, OUTPUT, AND INTERPRETATION

5.1 Preliminary Analysis

A dual method approach was used to run the univariate analysis of individual market series prior to establishing the causality between market pairs. The MODWT and CWT were applied as pre-processing tools to constitute the preliminary analysis in this study prior to addressing the central objectives, that is, distinguishing between interdependence and contagion, as well as assessing whether or not contagious spillovers vary among selected markets. It is important to note that the MODWT and CWT were used as visual precursors to assess whether or not there was a common trend between the variables used when they were decomposed in terms of signal processing, i.e., time-scale and frequency domain decomposition. Insight into the trend of these variables is important to assess the extent of the possible shock spillover, and subsequently contagion and interdependence. The MODWT is expressed in terms of both wavelet decomposition and volatility (variance) by scale, while CWT is expressed on the continuous wavelet power spectra. Details of estimation, output, and interpretation are outlined in preceding sections.

5.1.1 Maximal Overlap Discrete Wavelet Transform

As the first step in the overall wavelet analysis framework, this research study applied a maximal overlap wavelet transform on each studied market series with a Daubechies Least Asymmetric filter of length eight (LA8) and level of decomposition equal to eight. In the context of this study, the MODWT was used to run a multi-resolution univariate decomposition of selected market series to provide insight into the principal elements constituting observed volatility patterns throughout the sample period. Given its unique capacity to detect structural breaks and naturally occurring extreme volatility clusters[41], the MODWT was used to test for changes in volatility movement during the crisis periods in each market before investigating energy strength and then causality among market pairings in preceding sections. The choice of level of decomposition followed the $[J \leq \log_2(N)]$ criteria as prescribed by Bernard & Nyambuu (2016), where N represented the length of the time series and J provided the appropriate levels of decomposition. It should be noted that the higher the level of decomposition the greater the precision of analysis (Yang et al., 2016b; Bernard & Nyambuu, 2016). However, as level of decomposition rose, the likelihood of smoothing the data to the point of losing valuable information also increased (Lahmiri, 2014). Thus, this study applied a level of eight as a suitable compromise for effective decomposition. The research study also applied the Daubechies Least Asymmetric filter of length

[41] See Methodology chapter for more detail.

eight (LA8) as the filter, which is widely used in economic applications of this nature due to its high reliability, decreased variability, and lesser sensitivity to artefacts of rough edges in the wavelets (Dajcman, Festic & Kavkler, 2012; Bernard & Nyambuu, 2016; Zhang et al., 2016). The results of wavelet decomposition for each series are presented in Figures 5a-5h in this section.

Figures 5a-5h outline variations in each series on different scales and illustrate these as plots of orthogonal components ($D_1, D_2, \dots, D_8$), which indicate various frequency portions of the original market return index in details, and smoothed components (S_8). In other words, each market return series was decomposed into their principal elements across eight scales that highlighted the volatility in the data sets at different frequency levels and over time. Essentially, this provides insight into the markets' patterns and behaviours, particularly return volatility, at various resolutions (from the short to very long term) and offers a way to assess spikes in volatility more effectively as the excess of what would typically occur in a given scale.

Table 3: The MODWT Time Interpretation of Signal

Period	***Wavelet Scale***
Short Term	D_1 (2-4 -day cycles)
	D_2 (4-8 -day cycle)
	D_3 (8-16 -day cycles)
	D_4 (16-32 -day cycles)
Medium Term	D_5 (32-64 -day cycles)
	D_6 (64-128 -day cycles)
	D_7 (128-256 -day cycles)
Long Term	D_8 (256-512 -day cycles)
Very Long Term	S_8 (above 512 -day cycles)

Source: Author's adaptation based on Das et al. (2018).

In this study, the orthogonal and smoothed components are grouped into five major periods (indicated in Table 3) to interpret the relevance of different dynamics in the series on a time-scale basis. The first four components ($D_1,\ D_2,\ D_3, D_4$) represent short term (high frequency) variations caused by shocks occurring at frequencies of two, four, eight, and 16 days, respectively[42]. The next three components (D_5, D_6, D_7) account for variations in the medium-term at frequencies of 32, 64, and 128 days, respectively. Whereas, D_8 represent long-term variations at frequencies of 256 days, and S_8 accounts for very long-term variations at frequencies of 512 days or more[43].

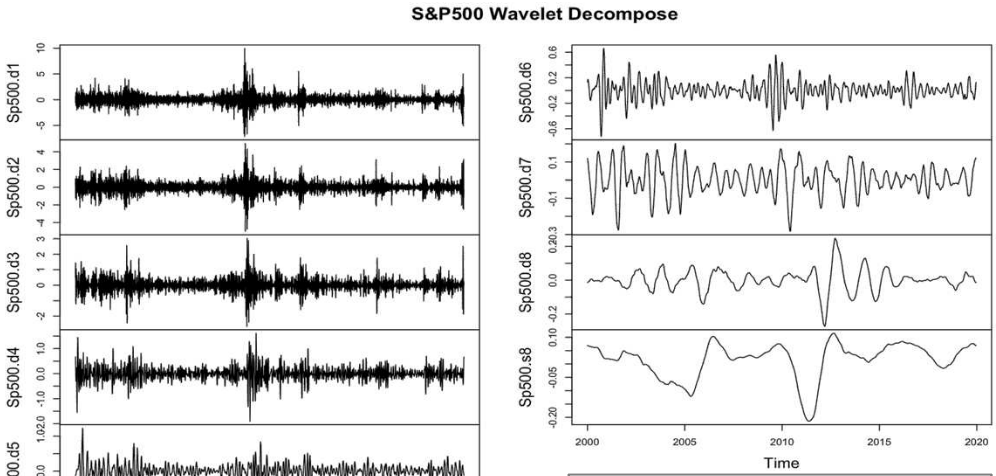
[42] Corresponding to the working days of a week.

[43] This also holds for ***Figure 6*** where the wavelet variance (volatility) distribution per period is expressed for each market.

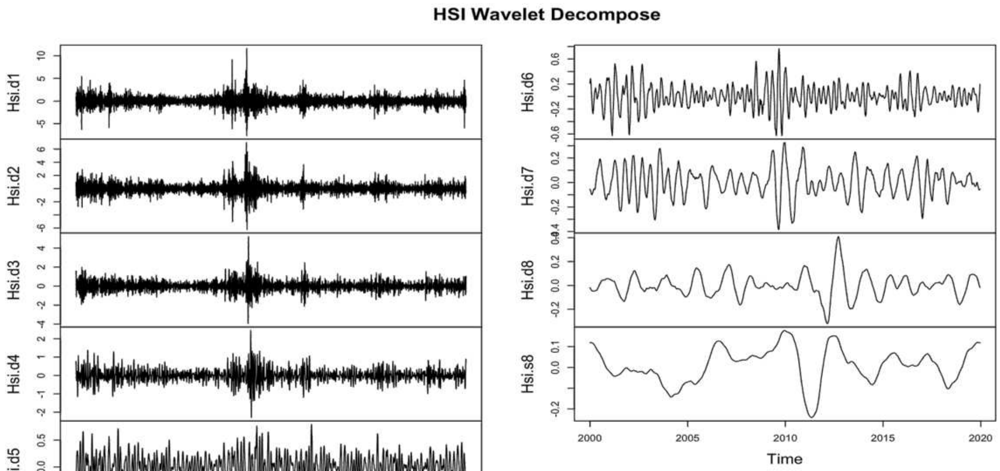
Altogether, the figures show that high frequency variations occur in the short term (D_1, D_2, D_3, D_4), while low frequency variations are more evident in the medium to very long term (D_6, D_7, D_8, S_8). In most markets it was observed that the high frequency variations in the short-term scales intensified during the 2008-2009 GFC period, before returning to a less intense state afterwards. According to Forbes & Rigobon (2002) and Rigobon (2019), the excess short-term high frequency variation that occurs during a crisis period indicates the likely presence of contagion effects in individual markets. It can be noted that the market series each showed variations at both high and low frequencies in the scales. However, the MODWT wavelet decompositions obtained in Figures 5a-5h above showed strong spikes in variations that are observed only during times of crisis (negative shock or macroeconomic event), but not throughout the sample period. A closer look at the figures reveals that in Figure 5c (wavelet decomposition of the Turkish market series) the variations in the first two levels (D_1, D_2) during the GFC appears to be weaker than those observed in the next two levels (D_3, D_4) during the same period. A sharp spike in variation was also noted in 2001-2002 and appeared to be stronger than the spike in variation observed during the GFC. This can be explained by the severe economic crisis experienced in the country at the onset of 2001, as well as a number of crises experienced in previous periods (Koch, Chaudhary & Bilquees, 2001; Terzi, 2010; Irem, 2013). According to Terzi (2010) and Irem (2013), before 2008, various economic reforms and programmes resulting from the impact of crises suffered in earlier decades better prepared Turkey to handle future shocks. As such, to some degree, the country's preparedness to manage the 2008 GFC could explain the weaker initial impact and resultant delay in effects observed in the first four scales (D_1, D_2, D_3, D_4) during this period. These earlier years of crisis could also possibly explain why short-term volatility in 2001-2002 appeared to be comparatively higher than the short-term volatility observed during the GFC period.[44]

Figure 3: The MODWT Wavelet Decomposition Output

[44] It can be noted that a fairly high short-term volatility during the 2000-2002 period is similarly evident in Figure 5g (wavelet decomposition of the South Korean market series). However, this spike in variation does not exceed the spike observed during the GFC and, according to Fratzscher & Oh (2002), is explained by speculative behaviour in derivative markets following the Asian Crisis.

