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What Multiscale Approach Can Tell About the Nexus Between Exchange Rate and Stocks in the Major Emerging Markets?

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Abstract

This paper tries to answer which theory – the portfolio balance approach or the flow-oriented model, better explains the nexus between the national stock and exchange rate markets at different time-horizons in the major emerging markets of Europe and Asia. For that task we employ wavelet coherence and phase difference. Wavelet coherence results suggest that correlation between the two markets is not particularly strong throughout the observed period and at different wavelet scales, except in the period of World financial crisis (WFC). Phase difference in the Czech Republic, Turkey, Poland, Russia and South Korea are in anti-phase position during WFC in short run, which is in accordance with the portfolio-balance approach, whereby the stock market has the leading role. Also, phase difference at longer time-horizon indicate that an anti-phase situation is relatively common phenomenon in Poland, Russia, Turkey and South Korea. However, when we do calculations on real values, the results suggest that the real stock returns and the real exchange rate changes overwhelmingly behave in line with the flow-oriented model in all emerging markets, except for Poland. As for the Czech and Indian cases, phase differences indicate that the markets behave predominantly in accordance with the flow-oriented model at long-term horizon, regardless of whether nominal or real values are used.

1. Introduction

The rise of capital markets and the adoption of more flexible exchange rate regimes in emerging economies, sparked the interest about the interlinkage between stock and exchange rate markets among academic researchers and practitioners in recent years. The reason why research studies pay more and more attention to emerging markets lies in the fact that these countries received huge amounts of capital inflows in last two decades due to robust economic growth as well as structural reforms that they undertook (see e.g. Hegerty, 2009; Cardarelli et al., 2010; Eng and Wong, 2016; Botoc, 2017; Hwang et al., in press). In such circumstances, national exchange rate and stock markets inevitable become intertwined, since growing participation of international investors in stock end exchange markets affects demand and supply of these assets. In particular, many institutional risk hedgers and portfolio managers try to understand the level of dynamic correlation and the magnitude of the shock spillover effect between the two major financial assets – foreign exchange and stocks, since investment in national stock market involves exposure to exchange rate risk (see e.g. Laidroo and Grigaliuniene, 2012; Liivamägi, 2016). On the other hand, in order to calibrate the optimal exchange rate interventions, policy makers strive to gauge in what extent capital inflows and outflows affect exchange rate stability.

Two theories in international finance offer an explanation for the nexus between stocks and exchange rate – the traditional or the 'flow-oriented' model and the portfolio-balance approach or the 'stock-oriented model'. The flow-oriented approach proposes the linkage via the international trading balance, explaining that when exchange rate depreciates it affects positively (negatively) competitiveness of domestic (foreign) goods, which consequently reflects on the balance of trade position. The growth of the real output affects current and future cash flows of domestic companies, especially those export-oriented, which pushes their stock prices up. This indirect linkage accentuates positive correlation between these two assets. Conversely, the portfolio-balance approach is based on the demand and supply of financial assets that occurs via capital-financial balance. The increased demand for domestic stocks could cause higher demand for domestic currency that could induce its appreciation, and *vice-versa*. Hence, the portfolio-balance model suggests negative correlation between the two variables. Aforementioned theories also differentiate regarding the length of time-horizon, that is, whether the causality appears in short or long-run. Common knowledge is that the portfolio-balance approach usually has precedence in short-term, while flow the oriented theory has an upper hand in long-term.

Although there is a lot of effort in the international finance literature to understand the dynamic nexus between stocks and exchange rate, majority of studies focus only on the time domain, while frequency domain remains unexplored. According to Tiwari et al. (2015), the link between stock returns and exchange returns can vary across frequencies and may even change over time. However, there are relatively limited number of studies in the extant literature that analyse interconnection between financial time-series at higher scales (longer time-horizons). The reason lies in the fact that long-term observations often imply the sample reduction problem, whereby valuable information is lost (see Conlon and Cotter, 2012). Huang (2011) asserted that this issue could be very important since the market interconnections vary across time and scales, and the features in frequency dimension can help in better and deeper apprehension of complex pattern of the cross-market correlations. In addition, it should be said that various market participants have diverse expectations, risk profiles, informational sets, etc., and thus they gravitate to heterogeneous goals, which can be achieved at different time-horizons. For instance, policy makers and institutional investors are part of low-frequency (long-term) traders, whereas speculators and market makers belong to high-frequency (short-term) group.

Therefore, this paper endeavours to investigate dynamic nexus and lead(lag) relationship between exchange rate and stocks in major emerging markets, observing the interconnectedness via different levels of frequency scales. Our sample covers six major emerging markets of East Europe and Asia – the Czech Republic, Poland, Russia, Turkey, India and South Korea. These countries pursue managed float exchange rate regime. In addition to the relative size of the selected stock markets and their daily trading volumes, these countries also characterize relatively high amounts of export and import, as well as capital flows (see Table 1). Table 1 suggests that five out of six selected emerging markets are net-receivers of capital, while South Korea is net-lender of capital. These characteristics provide us a reason to believe that some kind of interdependence between the stock and exchange rate markets exists in these countries. For the comparison purposes, we also analyse the U.S. case, which is the best proxy of the developed countries. To the best of our knowledge, only Tiwari et al. (2015) did a multiscale research, investigating the nexus between stocks and exchange rate at various time-horizons, but they investigated only the Indian case.

Table 1 Some Characteristics of Selected Emerging Markets

	Czech R.	*Poland*	*Russia*	*Turkey*	*India*	*S. Korea*
SMC*	40,912	138,691	622,052	171,765	1,566,680	1,254,540
Avg. trading volumes	3	40	34,800	518	19	399
Export**	160	196	282	139	256	483
Import**	138	186	180	188	344	389
Financial account***	-5,767	-5,505	-10,225	-9,710	-39,408	17,857

Notes: SMC stands for stock market capitalization in 2016. Export and import are expressed in billions of USD in 2016, while financial account and SMC are portrayed in millions of USD in 2016. Daily average trading volumes in the stock markets are presented in millions in local currency.
*source: www.indexmundi.com/facts/indicators/CM.MKT.LCAP.CD/rankings
**source: https://atlas.media.mit.edu/en/profile/country/
***source: OECD statistics

In order to explore the time-frequency relationship between the two major financial markets, we utilize a wavelet coherence (WTC) method, which is capable of unravelling the strength of the dynamic interactions between the observed variables at different frequency scales and in different time-periods. In particular, this model-free approach, does not rely on parameters' assessment nor depends on the estimation method, but, at the same time, it allows a higher level of comprehension and circumvents the problem of sample size reduction. In other words, the computation is done without wastage of valuable information. Many recent studies applied WTC approach to analyse various economic phenomena at different time-horizons (see e.g. Nikkinen et al., 2011; Barunik and Vacha, 2013; Dewandaru et al., 2014; Lee and Lee, 2016; Njegić et al., 2017; Tsai and Chang, (2018). In order to further determine the nature of the mutual coherence (correlation), as well as the lead(lag) relationship (spillover effect) between stocks and exchange rate, we consider the phase difference approach of Aguiar-Conraria and Soares (2011a). Many researchers used this method for various purposes (see e.g. Aguiar-Conraria and Soares, 2011b; Dewandaru et al., 2016; Lin et al., 2016). This complementary methodology provides an information about the direction of coherence as well as the leading(lagging) role of particular variable, throughout the observed sample and at specific frequency band. In this way, we can determine whether mutual interdependence between stocks and exchange rate is shaped in accordance with the flow-oriented model or the portfolio-balance approach. Also, this method can provide an answer which theory better explains the nexus in the emerging market, and which one in the U.S., that is, whether there exists congruence or divergence between these economies when it comes to the best explaining theory. Besides, this approach can suggest from which market the spillover shocks originated at some point in the past, and at which frequency scale. This is important for various global investors, since it could have significant implications in terms of risk management, trading and hedging strategies of international portfolios (see Dajčman, 2013). Our final effort involves the introduction of inflation, in order to see how the real stock returns and the real exchange rate changes behave. This paper contributes to the literature because it offers a fresh insight into the causal link between exchange rate and stocks in the emerging markets, whereby the accent is put on the time-frequency domain, which has remained hidden thus far.

Beside introduction, this paper is structured as follows. Brief literature review is given in second Section. Research methodology is explained in third Section. Section four contains dataset. Fifth and sixth Sections reveal wavelet coherence and phase difference results. Seventh Section contains multiscale results for the real stock returns and the real exchange rate changes. Last Section concludes.

2. Brief Overview of Related Literature

The connection between the two major financial markets in emerging economies has been theoretically and empirically examined extensively, but the consensus has not been reached, regarding the direction of correlation as well as their lead(lag) relationship (spillover effect). For instance, Živkov et al. (2016) investigated dynamic correlation via DCC-FIAPARCH model between the two major financial markets in for Eastern European countries. They asserted that the portfolio balance theory has predominance in short run in all selected economies. In addition, the results of rolling regression suggested that exchange rate's conditional volatility has higher influence on dynamic conditional correlation than stock's conditional volatility. The study of Liang et al. (2013) utilized the panel Granger causality and the panel DOLS methodologies on ASEAN-5 countries and found support for the portfolio-balance hypothesis. They claimed that exchange rates impact stock prices negatively via capital mobility. On the other hand, some papers found evidence of the flow-oriented model, which advocates positive correlation between stock and exchange rate markets, emphasizing that the nexus occurs via balance of trade. For instance, Diamandis and Drakos (2011) investigated short-run and long-run dynamics on monthly data between stock prices and exchange rates as well as the channels through which exogenous shocks influence these markets in Argentina, Brazil, Chile and Mexico. Their main finding suggests that stock and foreign exchange markets in these economies are positively related, and the U.S. stock market acts as a channel for these links.

As for the spillover effect, many researchers explored this topic and the results came heterogeneous. Bahmani-Oskooee and Saha (2016) claimed that exchange rate changes can affect firms differently depending on whether they are export oriented or they heavily use imported inputs, concluding that the overall effects of exchange rate changes on an aggregate stock price index could be in either direction. Yang et al. (2014) studied the relationship between stock returns and exchange rates via the Granger causality test in quantiles in India, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, Taiwan and Thailand. Their results indicated that during the Asian financial crisis, all the countries except for Thailand reported the spillover effect from exchange rates toward stock prices. The paper of Živkov, Njegić and Milenković (2015) researched bidirectional second moment spillover effect between stock returns and exchange rate changes on daily data in four Eastern European emerging markets. They managed to identify bidirectional volatility spillover effect. The results indicated that this effect has much higher impact from the currency market toward stock market, than *vice-versa*. The study of Andreou et al. (2013) investigated bi-directional return and volatility spillovers between the stock market and the foreign exchange market of twelve emerging economies. Their results revealed that there is a strong evidence of bidirectional causality in variance between the foreign exchange market and stock market in all emerging economies, but Colombia. Also, they claimed that global and regional stock markets contribute significantly to volatility spillovers. Sui and Sun (2016) studied the dynamic relationships among local stock returns, foreign exchange rates and interest differentials in BRICS. The results showed that the spillover shocks from the foreign exchange markets affect stock returns in all BRICS in short-run. On the other hand, the stock-market shocks only slightly impact the exchange rate market in Brazil and Russia.