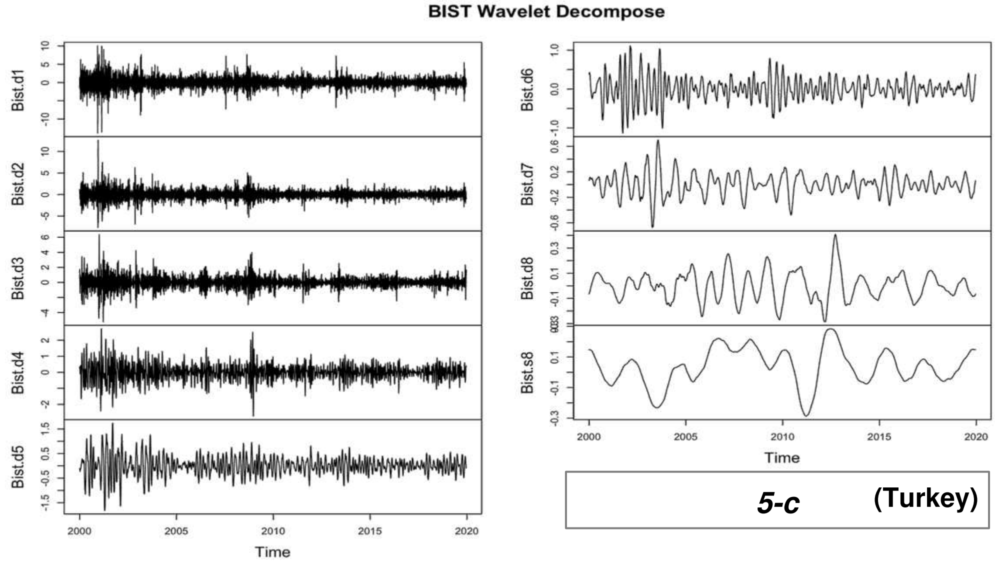


5-a **(US)**

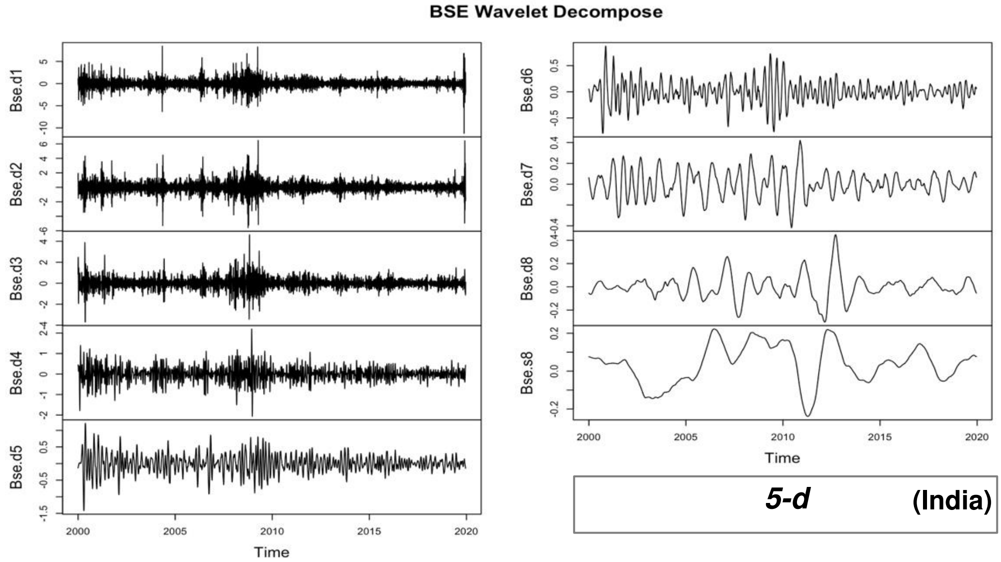


5-b **(China)**

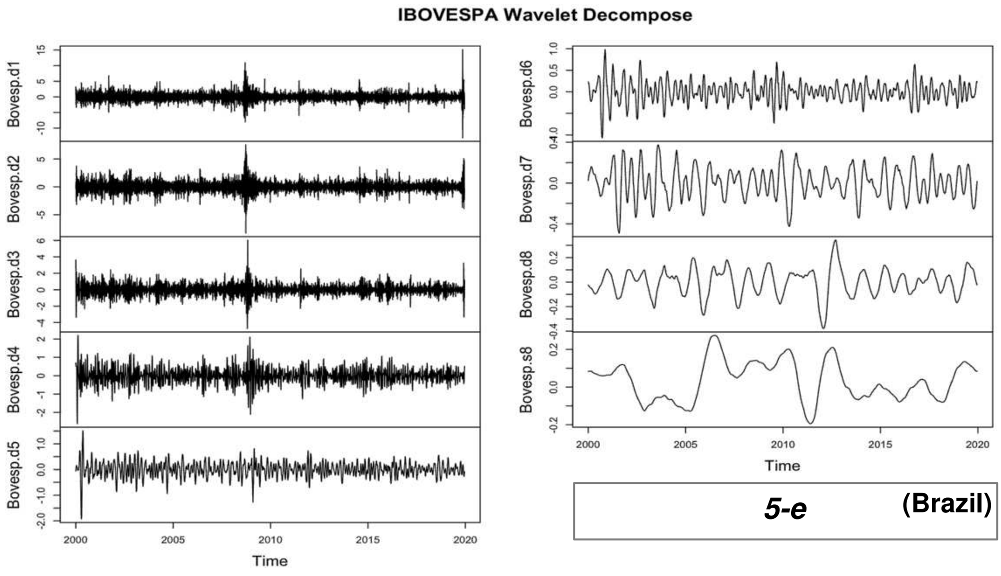
Figure 5: Continued



5-c **(Turkey)**

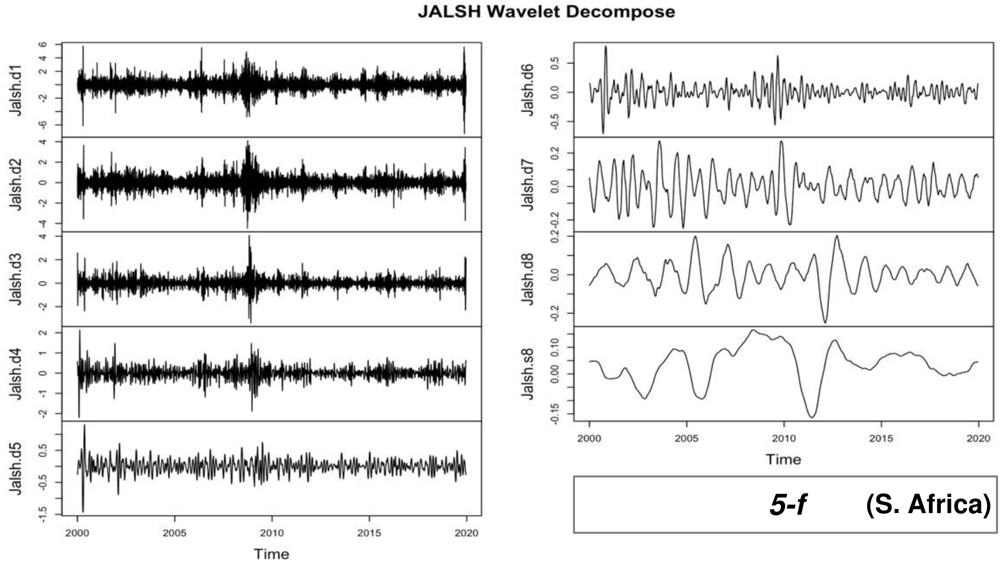


5-d **(India)**

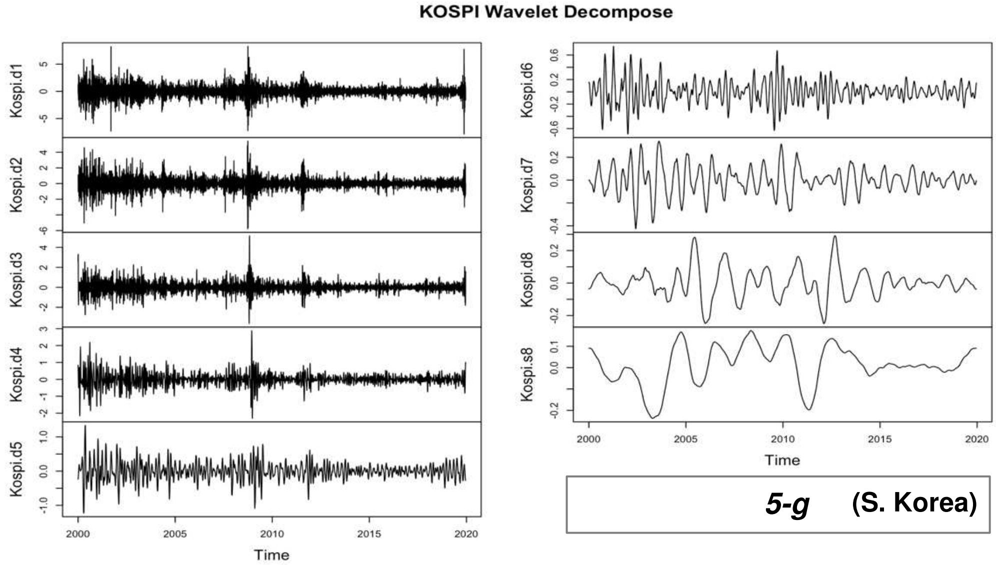


5-e **(Brazil)**

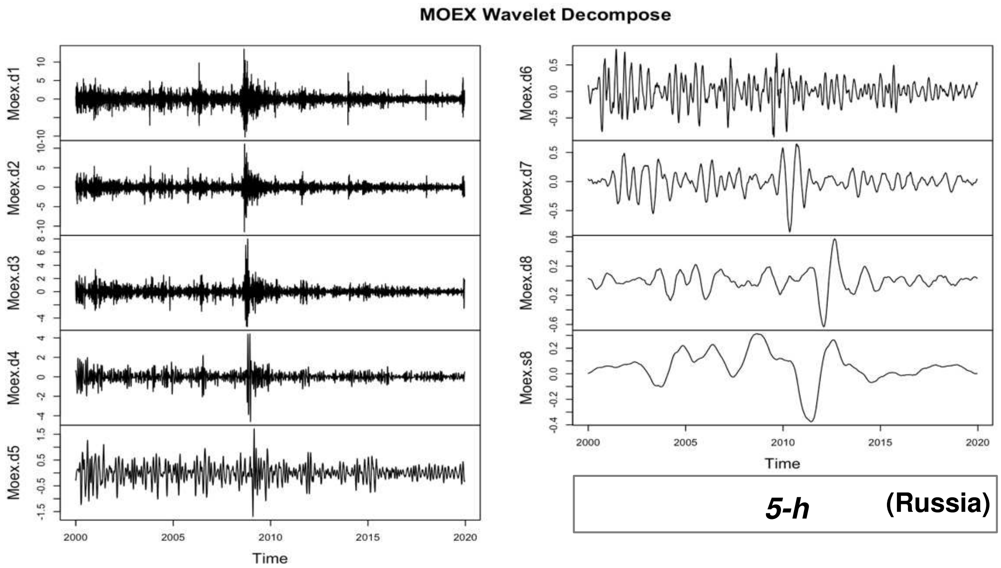
Figure 5: Continued



5-f **(S. Africa)**



5-g **(S. Korea)**



5-h **(Russia)**

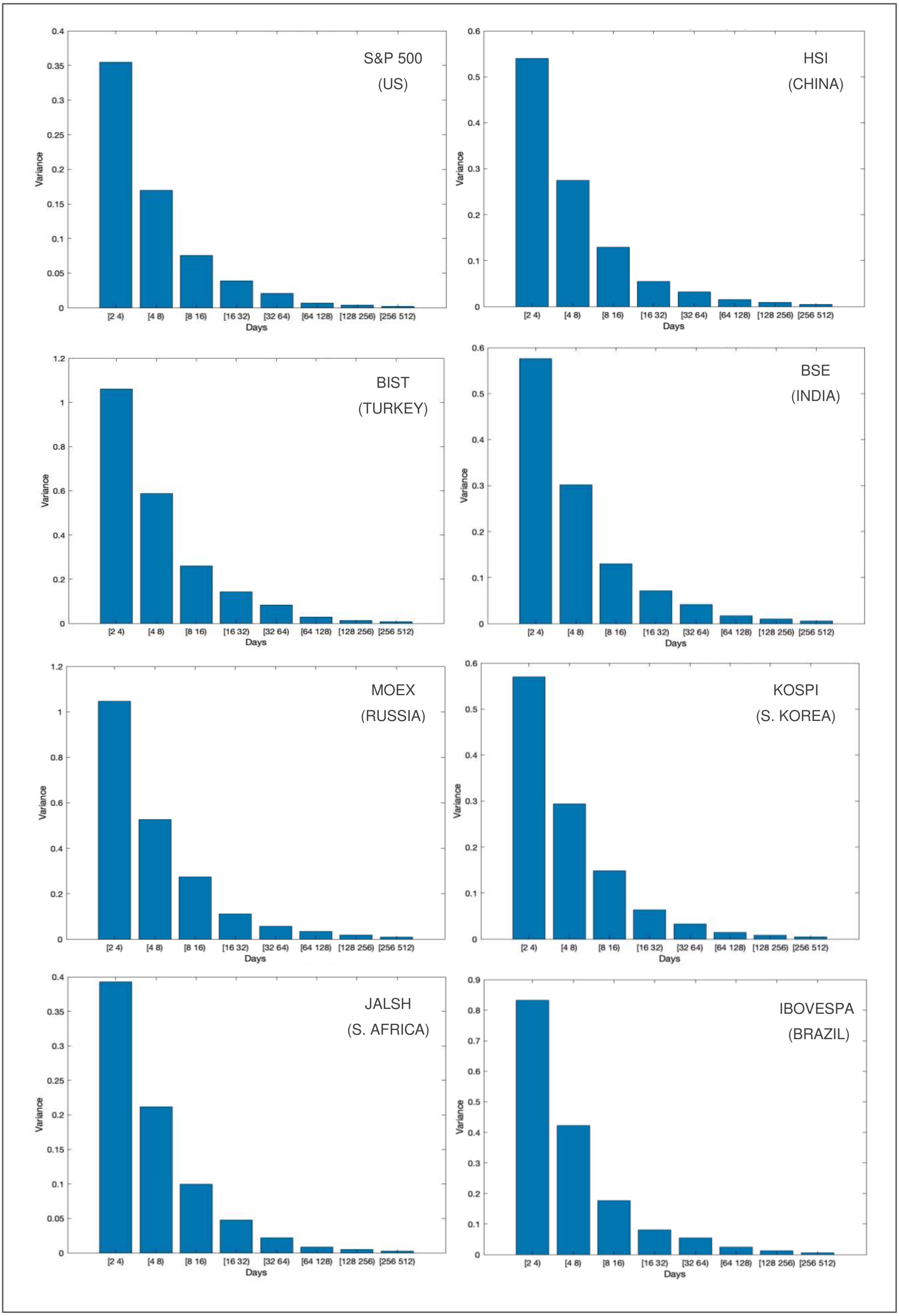
The results depicted in Figures 5a-5h are confirmed in the variance-by-scale bar plots presented in Figure 6 below[45]. A MODWT with Daubechies LA8 filter and level eight decomposition is similarly applied, as with the wavelet decomposition, to maintain uniformity and used to divide series variance by scale. In line with Figures 5a-5h, each scale is described in terms of day intervals. That is, the first scale (bar) captures a two- to four-day interval, the second captures a four- to eight-day interval, the third captures eight to 16 days, and so on. From the results depicted in Figure 6, it is evident that a significant portion of the volatility experienced in the markets is accounted for in the first two to four days, and then in the next four to eight days. That is, fluctuations in the data over a period of two to four days account for much of the variance observed in each market series, while the four- to eight-day period accounts for the next largest portion. This confirms initial findings of high frequency variance being observed in short-term scales. Notably, as the scale interval increases, the portion of volatility captured by the next interval declines, with the least variability being accounted for in the last two scales (128-256 days and 256-512 days). This observation is once again consistent with the findings depicted in Figures 5a-h in terms of lower frequencies being captured in the long-term scales. Within the context of this study, this has two implications. Firstly, it suggests that excess spillover effects are more likely to be seen in the very short run at high frequencies, resembling Rigobon's (2019) depiction of contagion. Secondly, it indicates that if contagion is present, the effects will likely dissipate over time, given that market variability observably decreases in frequency in long-term scales, as observed in Figures 5a-h and Figure 6. Thus, in the main analysis the study would expect to note a temporary effect of contagion among selected markets rather than a persistent one, as highlighted by several works, including Ranta (2010), Dungey et al. (2006), and Forbes (2012)[46].

In this regard, the use and benefit of the wavelet analysis in detecting contagious behaviour is therefore further re-emphasised by way of providing an effective means of assessing excess volatility patterns, even where these patterns are swift or quick to diminish in heteroskedastic stock market data (Ranta, 2010; Das et al., 2018).

[45] Note that the variance-by-scale is located in the study's MODWT estimation to enhance the analysis and to provide additional information in terms of volatility patterns in individual markets.

[46] See also Rigobon (2002) and Das et al. (2018).

Figure 4: Volatility-by-Scale Market Output



5.1.2 Continuous Wavelet-Transform

Although MODWT on the whole contributes to data decomposition on different levels and time scales, the ease of interpretation is limited by varying resolutions of frequency data at each level and as such requires further investigation in order to draw more insight (Sharif & Afshan, 2016). In this way, CWT is a useful component that expands the preliminary analysis by offering an augmented visual pre-processing tool which maps frequency behaviour onto a continuous wavelet power spectra (Sharif & Afshan, 2016). Therefore, in the context of this study, CWT is employed as a univariate analysis of changes in market behaviour through variations in volatility strength and comparative