3. Methodology

Wavelets are mathematical functions, utilized to extract information from empirical data in both space and scaling. Tabak and Feitosa (2009) and Jammazi (2012) explained that the wavelet method is handy for detecting extreme movements and removing noises in original data. Dewandaru et al. (2016b) asserted that the wavelet coherence methodology is particularly useful when researchers deal with non-stationary signals that contains numerous outliers. Since stock and exchange rate returns frequently exhibits asymmetry, abrupt changes, chaotic behaviour, and nonlinear dynamics, the wavelet methodology would be convenient for our research. Rua and Nunes (2009) contended that function of the continuous wavelet transform, $W_x(u,s)$, is obtained by projecting a specific wavelet ψ(.) onto the examined time series $x(t) \in L^2(\mathbb{R})$ by the following expression:

$$W_x(u,s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \overline{\bar{\psi}\left(\frac{t-u}{s}\right)} dt, \tag{1}$$

where u represents the position of the wavelet in the time domain, while s denotes the position in the frequency domain. Equation (1) suggests that information on time and frequency can be simultaneously obtained by mapping the original time series into a function of u and s in the wavelet transform.

In order to analyse the interaction between selected stock indices and exchange rates, we need to introduce a bivariate framework called wavelet coherence. Vacha and Barunik (2012) claimed that squared wavelet coherence measures the local linear correlation between two stationary time series at each scale, and it is equivalent to the squared correlation coefficient in linear regression. Torrence and Webster (1999) contended that WTC can be presented as a squared absolute value of the smoothed cross wavelet spectra normalized by the product of the smoothed individual wavelet power spectra of each selected time series. The cross wavelet transform of two time-series, x(t) and y(t), is defined as $W_{xy}(u,s) = W_x(u,s)W_y^*(u,s)$, wherein W_x and W_y are the wavelet transforms of x and y, respectively. Symbol u represents a position index, s denotes the scale, while the symbol * indicates to a complex conjugate. The squared wavelet coherence coefficient is given as follows:

$$R^2(u,s) = \frac{\left|S\left(s^{-1}W_{xy}(u,s)\right)\right|^2}{S(s^{-1}|W_x(u,s)|^2)S\left(s^{-1}\left|W_y(u,s)\right|^2\right)}, \tag{2}$$

where $S(.)$ stands for a smoothing operator and s is a wavelet scale. The squared wavelet coherence coefficient ranges $0 \leq R^2(u,s) \leq 1$, whereby values near zero point to weak correlation, while values near one indicate to strong correlation. Theoretical distribution for the wavelet coherence is not known, thus we follow Grinsted et al. (2004) and Torrence and Compo (1998), and test the statistical significance using Monte Carlo methods.

WTC methodology is unable to determine whether dependence between two time-series is positive or negative, because the wavelet coherence is squared, thus, we consider wavelet coherence phase difference, which provides details on the delays in the oscillation between scrutinized two time-series. According to Torrence and Webster (1999), the wavelet coherence phase difference is defined as follows:

$$\phi_{xy}(u,s) = tan^{-1}\left(\frac{\Im\{S(s^{-1}W_{xy}(u,s))\}}{\Re\{S(s^{-1}W_{xy}(u,s))\}}\right), \tag{3}$$

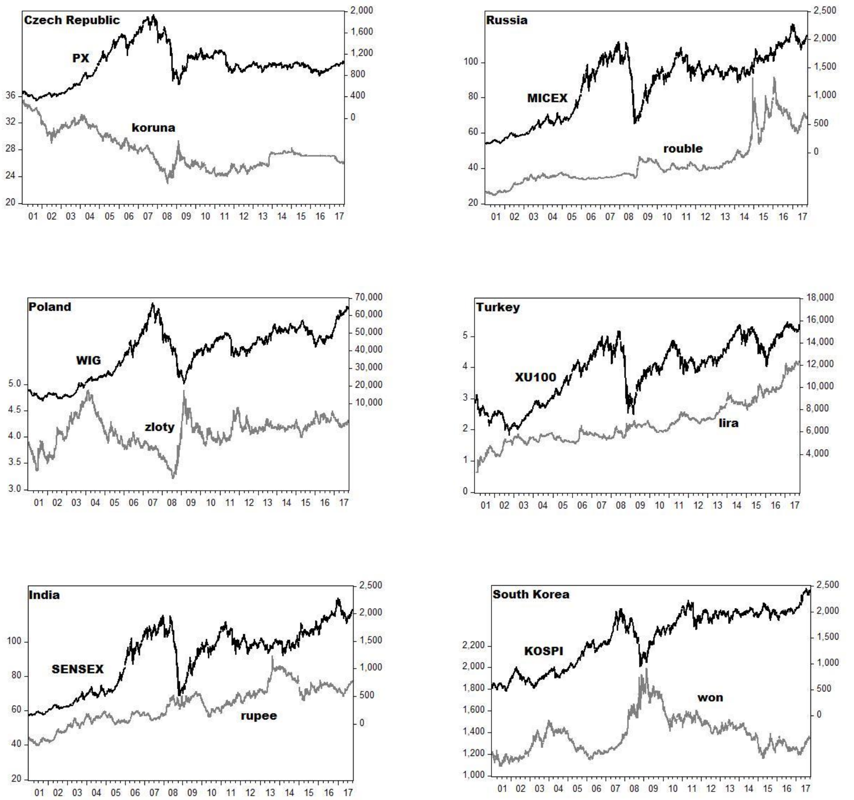
where $\Im$ and $\Re$ are the imaginary and real parts, respectively, of the smooth power spectrum. Phase difference between two series (x, y) is presented by vector arrows on the wavelet coherence plots. Vacha and Barunik (2012) indicated that right (left) pointing arrows indicate that the time series are in-phase (anti-phase) or are positively (negatively) correlated. If arrows point to the right and up, the second variable is lagging and if they point to the right and down, the second variable is leading. Reversely, if arrows point to the left and up, the second variable is leading and if arrows point to the left and down, the second variable is lagging.

In addition, according to the paper of Aguiar-Conraria et al. (2008), if $\phi_{xy} \in (0, \pi/2)$ then the series move in phase, with the time-series y leading x. On the contrary, if $\phi_{xy} \in (-\pi/2, 0)$ then it is x that is leading. An anti-phase situation (analogous to negative covariance) happens if we have a phase difference of π (or −π), meaning $\phi_{xy} \in (-\pi/2, \pi] \cup (-\pi, \pi/2]$. If $\phi_{xy} \in (\pi/2, \pi)$ then x is leading, and the time series y is leading if $\phi_{xy} \in (-\pi, -\pi/2)$. Phase difference of zero indicates that the time series move together (analogous to positive covariance) at the specified frequency.

4. Dataset

Our research encompasses six emerging markets of East Europe and Asia – the Czech Republic, Poland, Russia, Turkey, India and South Korea. We use daily closing prices of selected stock indices and nominal exchange rates, and all currencies are observed *vis-a-vis* euro. We consider following indices and corresponding currencies – Czech PX and koruna, Polish WIG and zloty, Russian MICEX and rouble, Turkish XU100 and lira, Indian SENSEX and rupee, and South Korean KOSPI and won. For comparison purposes, we choose American S&P500 index and USD, which represents developed country. All daily prices are transformed into log-returns according to $r_{i,t} = 100 \times \log(P_{i,t} / P_{i,t-1})$, where $r_{i,t}$ is the market return and $P_{i,t}$ is the closing price of particular currency or stock index at time (*t*). The sample covers the period from January 1, 2001 to September 30, 2017 and all data were obtained from Datastream. Due to the unavailability of some data because of national holidays and non-working days in selected stock markets, the daily dates are synchronized between two markets according to the existing observations. Using wavelet coherence method, we observe interdependence between these assets at six different scale levels, which corresponds to following time horizons – scale 1 (2-4 days), scale 2 (4-8 days), scale 3 (8-16 days), scale 4 (16-32 days), scale 5 (32-64 days) and scale 6 (64-128 days). We treat first four scales as short-term observations, whereas fifth and sixth scales correspond to long-term. Utilizing wavelet coherence and phase difference methodologies, we are in a position to investigate the dynamic nexus in different frequency levels, and the obtained results could serve well for various economic agents who have different term objectives. Figure 1 presents empirical movements of selected stock indices and exchange rates.

Figure 1 Empirical Dynamics of Selected Stock Indices and Exchange Rates



Notes: Black (grey) line denotes stock index (currency) movement.

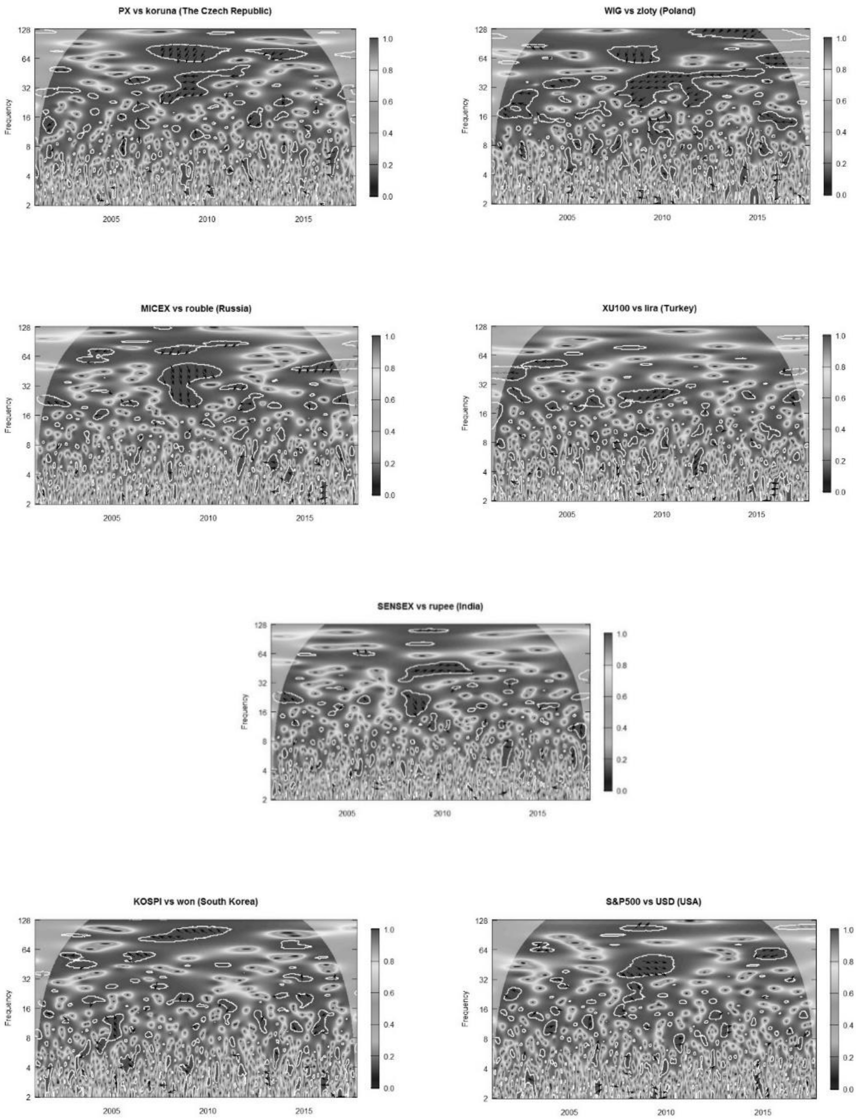
5. Wavelet Coherence Results

We apply wavelet coherence[1] in the continuous form to decompose the empirical series, and to determine the strength of the mutual nexus in the time-scale domain. This section presents our findings. Figure 2 contains seven wavelet coherence contour plots, which depict the level of correlation (coherence) between selected pairs of national stock indices and currencies. This technique is able to simultaneously observe two dimensions – time and frequency, whereby the horizontal axis denotes time component, while the left vertical axis represents frequency component, which goes up to sixth scale (128 days). The strength of the co-movement between analysed group of countries is measured via black and white surfaces, were light-black shade indicates low coherence, while dark-black shade points to higher coherence. The black and white pallet is presented at right Y-axis and it ranges from 0 to 1. The cone of influence designates the statistical significant area at 5% significance level.