contributions of key elements to market variance across time-frequency scales (Sharif & Afshan, 2016; Ferrer et al., 2018). To implement CWT, the study used a Morlet wavelet with ω_0 equal to six. In accordance with various financial and economic applications of this nature[47], a Morlet wavelet with ω_0 equal to six, was selected for its capacity to provide a good balance between frequency and time localisation, while simultaneously simplifying the interpretation of the inversely related wavelet scale and frequency (Ferrer et al., 2018). The subsequent scalograms obtained were interpreted with the aid of the period-to-date guide depicted in Table 4 below.

Table 4: Period-to-Date Guide

Period	Date
1000	2004/01/01
2000	2008/01/04
3000	2012/01/24
4000	2016/02/16
5000	2020/03/09

Figures 7a-h depict the results obtained from the continuous power spectra for each market. The data patterns observed were interpreted in terms of three elements – time, frequency, and strength of variation (as implied by the colour code). Firstly, the time periods were interpreted according to the corresponding dates, as shown in the period-to-date guide in Table 4. Secondly, frequency was represented by days as indicated in Table 5 hereunder, and can also be grouped into short-term, medium-term, long-term, and very long-term periods, as in Table 3 in the MODWT section.

Table 5: CWT Time interpretation of various frequencies

[47] See Grinsted et al. (2004), Aguiar-Conraria et al. (2008), González-Concepción, Gil-Fariña & Pestano-Gabino (2012), and Aloui & Hkiri (2014) for more detail.

W_{i1}	2-4 days	Semi-Weekly scale
W_{i2}	4-8 days	Weekly scale
W_{i3}	8-16 days	Fortnightly scale
W_{i4}	16-32 days	Monthly scale
W_{i5}	32-64 days	Monthly to Quarterly scale
W_{i6}	64-128 days	Quarterly to Biannual scale
W_{i7}	128-256 days	Biannual to Annual scale
W_{i8}	256-512 days	1 to 2 years scale

Source: Author's own adaptation from Das et al. (2018).

Thirdly, the colours seen on the spectrum indicate the variation strength at any given time-frequency point, and are interpreted as per the colour bar alongside each scalogram. The red-orange colour indicates high energy or strong variation (red being stronger than orange), while the yellow-green represents medium energy or mild variation (green being milder than yellow), and the blue (light to dark) suggests low energy or low variation (dark blue being the lowest)[48]. The thick black contours (circles on the power spectra) visible around the colours represent a five percent significance level against "red noise", while the U-shaped dome indicates the cone of influence (COI), outside of which (as shown by the shaded area) edge effects may distort observations (Grinsted et al., 2004).

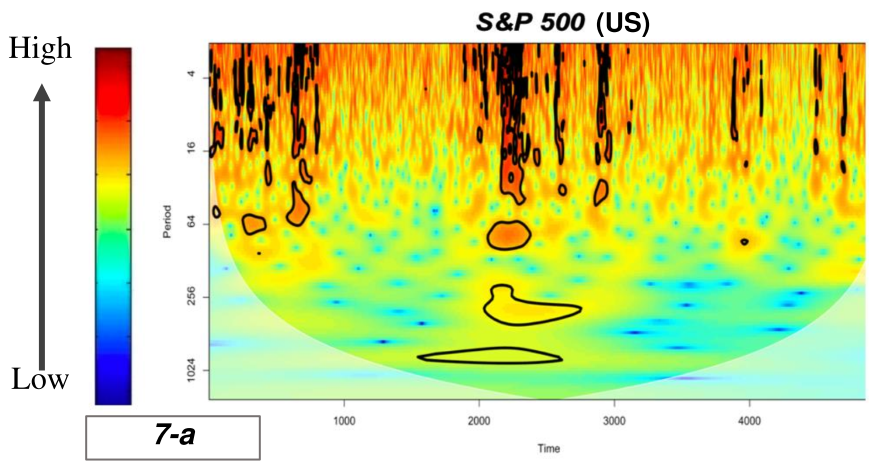
Similar to observations from the MODWT analysis, the continuous power spectra shown in Figures 7a-h below suggest significantly high variations in weekly to monthly scales (short term) during the 2008-2009 period, but more stable variations in the one-to-two- and two-to-four-year scales (long to very long term) for all selected markets. This implies the presence of short-term excess volatility during the time of crisis and confirms initial findings that contagion could be present among the studied economies. The transitions observed on the power spectra–movement from red regions of high variation in the short term to bluer regions of low variation in the long term–each further suggest that if contagion is present, the effects will likely occur momentarily, or on a temporal basis, and dissipate as the scales increase (move towards the long term). Again, this overall result is consistent with previous findings and corresponds to initial expectations. However,

[48] See Rashid, Beecham, and Chowdhury (2015) for more detail.

it can be noted that the markets each exhibit different characteristics at various points on the time-frequency plane, as highlighted by the power spectra.