Wavelet coherence plots show that strength of the coherence is heterogeneously distributed throughout the observed time-sample and across the scales, which justifies the usage of this methodology. It can be seen that majority of WTC surfaces is covered with relatively bright shades on all WTC plots, and this applies particularly to high frequency scales. It is obvious that bright shades dominate up to 16 days in all WTC plots. These findings indicate that correlation between stock and exchange rate markets is not particularly strong, and this pattern replicates itself at higher wavelet scales as well. Our results concur with the findings of other studies. For example, Živkov, Njegić and Milenković (2015) explored four East European economies – the Czech Republic, Poland, Hungary and Russia via DCC-FIAPARCH model. The calculated dynamic conditional correlations disclosed that the average daily dynamic correlations between stock and currency markets varies between 0.2 and 0.3, which is not high, and which coincides with our wavelet findings.

[1] All WTC computations were done in 'R' software.

Figure 2 Wavelet Square Coherence Between National Stock Indices and Currencies



The only situation in which we find high correlations between stocks and currencies is the period around World financial crisis (2008-2010) and subsequent European sovereign debt crisis (ESDC) that lasted during 2011-2012. It can be seen that dark-grey islands are present at relatively low frequencies (higher scales) in these periods, that is, from 32 days onwards. This is characteristic for all emerging markets as well as the U.S. economy. Regarding the emerging market plots, particularly conspicuous are the Czech, Polish and Russian cases. Dark-grey surfaces during WFC and ESDC periods undoubtedly indicate to increased market contagion and investors' panic. Bekaert et al. (2005) explained that contagion is a correlation over and above what one would expect from economic fundamentals. In other words, due to extreme market uncertainty during WFC and somewhat ESDC, economic agents started frantically to withdraw capital from the emerging markets and to sell domestic currencies. That type of behaviour caused steep fall of stock indices and enhanced exchange rate depreciation. Our findings concur with Syllignakis and Kouretas (2011), who showed that herding behaviour actually happened in the Central and East European (CEE) economies during the U.S. stock market crash (2008-2010), which consequently forced the CEE financial markets to plunge in a relatively short amount of time. Looking at the empirical movements of stock indices and currencies in Figure 1, we can witness that this scenario is apparent for the Czech Republic, Poland, Russia, South Korea and somewhat India. In addition, our results are in line with some studies, such as Lin (2012), who explored six Asian emerging countries and found that the co-movement between exchange rates and stock prices becomes stronger during crisis periods than during tranquil ones, in terms of long-run co-integration and short-run causality. Also, Živkov, Njegić and Pavlović (2015) investigate dynamic correlation between stock returns and exchange rate via DCC-EGARCH model in four Eastern European emerging markets. They found increased negative dynamic correlation during WFC, which coincides with our wavelet-based results.

However, in spite of huge market turbulence that was present during WFC and somewhat ESDC, our WTC results suggest that high correlation between national stocks and exchange rate happened in a delayed time, that is, at longer time-horizons. According to Figure 2, increased correlation during WFC is detected between 32-128 days in Czech case, between 16-64 days in Polish, Russian and Indian cases, between 16-32 days in Turkish case and between 64-128 days in South Korean case.

In addition, it should be said that most of the phase arrows in dark-grey areas point to left, which suggest negative coherence (anti-phase) situation, which means that stock prices downfall was accompanied by the exchange rate depreciation. This applies for the Czech Republic, Poland, Turkey and South Korea. In addition, we also find phase arrows tilted to left-down in the Czech Republic, Poland and Turkey, which indicates that stock markets have a leading role during WFC and ESDC. Only in case of India, phase arrows are directed to straight right or to right-down, which indicates that rupee lead SENSEX at 16-32 days' time-horizon, while at longer time-horizon they suggest an in-phase position. Similar to the Indian case, Russian phase arrows point to right-down, which is a sign that second variable (rouble) is leading. Negative coherence in majority of the emerging markets, indicates that the portfolio-balance approach or capital outflow stands behind the nexus between the two major financial markets during WFC and probably during ESDC in these economies.

As for the U.S. case, we also find strong coherence area during WFC at relatively lower frequencies, between 32-64 days. It can be seen that U.S.'s phase arrows point to right or right-down, indicating positive coherence or leading role of USD. Unlike emerging markets' currencies, USD actually appreciated during WFC (see Figure 1), which suggests that global investors saw American currency as some kind of safe haven during that stressful time. Contrary to USD, American index, S&P500, had similar fate as all emerging markets' indices, that is, it dramatically lost its value during WFC. Due to these concurring events, we find straight-right phase arrows in the American case, which is in line with the flow-oriented model that is associated with the current account balance.

However, applying the phase arrows methodology within WTC framework, we can get limited insight about the phase direction, that is, only at high coherence areas, while in tranquil periods it is not possible. Thus, trying to determine which theory better explains the stock-exchange rate nexus throughout the observed period solely on this indicator, could be superficial and biased, because in extreme market periods irrational and idiosyncratic factors are more dominant in comparison to fundamentals. This applies for both developed and emerging markets. Therefore, in order to provide more solid grounds for our conclusions, we present the results of phase difference approach by Aguiar-Conraria and Soares (2011a) in sixth Section.