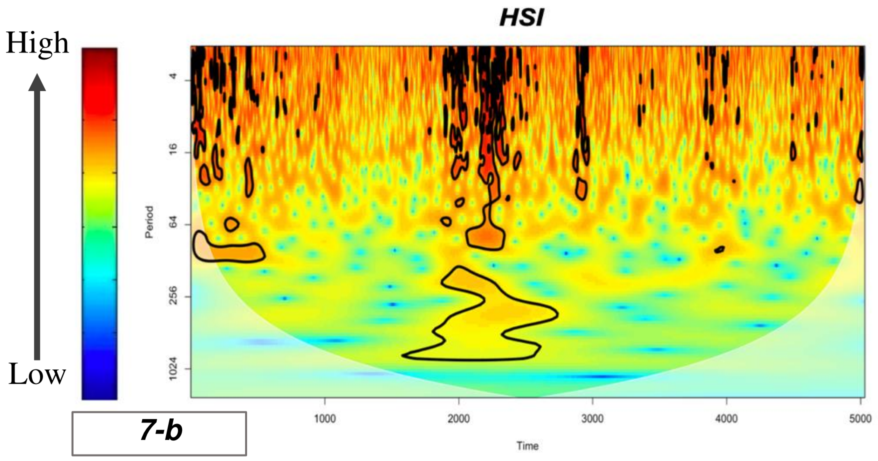
For instance, Figure 7a below displays data movements for the S&P 500 market and shows much of the significant high variation (red regions within thick black contours) movement occurring over short-term scales (weekly to monthly and in some cases quarterly). This significant short-term burst of high variation (red energy) concentrated along the 2008-2009 period indicates the negative shock to the US economy experienced during the onset of the GFC. Although much of the variation stabilised towards the long-term to very long-term periods, there appears to be significant lingering medium variation (yellow-green energy within thick black lines) into the long-term and very long-term periods of the GFC years (2008-2009). This could imply a prolonged impact of the crisis on the American market, which is to be anticipated given that it was the country of shock origin (Baily & Elliott, 2009; Gros & Alcidi, 2010). Figure 7b suggests similar evidence for the Chinese market in terms of significant short-term bursts of high variation (red energy) during the GFC period, equally denoting possible contagious effects between the two markets after initial shock to the US. Another look at Figure 7b reveals that the medium power variations along the one-to-two-year and two-to-four-year scales (near the bottom of the spectrum) extend across a larger area than the corresponding portion observed in the US market. This could imply a larger long-term impact and possibly strong influence of US market movements on Chinese stock markets.

Figure 5: Continuous Wavelet Power Spectra Output



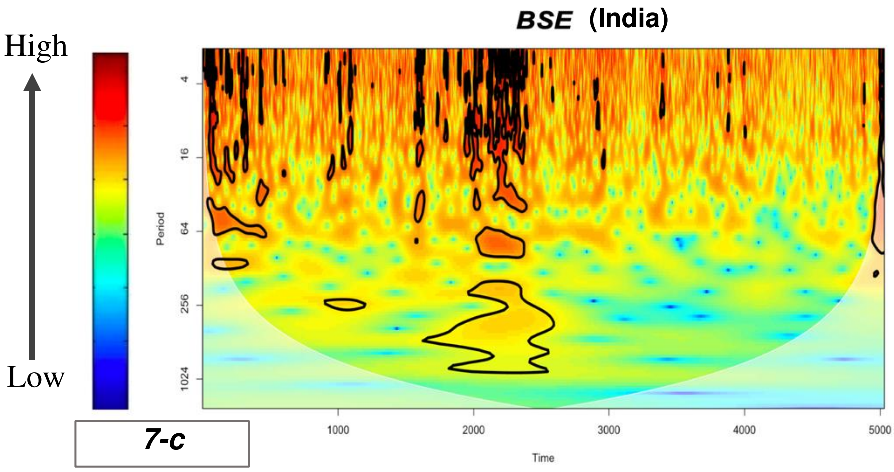
The thick black contour denotes 5% significance level, while the colour code ranges from ***low power (blue) to high power (red).***

(China)



7-b

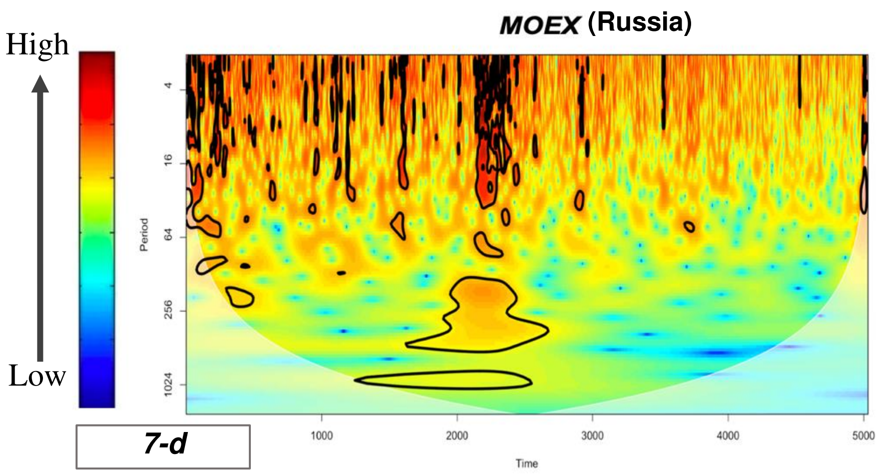
The thick black contour denotes 5% significance level, while the colour code ranges from ***low power (blue)*** to ***high power (red).***



7-c

The thick black contour denotes 5% significance level, while the colour code ranges from low ***power (blue)*** to ***high power (red).***

Figure 7: Continued

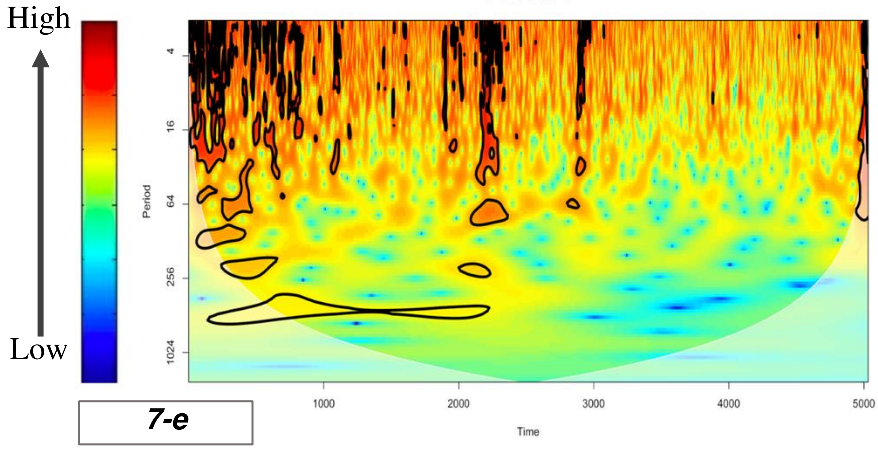


7-d

The thick black contour denotes 5% significance level, while the colour code ranges from ***low power (blue)*** to ***high power (red).***

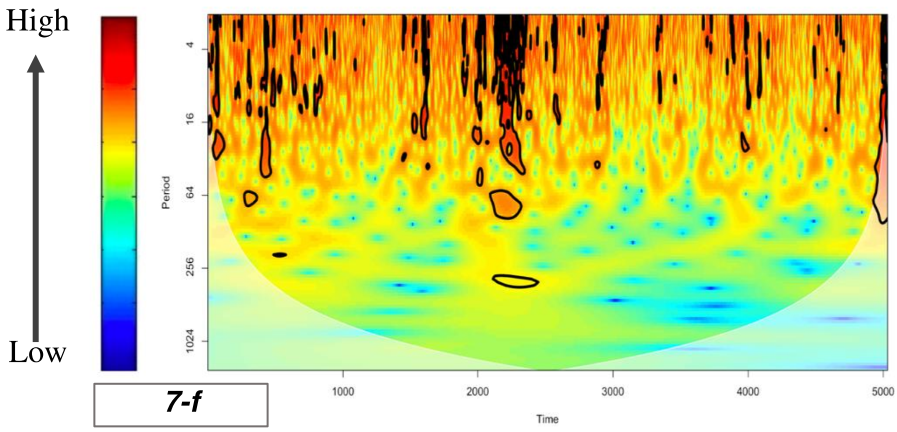
(S. Korea)

KOSPI



The thick black contour denotes 5% significance level, while the colour code ranges from ***low power (blue)*** to ***high power (red)***.

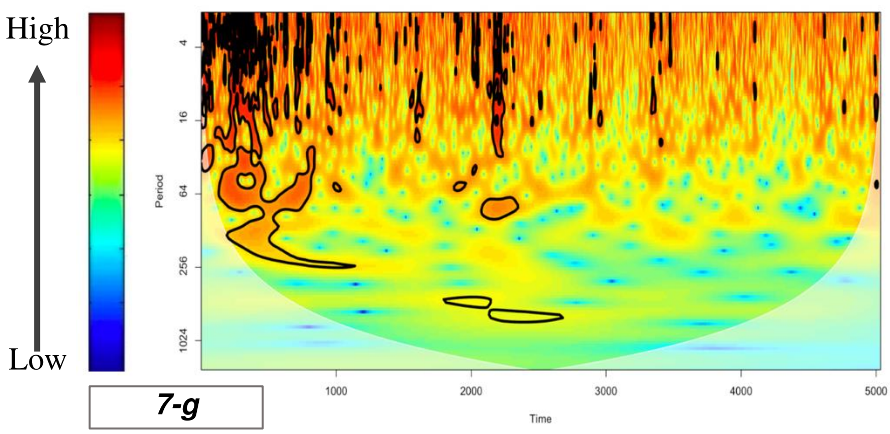
***JALSH* (S. Africa)**



The thick black contour denotes 5% significance level, while the colour code ranges from ***low power (blue)*** to ***high power (red).***

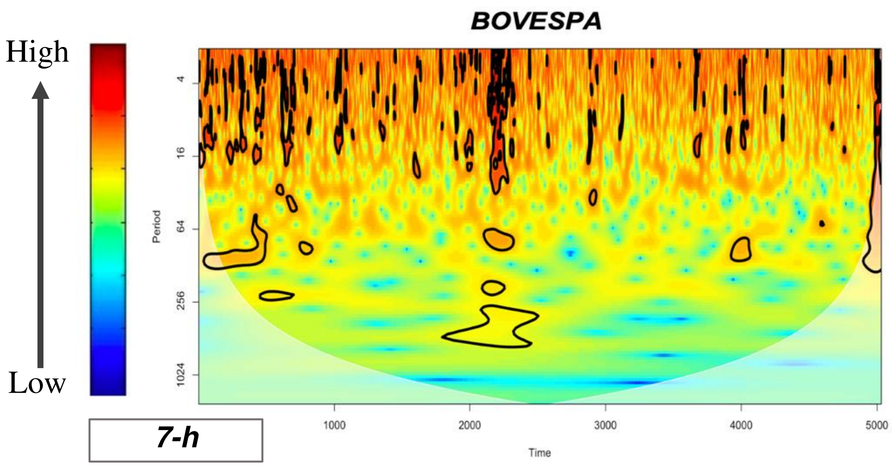
Figure 7: Continued

***BIST* (Turkey)**



The thick black contour denotes 5% significance level, while the colour code ranges from ***low power (blue)*** to ***high power (red).***

(Brazil)



The thick black contour denotes 5% significance level, while the colour code ranges from ***low power (blue)*** to ***high power (red).***

In Figure 7g the Turkish market shows a larger area of significant high variation over the 2000-2004 period than during the time of GFC. Additionally, although there is some significant high variation in the short-term scale, the long-term scale reveals less medium power variation in the Turkish market than is the case for most other markets[49] (with the exception of South Africa, which shows the least medium variation on this scale during the GFC period). Following the implementation of an IMF engineered "exchange rate-based disinflation program", the Turkish economy experienced a severe crisis in November 2000 and again in February 2001 (Yeldan, 2008; Irem, 2013). In addition to previous crises, the 2000/2001 crisis forced the country to establish stabilisation programmes, tighten financial regulations, and better manage macroeconomic factors (Terzi, 2010; Irem, 2013). This, coupled with limited exposure to the US subprime mortgage housing market that triggered the GFC, could explain why high variation during 2008 is lower than the high variation observed in the market during the 2000-2004 period in the medium- to long-term scales as the country slowly recovered from years of economic slump (Yeldan, 2008; Terzi, 2010). For the Asian emerging markets, India (Figure 7c) is observed as behaving in much the same way as China, while South Korea (Figure 7e) shows more significant high variation in the short- to long-term scales during the early 2000s than at the time of the GFC. Much like Turkey, South Korea experienced an economic downturn during the 2000-2001 period. However, the country's crisis was triggered by the 1997-1998 Asian crisis, along with North-South Korea tensions, among other socio-political challenges that collectively exacerbated and prolonged the effect of the Asian crisis on the South Korean economy (Ha, 2002; Nam, 2008). Notably, policy reforms and programmes implemented after this period better prepared the country for future crises, and could explain why the reduced area of high variation was observed the time of the GFC,

[49] This result is similarly observed in the Descriptive Statistics and explains initial evidence of high volatility in the Turkish market.

as in the case of Turkey (International Labour Organization (ILO), 2011). In Figure 7d, a similar observation can be made for Russia as with China and India. According to Gaddy & Ickes (2010), among other factors, Russia's heavy reliance on resource rents (along with capital flight triggered during the GFC) limited the effectiveness of pre-existing measures meant to manage a crisis. As a result, the substantial impact of the GFC on the country could explain the strong and prolonged effects on volatility in terms of the slightly high variation observed during that time. On the other hand, Figure 7f shows series movement in the South African index, and highlights significant high variations in the weekly to quarterly scales (short- to medium-term) during the GFC period. However, in the long-term scale the significant variation is further reduced, with no significant variation in the very long-term scale. This result is expected given that at the time, the South African market was well regulated and had limited exposure to US subprime mortgages. However, it did suffer the short-run impact of the GFC on global capital movements and consumer spending, explaining the significant high variations observed in the weekly to monthly scales (Madubeko, 2010). Series movement for the Brazilian index (shown in Figure 7h) indicate similar behaviour to the US market depicted in Figure 7a, albeit to a lesser extent, indicating a possible correlation between the two markets.

Altogether, the preliminary analysis suggests the possible presence of shift-contagion among selected markets. From the MODWT, the study established that high frequency variations are typically observed in short run scales before moving to lower frequencies as the scales increase. As such, contagion effects are expected to yield a larger impact over short-run periods before disappearing in the long-run. A CWT assessment of the data provides further insight into series behaviour at various scales, periods of time, and strength of variation, and reveals possible distinctions in contagious impact that are better addressed in the next section.

5.2 Principal Framework

In order to establish the presence of cause-and-effect relations or the extent of shock spillovers between emerging and source markets and to fully tackle the research study's objectives, a WTC is included in the analysis (Raza, Sharif, Wong & Karim., 2017). That is, although MODWT and CWT provide very useful insight into market behaviour through volatility patterns, WTC answers the question of whether or not contagion is indeed present and distinguished from interdependence, while also accounting for the causality direction. The estimation, output, and interpretation of the WTC for market pairs are presented in this section.

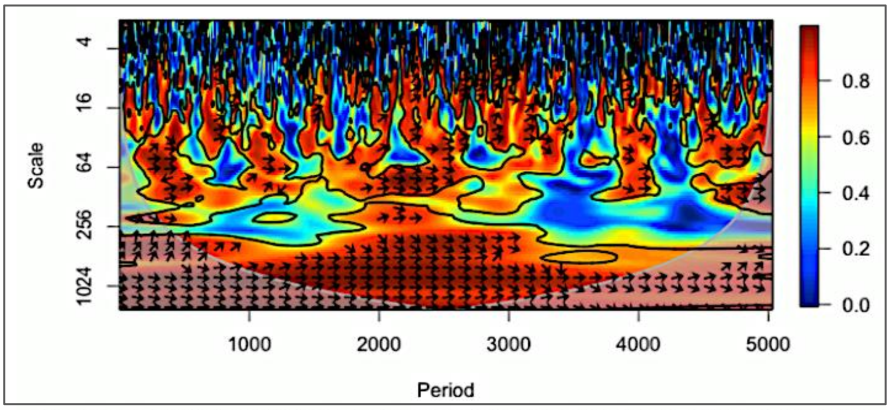
5.2.1 Wavelet Coherence

In this final step of wavelet analysis, this research study estimates WTC between different market pairs using XWT and phase differencing (arrows) for added ease of analysis. The results obtained are presented in Figures 8, 9a-f and 10a-f in this section. In these figures, the colour bar denotes the degree of interdependence between the selected market series, with red reflecting a very strong degree and blue reflecting a very weak one. Subsequently, a red area at the top of the WTC plot signifies strong interdependence at high frequencies, while a red area at the bottom of the plot suggests strong interdependence at low frequencies (see the legend to the right of each figure). Given that the WTC is interpreted in terms of interdependence, the study notes contagion as a very strong WTC at high frequencies over short-term periods, and interdependence as a very strong WTC at lower frequency over long-term periods, consistent with Ranta (2010) and Rigobon's (2019) description of each notion[50]. The relationship between the two source markets is discussed first, and then their individual influence on respective emerging markets is outlined. Table 3 in the previous section is used for frequency interpretation, while Figure 3, under the methodology, provides an arrow (phase difference) guide.

a) US–China Market Co-movement

Figure 6: Wavelet Coherence Output (S&P 500 and HSI)

(US and China)



Period	Date
1000	2004/01/01
2000	2008/01/04
3000	2012/01/24
4000	2016/02/16
5000	2020/03/09

Note: **thick black contour denotes 5% significance level against the red noise, while the colour code ranges from low power (blue) to high power (red). Arrows show nature of causality and correlation.**

Figure 8 shows the WTC between the US and Chinese stock markets. A wide area of significant interdependence is observed at low frequencies in the COI between both markets, suggesting a long-term relationship. There further appears to be significantly strong co-movement at high frequencies (over the short- to medium- term) during the crisis period, indicating contagion rather than interdependence between S&P 500 and the HSI at that time, and confirming earlier findings

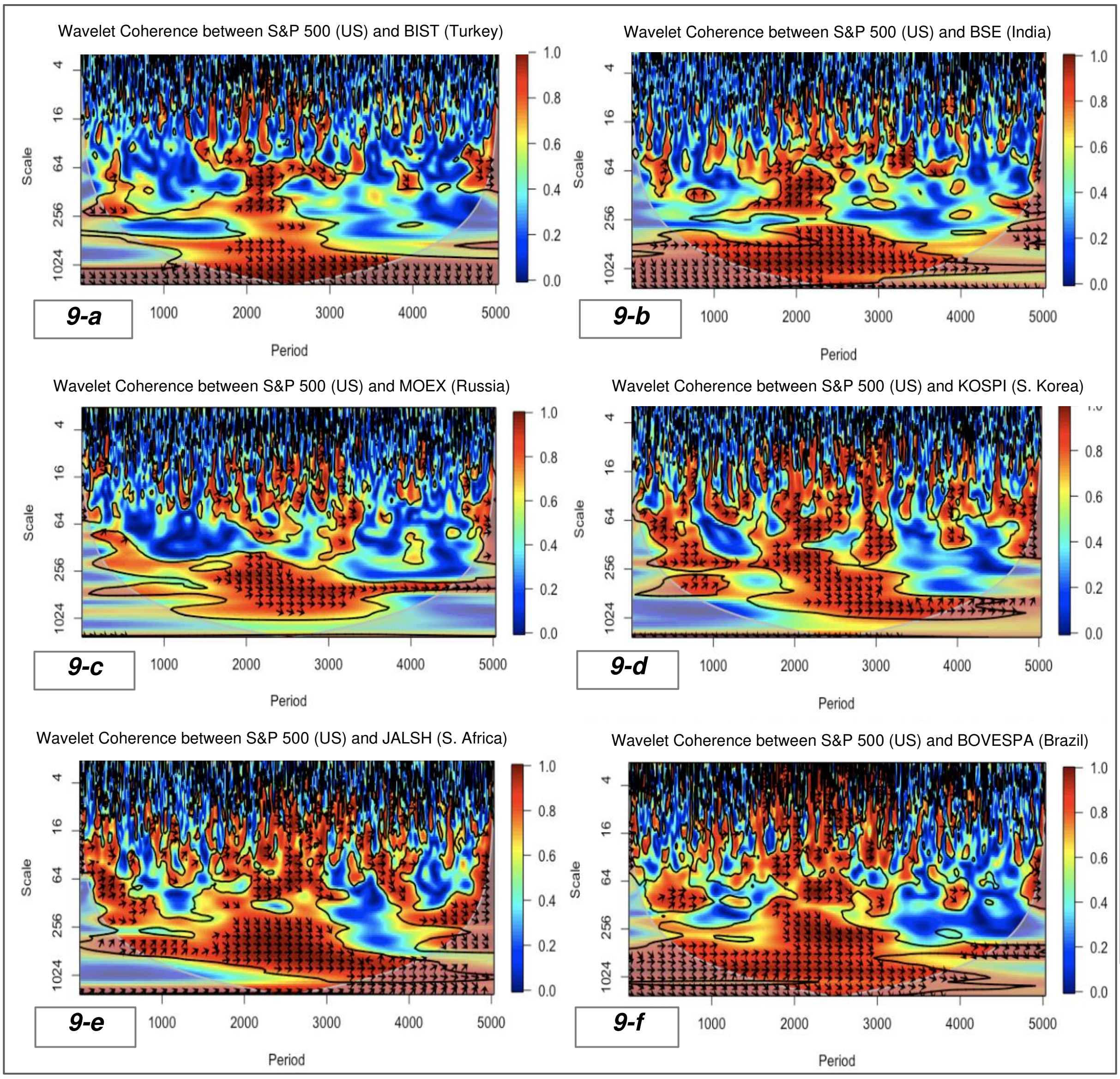
[50] See also, Bodart & Candelon (2009) as well as Saiti et al. (2014).

in the preliminary analysis. A look at the phase differences reveals that the arrows appear to be in-phase, pointing to the right-down at lower frequencies and to the right-up at higher frequencies. This indicates that in the short term (in the two to 32-day scales), the positive correlation between the two markets is led by the US market, but in the long term (256 to 512-day scale) the positive correlation is led by China. This short-term result is expected, given that US stocks tend to positively influence Chinese stocks in terms of investor sentiment and capital movement (Shu, He, Wang & Dong, 2015). As such, a negative shock in the US market would likely result in a negative effect on Chinese market movements in excess of existing interdependence over the short term (contagion). However, in the long term, this relationship is reversed, that is, China leads and has a causal effect on US markets. China is one of the US's largest commercial partners, with total trade between the two countries estimated at roughly $660 billion in 2018 (Morrison, 2018). It is also the largest external holder of US Treasury securities, and continues to be a key manufacturer for several US firms (Morrison, 2018). Thus, it is expectable that changes in the Chinese economy (as hinted in equity movements) are likely to have long-term implications on US stock market movements as observed above. Generally, regardless of which market leads, it is evident that American and Chinese stocks move in the same direction (have a positive relationship) over short- and long- term periods. Whereas, in the very long-term, the markets show in-phase co-movement, but no causal relationship. This suggests that over very long scales (more than two years) the correlation between the two cannot be attributed to one or the other, with neither market leading, even though both continue to be significantly interdependent.