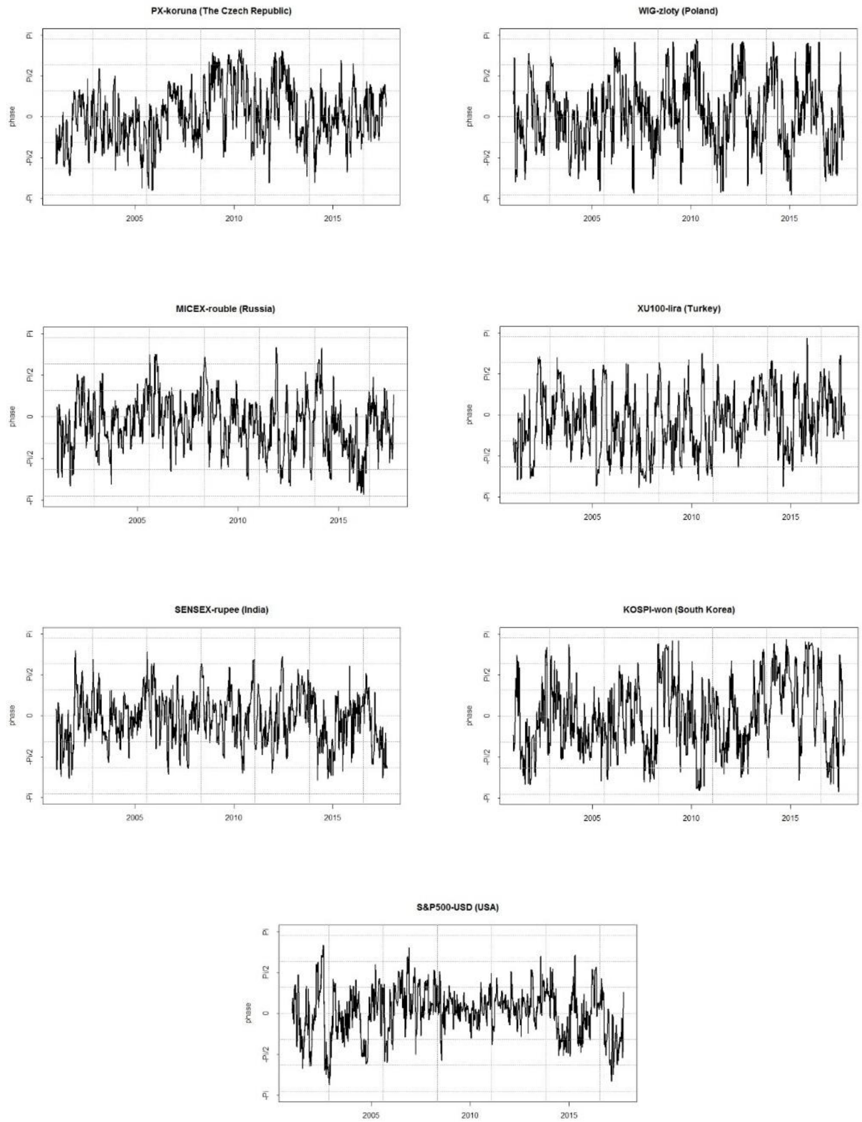
6. Phase Difference Results

6.1 Short-Term Phase Difference Results

This subsection presents the findings for phase difference at 2-32 days frequency bands, that is, at shorter time-horizon. Researchers do not normally observe phase difference at high frequencies, because of its pretty chaotic dynamics. However, Leung et al. (2017) asserted that volatility between exchange rate and stock markets is transmitted at high speed, so we calculate short-term phase difference plots alongside with their long-term counterparts. Figures 3 and 4 contain these plots. In order to properly determine the lead(lag) connection between assets, we need to know the order of variables in the phase difference computation process. Thus, caption of the plots helps out, in a sense that the stock indices are X, while the currencies are Y variable.

Observing short-term phase difference dynamics during WFC and ESDC, we can assess whether irrational investors' phenomena like financial panics, herd behaviour and loss of confidence instigated motion of stocks and exchange rate in accordance with the portfolio balance approach in the emerging markets. Figure 3 reveals that phase difference line is clearly in anti-phase domain (between $\pi/2$ and π) during WFC and ESDC in cases such as the Czech Republic, Poland, Russia, South Korea and somewhat Turkey. Rationale behind these findings is that most likely the portfolio balance approach explains the nexus in these countries at that turbulent time at short-term, whereby pure contagion and capital flight might be the main culprits for such interdependence. In addition, since phase difference line find itself in the second quadrant, it means that stock markets had leading role during WFC, that is, spillover shocks were transmitted from stock markets toward currency markets. These findings concur with the results of Lin (2012) who found that slowdown of an economy affected emerging stock prices during WFC, subsequently prompting international investors to withdraw their capital, thus putting downward pressure on the currency. On the other hand, such scenario is not so obvious for Indian economy during WFC. As for the U.S., we find very little evidence that the two markets behave in line with portfolio balance theory throughout whole sample, because phase difference predominantly takes in-phase position, in the realm between $\pi/2$ and $-\pi/2$.

Figure 3 Phase Difference Results of Shorter Time-Horizon (2-32 days frequency band)



6.2 Long-Term Phase Difference Results

Longer time-horizon phase difference plots offer somewhat clearer picture about the stocks-exchange rate interconnections, because phase difference is smoother and less erratic comparing to its short-term counterpart (see Figure 4). It can be seen that phase difference in some countries spends significant amount of time in anti-phase domain even at longer-term, which particularly applies for Poland, Russia, Turkey and South Korea. This is not unusual since some related studies also revealed the presence of long-run relationship between exchange rates and stock prices. For instance, Yau and Nieh (2009) investigated the Taiwanese case, while Wu et al. (2012) researched the nexus in the Philippines. They both reported the existence of long-run relationship in these economies.