b) US–Emerging Markets Co-movement

Figures 9a-f highlight significantly strong co-movement of the US with each selected market at high frequencies (short- to medium-term) during 2008-2010. Once again this confirms the presence of contagion triggered by the GFC, originating from the US at that time. The US-Brazil and US-South Africa WTC spectra each reveal wide areas of significant strong interrelations in low frequency scales, as shown in Figures 9e and 9f. This is distinguished as interdependence in each case for long- and very long-term periods. In both instances, the phase difference indicates the arrows being in-phase and pointing right-down, suggesting positive, US lead co-movements for each pair. In the case of South Africa, this result (significantly strong long-term correlation lead by the US) is expected, given the country's bilateral (economic and political) ties with the US, which is a major trading partner. In the short-term, strong trade and financial linkages could also explain the transmission of contagion effects through investor behaviour and reduced consumer spending (Heymans & Da Camara, 2013). Notably, although tough regulations and limited exposure to US subprime mortgages mitigated the overall effect of the crisis on the country (as observed in Figure 7f in the CWT analysis), its impact was still experienced through various channels, and could explain the patterns observed in Figure 9e (Heymans & Da Camara, 2013). Similarly, direct financial and trade linkages provide the basis for observed short-term contagious effects and the long-term positive correlation (interdependence) between Brazil and the US in Figure 9f in the output (Cooney & Marquez, 2016).

Figure 7: Wavelet Coherence Output (S&P 500 and Emerging Markets)



Period	Date
1000	2004/01/01
2000	2008/01/04
3000	2012/01/24
4000	2016/02/16
5000	2020/03/09

Period	Date
1000	2004/01/01
2000	2008/01/04
3000	2012/01/24
4000	2016/02/16
5000	2020/03/09

Period	Date
1000	2004/01/01
2000	2008/01/04
3000	2012/01/24
4000	2016/02/16
5000	2020/03/09

Note: thick black contour denotes 5% significance level against the red noise, while the colour code ranges from low power (blue) to high power (red). Arrows show nature of causality and correlation.

In Figure 9b the spectrum highlights a significantly strong correlation at high frequency (mostly in the medium-term) that extends towards low frequency scales during the 2008-2010 period between the US and India. This indicates contagious effects over the short run, as previously implied in the preliminary analysis, as well as long-standing interdependence throughout the sample period.

Although the initial impact of the crisis may have been somewhat weakened due to limited exposure to subprime lending in the US, investor behaviour, decreased liquidity, and general uncertainty accounts (among other things) for the severity of impact in its second wave, which could explain the wider area of significantly strong correlation in the medium term rather than in the short term (Vidyakala, Madhuvanthi & Poornima, 2009; Arunachalam, 2011). Furthermore, pre-existing political and economic ties between India and US provide the basis for observed long-term interdependence (Lane & Schmukler, 2007; Cesa-Bianchi, Pesaran, Rebucci, Xu & Chang, 2012).

In Figures 9a and 9c significantly strong co-movement at high frequencies is equally observed through the 2008-2010 period, signifying contagious effects on the Turkish and Russian markets, respectively. Interestingly, however, these figures (9a and 9c) show smaller areas of significantly strong correlation with the US in comparison to other market pairs in the medium to long term. While the Turkish market is vulnerable to external shocks, particularly those emanating from the US, pre-existing policy measures lowered the initial impact of the crisis in the short term, as highlighted in the preliminary analysis. Whereas in the long term, returns have typically been more heavily influenced by an aggregate of domestic and regional factors rather than international elements (Tiryaki & Tiryaki, 2019). Although international factors, such as US policy uncertainty, do influence Turkish markets, the combined effect of various other factors generally contributes more to market behaviour and could explain the comparatively lower correlations observed over the long term (Tiryaki & Tiryaki, 2019). For Russia, a heavy reliance on resource rents, coupled with capital flight triggered by uncertainty during the 2008-2009 period, explain the delayed but intense impact of the crisis in the medium term (Gaddy & Ickes, 2010). In the long term, the importance of macroeconomic factors on market performance increase, and could further explain the smaller area of significantly strong correlation that appears to shrink across the sample period (Goriaev & Zabotkin, 2006; Gaddy & Ickes, 2010).

Figure 9d shows the WTC between the US and Korean markets and suggests similar behaviour to that in South Africa and Brazil. However, in the short term, the positive relationship is led by Korea, while in the long term it is led by the US. This short-term outcome can be explained by the strong driving influence of domestic and regional factors on market movements, as well as the country's general preparedness, which reduced the crisis's initial impact (ILO, 2011). In the long term, a general US-lead interdependence is observed which could be explained by various trade, financial, and political linkages (Arouri et al., 2010; ILO, 2011).

c) China–Emerging Markets Co-movement

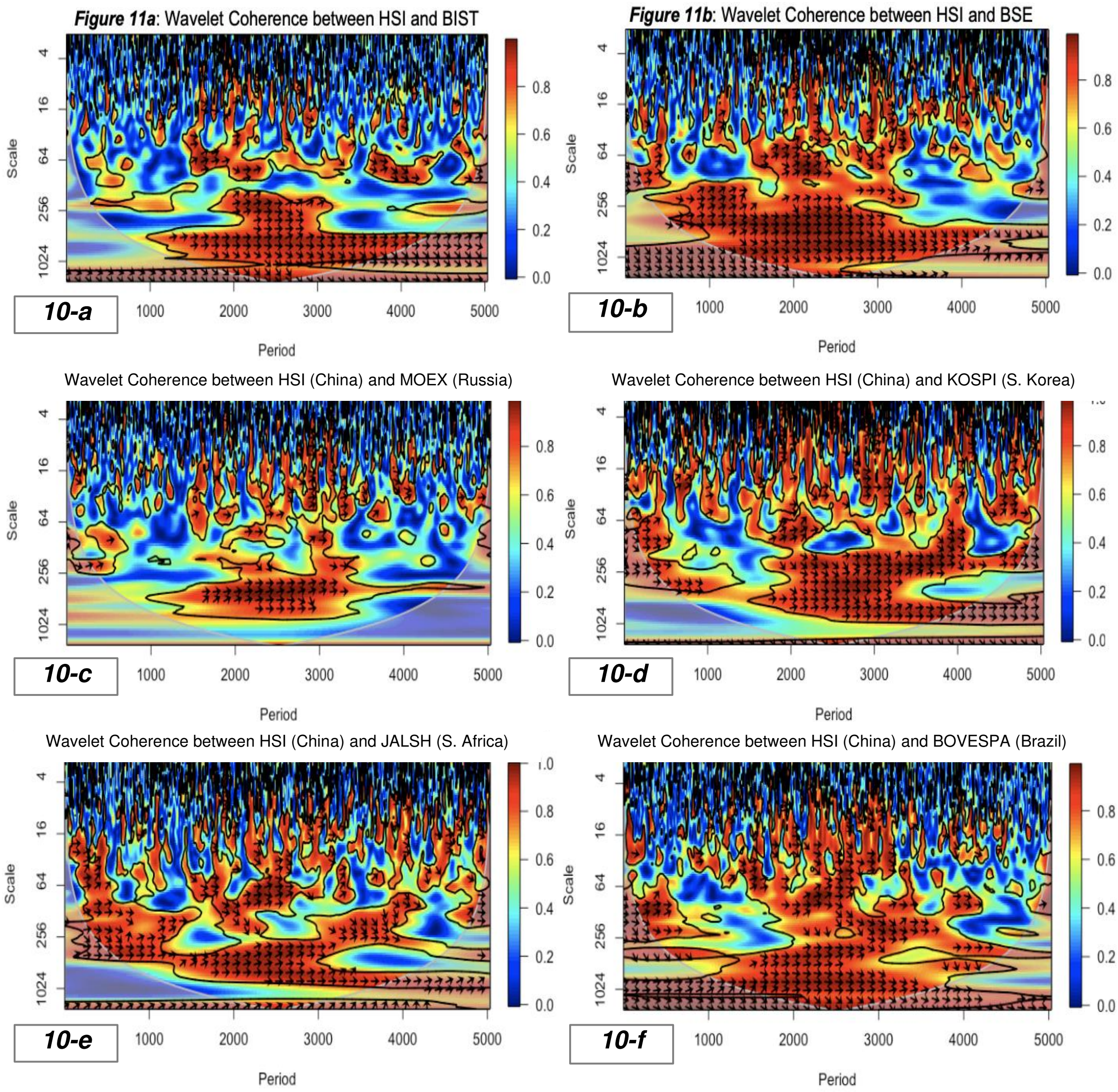
Figures 10a-f show the WTC between China and selected emerging markets. In this regard, countries such as South Korea and Turkey (depicted in Figures 10d and 10a, respectively) display comparatively wider areas of significantly strong correlation with the Chinese market than the US at low frequency scales in the COI. At higher frequencies, Korea shows several areas of significantly strong positive correlation with the Chinese market throughout the sample period, whereas the Turkish-Chinese market co-movement is more substantial in the medium-term scale. In both instances, the emerging market leads in the short to medium term at higher frequencies, while China leads in the long-term at lower frequencies. Again, this result could be explained by the stronger influence of changes in domestic macroeconomic factors over international factors on market behaviour in the short term, whereas long-term co-movement patterns lean more towards the influence of global elements (Goriaev & Zabotkin, 2006; Arouri et al., 2010; ILO, 2011; Tiryaki & Tiryaki, 2019; Chen et al., 2020)[51]. Notably, in the medium term, Turkey similarly indicates a slightly greater area of significant strong correlation with China than with the US. This result in both the short- and long- term for either country can be explained by the growing regional influence of China mainly through trade linkages and, to a lesser extent, increasing financial ties (Shu et al., 2015; Sznajderska, 2019). Although the 2008/2009 GFC originated from the US, empirical evidence suggests that negative shocks to the Chinese economy–both real and financial, have had a strong impact on many emerging countries, particularly its trade partners (Nicolas, 2009; Lavi & Lindenstrauss, 2016; Huang et al. 2019; Sznajderska, 2019). For example, in Korea, tightening trade and investment relations with China since the late 1990s have left the country more dependent, and thus more vulnerable to shocks in the Chinese economy, particularly during the GFC (Nicolas, 2009; Shu et al., 2015; Sznajderska, 2019). This could explain the strong short- to medium-term high frequency co-movement (contagion), as well as the strong long-term low frequency co-movement (interdependence) observed in ***Figure 10d*** below.

Figure 8: Wavelet Coherence Output (HSI and Emerging Markets)

Wavelet Coherence between his (China) and BIST (Turkey)

Wavelet Coherence between HSI (China) and BSE (India)

[51] According Piljak's (2013) study on co-movement dynamics of frontier/emerging and developed financial markets, macroeconomic fundamentals can explain changes in co-movement at different frequencies and time horizons. Particularly, in the short-term domestic macroeconomic elements typically hold greater influence of stock return co-movements than global factors.



Period	Date
1000	2004/01/01
2000	2008/01/04
3000	2012/01/24
4000	2016/02/16
5000	2020/03/09

Period	Date
1000	2004/01/01
2000	2008/01/04
3000	2012/01/24
4000	2016/02/16
5000	2020/03/09

Period	Date
1000	2004/01/01
2000	2008/01/04
3000	2012/01/24
4000	2016/02/16
5000	2020/03/09

Note: thick black contour denotes 5% significance level against the red noise, while the colour code ranges from low power (blue) to high power (red). Arrows show nature of causality and correlation.

In terms of Brazil, the WTC in Figure 10f suggests a similar outcome in China and the US. That is, a strong positive significant co-movement exists in different scales, generally lead by China during the 2008-2010 period and beyond. In high frequency scales, this observed result indicates contagious effects, most likely caused by indirect spillovers from shocks to China's real economy during the GFC[52] (Cesa-Bianchi et al., 2012). In the long- term, the observed behaviour is indicative of pre-existing interdependence. However, a closer look at Figure 10f reveals a wider area of significantly strong co-movement in medium- to long-term scales after 2010, possibly

[52] Specifically, shocks to China's GDP have had a growing indirect influence on Brazilian market movements since the mid-1990s (Cesa-Bianchi et al., 2012).

highlighting continued indirect and, to a lesser extent, direct effects on Brazilian markets from real side movements in China's economy (Cesa-Bianchi et al., 2012; Sznajderska, 2019).

For South Africa, Figure 10e indicates significantly strong positive interdependence at the beginning of the sample period, generally lead by the South African market in the medium frequency scale, and then by China in lower frequencies. The overall area of significantly strong correlation is smaller in the China-South Africa coherence than it is in the US-South Africa case. Furthermore, high- to medium-scale significantly strong correlations were evident throughout much of the sample period, albeit to a lesser extent than those observed in the US market. These results are likely attributable to trade relations between South Africa and China, which have typically affected investor sentiments and had an increasing influence on real economic activity over time, even though US market movements continue to have a relatively stronger impact (Lamba & Otchere, 2001; Chinzara & Aziakpono, 2009; Heymans & Da Camara, 2013). Conversely, in Figure 10c, Russia shows more areas of significantly strong co-movement in the short to medium term than in the long term where positive interdependence is mainly centred around the 2008-2014 period, after which it begins to fade. A possible explanation for this could be that because China is one of Russia's largest importers of oil and gas, shocks to the Chinese economy would have strong short-run indirect implications for Russian markets in terms of investor sentiment, given the country's heavy reliance on resource exports and prices (Sznajderska, 2019). However, in the long term, falling trade volume between the two countries after the GFC could explain the declining degree of interdependence post 2014 (Solomentseva, 2014; Malle, 2017). Moreover, weaker trade relations and competitive patterns have hampered potential commercial partnerships that could have led to significant interdependence over time, further explaining the observed decline in correlation (Solomentseva, 2014; Malle, 2017).

In the instance of India, Figure 10b illustrates a significantly strong positive co-movement lead by India, mainly in the medium-frequency scales during 2008-2010, while strong-significant positive co-movement is observed in low-frequency scales for much of the sample period. A possible reason for this could be the delayed impact of indirect effects triggered by the GFC from China to India. Essentially, both countries have strong economies and compete to be the Asian region's leading manufacturing and service destination, respectively (Lane & Schmukler, 2007; Cesa-Bianchi et al., 2012). Thus, it is more than likely that movements in China's markets could be indirectly affected by changes in India's real economy, particularly due to the country's level of global integration and strong ties with the US which strengthen its position in the region (Lane &

Schmukler, 2007; Cesa-Bianchi et al., 2012; Sznajderska, 2019). Although both countries move in the same direction, in the long term, generally no causal relationship is observed - as can be expected given the nature of India and China's economic interactions (Sznajderska, 2019).

5.3 Discussion of Results

The results obtained throughout the entire framework offer valuable insight into volatility patterns as well as the behaviour of shift contagion between selected markets. Significant spikes in volatility are distinctly observed in the wavelet decompositions in the short term throughout the crisis period at high frequencies for each market series. Using variance by scale, the study confirms that high frequency variation occurs more in the short to medium term, while low frequency variation is evident in the long-term. This is in accordance with Campbell & Viceire (2002, 2005) and Siegel's (2008) research which highlight that stock market returns are often more volatile in the short-run horizons than in the long-run horizons, based on the concept of mean-reversion among returns. The MODWT variance by scale analysis further indicates that contagious effects are likely to be seen as momentary observations (the first 2-32 days), before dissipating across longer horizons (256 days or more). The CWT establishes these findings and concur with Rigobon (2002), Ranta (2010), Albulescu et al. (2017), and Das et al.'s (2018) findings, highlighting the significance of wavelet analysis in the context of contagion studies as an effective tool to capture swift changes in volatility in terms of both time and frequency levels. The analysis (CWT) additionally highlights that where contagion is present, these effects may vary across markets during the crisis period due to the presence of numerous factors, including initial preparedness, existing trade and financial linkages, and socio-political factors. Particularly, in addition to the limited exposure to subprime lending in the US, initial preparedness by way of existing domestic macroeconomic policy, regulation, and stabilisation programmes appears to have played a vital role in curtailing the primary impact of crisis spillover in selected emerging economies in terms of market volatility. The WTC results confirm these findings, and provide greater insight into co-movement dynamics between market pairs before, during, and after the GFC.

As with the preliminary analysis, variations in volatility patterns across different time horizons were observed and re-emphasised in the WTC. A clear distinction is evident between strong short-term high frequency interdependence during the crisis period, and strong long-term low frequency interdependence throughout the sample for each market pair, the former being indicative of shift contagion and the latter indicating interdependence, according to Rigobon (2019) and Ranta's (2010) descriptions of each phenomena. Consistent with CWT output, the WTC spectra reveals variations in the strength of the contagious impacts on each emerging market, with prepared markets experiencing the least (delayed) impact at the onset of the crisis. The spectra also indicate wider areas of strong long-term coherence at low frequencies between the China-Turkey, China-India and China-South Korea pairs in comparison to the corresponding US case. Conversely, the US presents wider areas of strong long-term coherence at low frequencies with Brazil, South Africa, and Russia, than China does for the same markets. This observation could be ascribed to strong bilateral ties in the form of trade, financial linkages, or political relations, and indicates the significance of regional or international factors in long-term co-movement dynamics (Goriaev & Zabotkin, 2006; Arouri et al., 2010; Piljak, 2013).

In both the US and China market pairs, the phase differences reveal positive co-movement led by emerging markets in high frequencies in the short run, and then by source markets in low frequencies in the long run. This suggests that in high frequencies in the short-term, domestic macroeconomic factors show stronger impacts over market volatility or co-movement, whereas once again, international factors are seen to have more impact over the long-term horizons at lower frequencies (Goriaev & Zabotkin, 2006; Arouri et al., 2010; ILO, 2011; Tiryaki & Tiryaki, 2019; Chen et al., 2020). Evidence also suggests the US's continuing influence on emerging market economies, particularly in financial terms, through capital flows and effects on investor sentiment. Although this strength seems to have remained unchanged over time and stronger during crisis periods, China's rising significance is observed in most of the selected emerging markets (Chinzara & Aziakpono, 2009; Heymans & Da Camara, 2013; Shu et al. 2015; Sznajderska, 2019).

In essence, spillovers from shocks to the real side of the Chinese economy have grown significantly in recent years, extending beyond Asian markets to several emerging economies, specifically commodity exporters (Adrian & Rosenberg, 2008; Cesa-Bianchi et al., 2012; Shu et al. 2015; Sznajderska, 2019; Chen et al., 2020). Beyond China's traditional role in global trade and supply chains, increasing financial liberalisation and assimilation of the renminbi into world financial systems has further added to the country's influence and overall economic prominence (Adrian & Rosenberg, 2008; Ahmed & Huo, 2018; Huang, Huang & Wang, 2019; IMF, 2019). For instance, according to Morrison (2013) and Sznajderska (2019), turbulence in Chinese stock markets has been found to have significant negative effects on emerging market movements, as well as their currencies. As such, for the modern international investor or emerging economy policy-maker, it would be considered necessary to account for China's effect on different individual emerging economies.

Ultimately, the study established that while individual emerging markets are likely to share some similarities, the dynamics of market volatility patterns and the impact of contagion between them may indeed vary, based on pre-existing domestic conditions as well as the nature of the shock source. As with Das et al. (2018), the study established that emerging markets do not behave as a homogenous block, but acknowledges that they are also influenced by a number of factors beyond regionally shared attributes.

5.4 Robustness Test

This research study ran a wavelet correlation in order to establish robustness in terms of the results obtained from the main framework. Given that wavelet correlation offers an alternative bivariate technique which determines whether or not correlation coefficients vary significantly after crises (signalling contagion and establishing the subsequent direction of change experienced by each market), the method is applied to test the strength of this research study's observations. In line with several economic and financial applications of this nature, the MODWT estimator with LA8 filter and a length of decomposition equal to eight is adopted as a suitable, reliable, and widely used filter to assess the wavelet correlation (Gençay et al., 2001; Gallegati & Gallegati, 2005; Dajcman et al., 2012; In & Kim, 2012; Bernard & Nyambuu, 2016; Das et al., 2018). The results obtained for all market pairs are presented in Figures 11 and 12. The blue lines denote the upper and lower bounds at a 95% confidence interval, respectively, while the x-axis indicates the wavelet scales as described in Table 1, and the y-axis indicates the level of wavelet correlation.

Figure 11 confirms results observed in the main framework for US-emerging market pairs, that is, a strong positive correlation was observed in each market in the long-term scales, particularly for the US-South Africa and US-Brazil pairs, as previously noted. Sharp increases in correlations are also noted in the US-Turkey and US-Russia pairs in the monthly scales, confirming earlier observations of a delayed reaction in the two emerging markets during 2008. A sharp decline in correlation is further observed between the US and Brazilian markets in the monthly to quarterly scales, while short-run correlations appear comparatively higher in comparison to other pairs. This could indicate unexpected movements triggered by investor sentiment and uncertainty during the GFC (Cooney & Marquez, 2016). As such, strong relationship can be concluded between the two markets. Conversely, Figure 12 presents evidence similar to what was noted in the main framework between the various China-emerging market pairs. The wavelet correlation pairs suggest strong positive correlations in the long run, with South Korea also showing strong positive correlations in the short run, as initially observed.