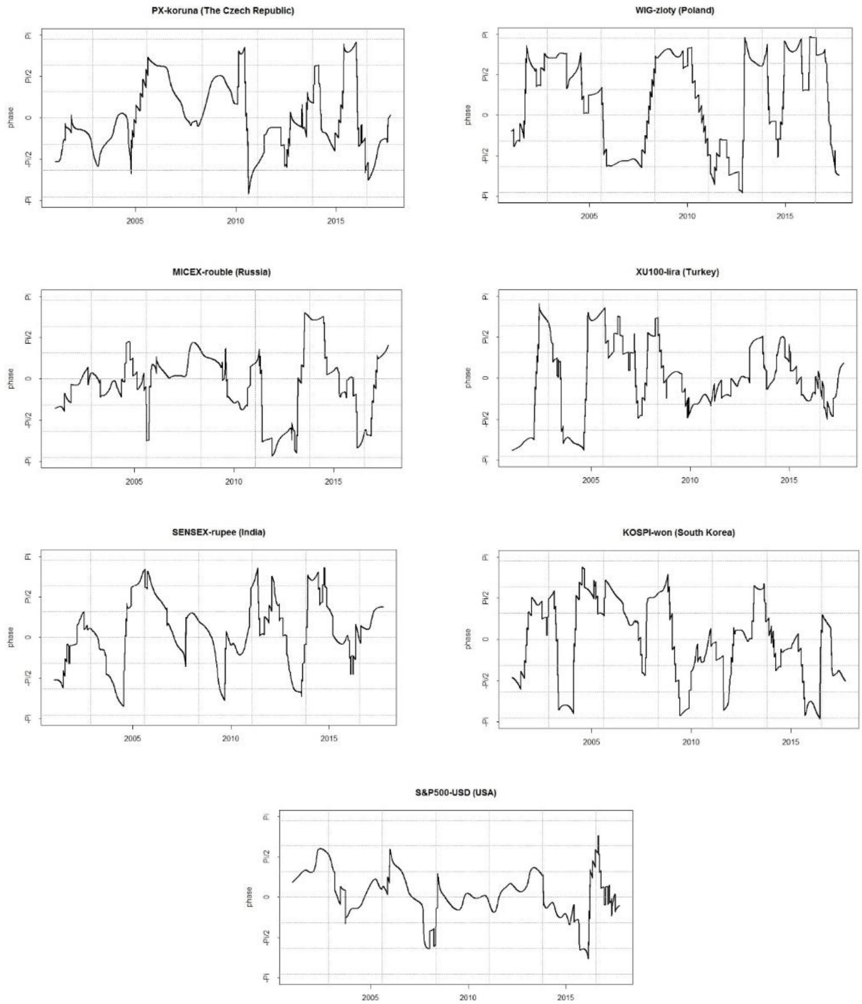
As for our results, Polish phase difference is dominantly in anti-phase region (between $\pi/2$ and π), which also means that shocks are transferred from the stock market to the exchange rate market at longer-horizon. These results coincide with the previously calculated phase arrows. It is obvious for the WFC period, but also for period between 2002-2004 that could be associated with crisis in Iraq. Another Polish anti-phase situation is found around 2011 and 2012 (ESDC crisis), but this time exchange rate has leading role. As can be seen in Figure 1, Polish zloty significantly depreciated around 2011 and 2012, while WIG also lost its value. We find an anti-phase situation with the leading role of WIG in the period around 2015 and 2016. At that time, WIG lost its value, which transferred to zloty eventually.

Russian plot reports first obvious antiphase situation around 2012 and 2013 with the leading role of rouble. From the sample beginning till that years, phase difference is constantly in in-phase position, whereas it takes an anti-phase position quite often after these years. Probable reason for such long in-phase period in case of Russia is the fact that Russian currency was under tight management regime until 2008, and heavy exchange rate interventions afterwards. Another anti-phase situation is found around 2014, whereby MICEX has leading role this time. Rouble leads again in anti-phase situation around 2016, which can be linked with the time when rouble depreciated substantially due to the steep oil price drop (see Figure 1).

In Turkish case, we found an anti-phase situation, according to the portfolio balance approach, between 2003 and 2006 with the changing leading(lagging) rolls between XU100 index and Turkish lira. At that time, XU100 had strong path of growth, while lira showed appreciation tendencies (see Figure 1). From 2009 to the end of observed sample, XU100 and lira are in-phase, in accordance with the flow-oriented theory.

In South Korean case, first anti-phase pattern is reported around 2003 with leading role of won. Korean currency depreciated and KOSPI lost its value during that year. Second anti-phase situation was between 2004-2007 when reverse happened, that is, KOSPI had leading position. Phase difference lies in anti-phase domain (between $-\pi/2$ and $-\pi$) during WFC. Unlike short-term horizon, in the long-term perspective, won actually affected KOSPI, that is, delayed depreciation effects subsequently dragged stock prices downward. Anti-phase situation in Korea is also present around 2014 and 2016, whereby in former case KOSPI has leading role, while in the latter case won is the one that leads.

Figure 4 Phase Difference Results in Long-Term Horizon (32-128 days frequency band)



As for the Czech and Indian cases, phase differences do not enter an anti-phase domain frequently (beyond $\pi/2$ and $-\pi/2$ boundaries), and even when they do, it does not last for long. These results indicate positive coherence, whereby Czech koruna and Indian rupee have leading role for most of the time (domain between 0 and $\pi/2$). This suggests that interconnection between the major financial markets in the Czech Republic and India behaves predominantly in accordance with the flow-oriented model at 32-128 frequency band. In other words, capital inflows and outflows do not play a big role when it comes to the determination of stock-exchange rate nexus at longer time-horizon, but rather increase in trade balance binds the ties between stock and foreign exchange markets for these economies. This is not unusual for emerging markets, since Phylaktis and Ravazzolo (2005), who studied a group of emerging

Pacific-basin countries, also found an evidence of positive correlation between stock and foreign exchange markets in long-run, which is in accordance with the flow-oriented model.

Phase difference of the U.S. goes very rarely in an anti-phase region, and when it happens it is short-lived. These results suggest that capital mobility is not a major factor that determines stocks-exchange rate nexus in 32-128 frequency band in the U.S. In other words, unlike investors in emerging markets, the U.S. investors neither abandon USD when American stocks demonstrate tendency to fall, nor they invest more in the U.S. stocks when USD has appreciating trends. Therefore, positive coherence that we found in the U.S. can be explained more likely by the fact that depreciating USD helps, while appreciating USD harms American exporters, and due to that connection, American stocks rise or fall accordingly, which is in line with the flow-oriented model.