Figure 9: Wavelet Correlation Output (S&P 500 and Emerging Markets)

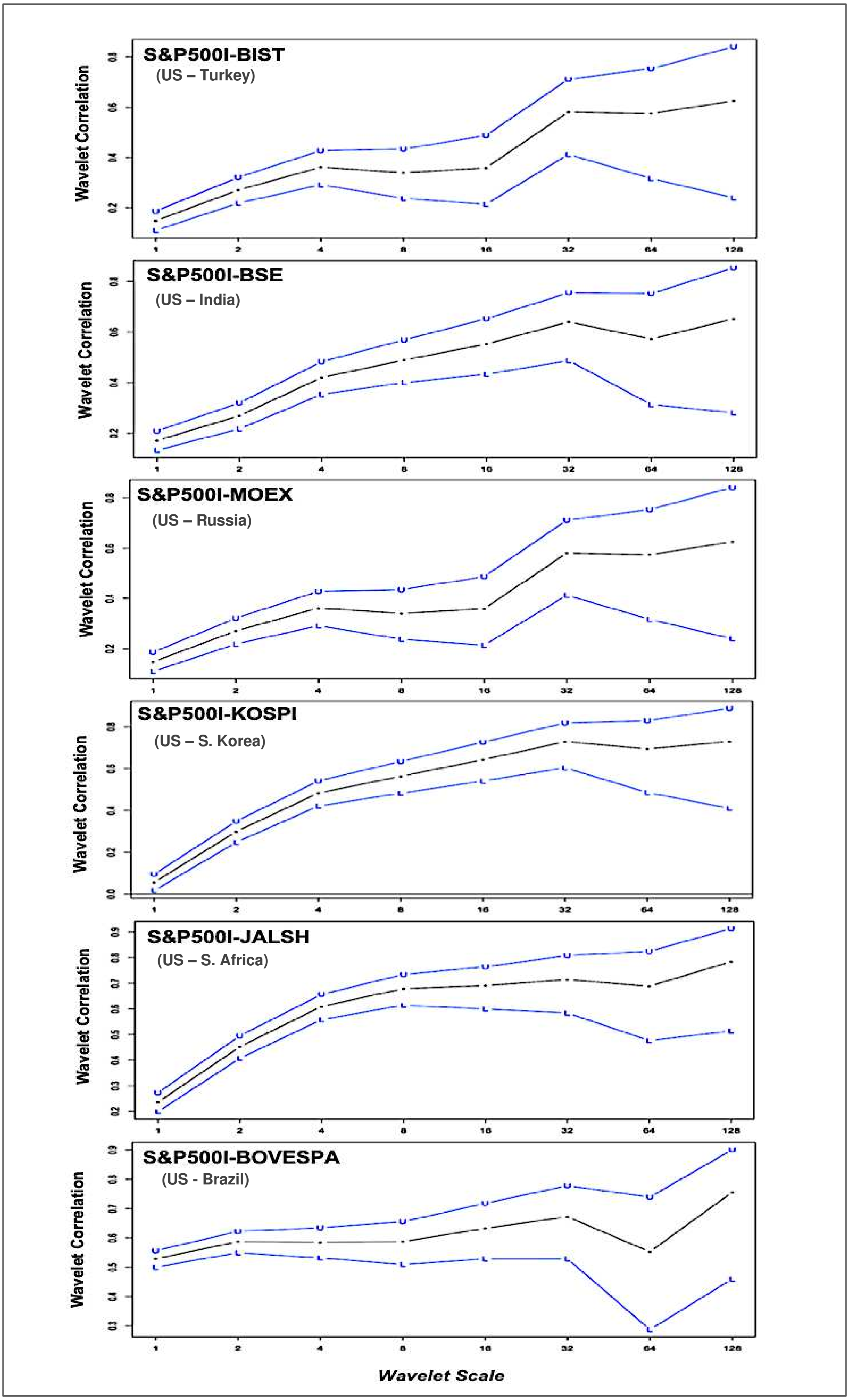
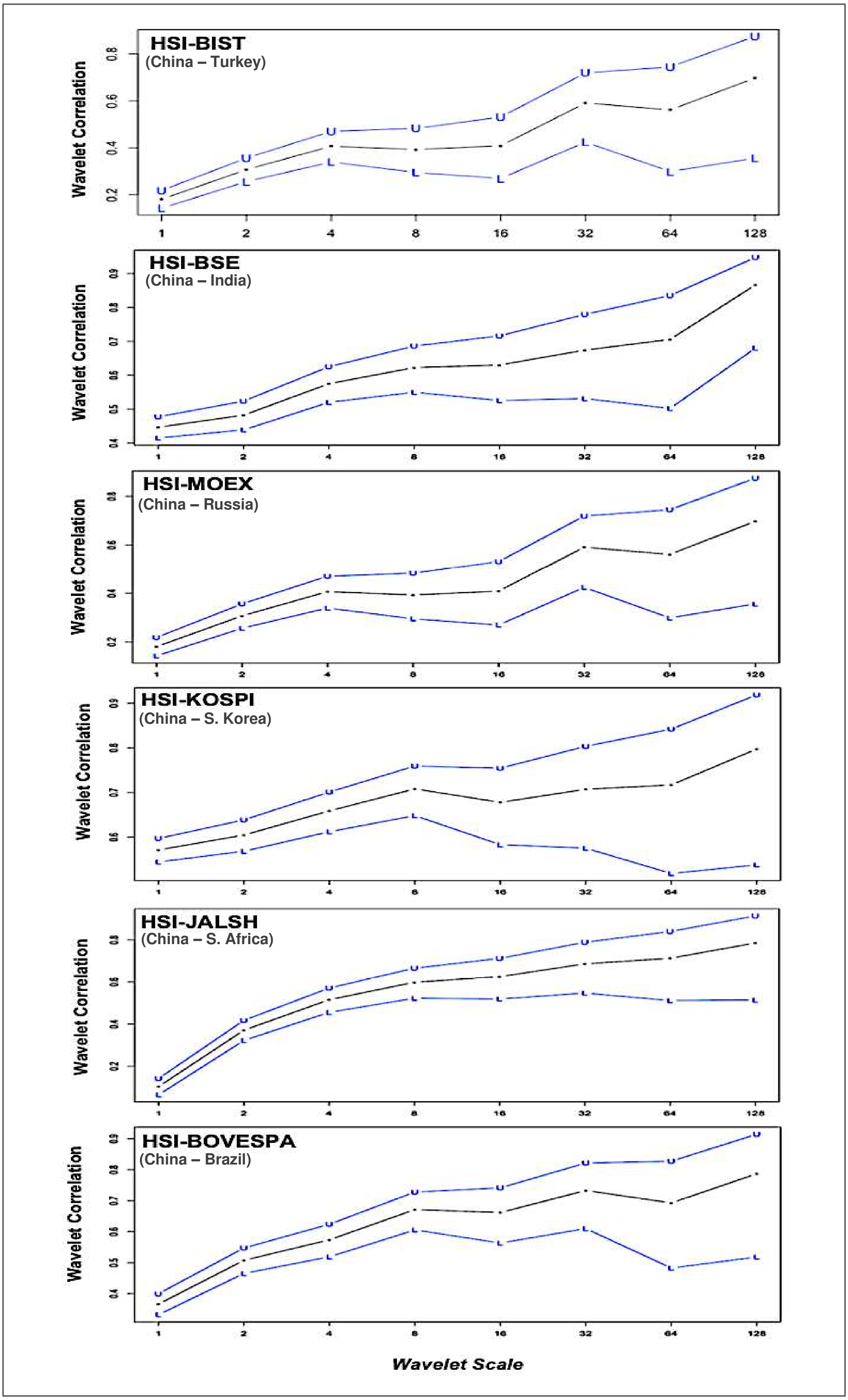


Figure 10: Wavelet Correlation Output (HSI and Emerging Markets)



Although generally positive, China's correlation with Russia shows increasing and decreasing patterns beyond the fortnightly scale, which confirms the behaviour established and explained in previous sections. Altogether, the wavelet correlations validated the evidence presented in the main framework and justify the robustness of results as a suitable measure for effective inference.

CHAPTER SIX - CONCLUSION AND RECOMMENDATIONS

This study sought to identify and assess the behaviour of contagious spillovers during the last two decades in an advanced (US) and a major emerging economy (China) on six emerging markets from different regions using wavelet analysis. The main objectives were to effectively distinguish between pure contagion and interdependence in the context of shock spillovers, assess whether or not the impacts of contagious spillovers differed across the selected emerging markets, and compare these variations between the different shock sources during periods of crises. Contrary to studies that have applied time-scale methodologies, this research study contributed to existing literature by applying a wavelet approach in order to provide a broader perspective of contagion dynamics, by presenting observable patterns on a time-frequency level and providing greater detail around correlation strength and structure.

Notably, the analysis showed marked distinctions between temporary excess co-movement (contagion) and pre-existing interdependence, with shift contagion typically being observed in short- to medium-term periods, and interdependence observed over the long term. The results also indicated the presence of contagious effects among each shock source-emerging market pair, and highlighted that the impact of these effects differed not only on the basis of selected emerging market, but also in terms of source markets. The evidence further suggests that although the US continues to have a significant impact on the studied markets, China's influence appears to have grown in significance over time. That is, the impact of spillovers from shocks to China's real economy have become more substantial throughout the last two decades, and could possibly be explained by the country's developing trade relations, growing global investments, and increasing financial integration.

Altogether, the findings in this research study support a wide range of literature, such as Yiu et al. (2010), Chudik & Fratzscher (2011), and others, in identifying the presence of contagion among emerging markets during the 2008/2009 GFC. The results suggest a difference in spillover impact among emerging markets and highlight the relevance of context-driven analysis in studying contagious effects. Unlike a number of studies, this research study's application of a wavelet analysis to individual markets provides a more detailed assessment of volatility patterns and contagious behaviour in each economy. This insight could be particularly useful for decision-making among investors and asset managers seeking to diversify towards frontier (emerging) economies while considering market behaviour related to contagion during crisis. In the case of short- and long-term investors, the time-frequency analysis obtained could also offer beneficial information in terms of portfolio rebalancing in studied markets in the face of potential excess negative economic effects. In particular, developing a thorough contextual sense of each market, its business cycles and subsequent levels of exposure to financial crisis from the world's largest economies could inform portfolio managers on which asset classes would best hedge against negative spillovers in each case. For those investing among China's emerging market trade partners, taking into consideration the country's growing influence on the real side of these markets could further validate the use of diversification in improving portfolio outcomes. Moreover, given the increased interdependence of global economies in the both finance and trade sectors, accounting for unique response patterns in potential investment areas (emerging market) to crisis spillovers from various shock sources, could play a vital role in safeguarding overall investor interests.

The evidence in this research study also highlights the benefit of initial preparedness among selected markets towards limiting the initial impact of contagion at the onset of the crisis. As such, these findings could further aid policy-makers in developing and adapting regulations and policies to better withstand crises. Particularly, improved and well-enforced regulations could help policy makers monitor and, where necessary, limit exposure to foreign market bubbles as in the case of Turkey and South Africa. Allowing for contextual elements such as GDP structure, nature of domestic business cycles, influence of political factors or other socio-economic trends which could be unique to a given region or country would equally aid policy makers in improving the effectiveness of stabilisation policy (i.e., which channel would best fit that country's attributes and response patterns).

Although the study used a wavelet analysis to offer a comprehensive assessment of contagion in different emerging markets, it can be noted that the markets chosen are limited and the number of shock sources are non-exhaustive. Additionally, the potential reasons behind observed variations included in this study are only discussed briefly, a more in-depth assessment is warranted to consolidate understanding of the contributing factors. Subsequently, this research study recommends each these aspects for future research.

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