7. Interrelationship Between Real Stock Returns and Real Exchange Rate Changes

This section presents the results of wavelet coherence and phase difference calculated on the real stock returns and the real exchange rate changes. Calculations on real values are considered because some of the selected countries have experienced much higher inflation than the euro area. Therefore, it is reasonable to check whether the results remain the same if we also take into account the level of inflation in our computation processes. Table 2 presents average annual inflation rates for the selected emerging markets. It can be seen that Turkey, Russia and India have relatively higher average annual inflation, than the other three countries of the sample. In order to calculate real values of the assets, we observe monthly stock returns and exchange rate changes. Real values are calculated via following equation: $\mathbb{R}_i = \mathbb{N}_i \times CPI^*/CPI_i$, where $\mathbb{R}$ and $\mathbb{N}$ stand for real and nominal values, respectively, whereas CPI* and CPI indicate consumer price index for euro area and for emerging markets, while (i) denotes particular emerging market. Figures 5 and 6 present calculated plots of wavelet coherence and phase difference, respectively.

Table 2 Average Annual Inflation for the Period 2001:M1 – 2017:M9

	Czech R.	*Poland*	*Russia*	*Turkey*	*India*	*S. Korea*
Average annual inflation	2.12%	2.19%	10.60%	14.10%	6.59%	2.60%

Source: OECD statistics.

As for the wavelet coherence results, the real WTC findings are not much different in comparison with the nominal counterparts, that is, we find high coherence areas at relatively high frequencies (2-4 months) during the periods of WFC and ESDC in the Czech Republic, Poland, Russia and India. Relatively low coherence is present in other non-crisis areas, which is in line with our previously calculated daily plots. The only obvious difference between real and nominal plots lies in the fact that all phase arrows in high coherence islands during WFC and ESDC are pointed to right-down in real WTC plots. It means that second variable, that is, real exchange rate, leads real stock returns by 90°. High coherence that we find between the real assets very much concur with the study of Wong (2017), who did the research on real stock returns and real exchange rate changes in five Asian and two European countries and found that real values of these markets are significantly correlated in the period of the financial crises.

Figure 5 Wavelet Square Coherence Between Real Stock Returns and Real Exchange Rate Changes

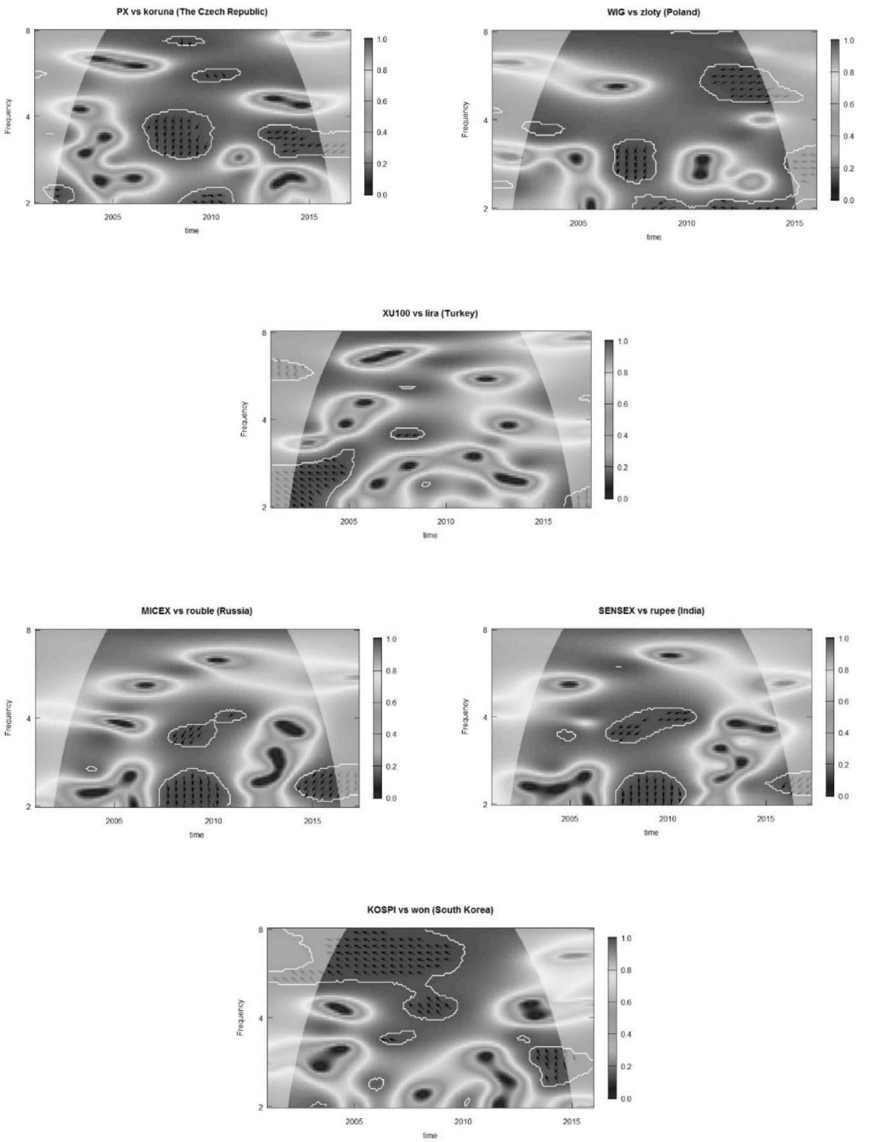


Figure 6 Phase Difference Between Real Stock Returns and Real Exchange Rate (2-8 months frequency band)

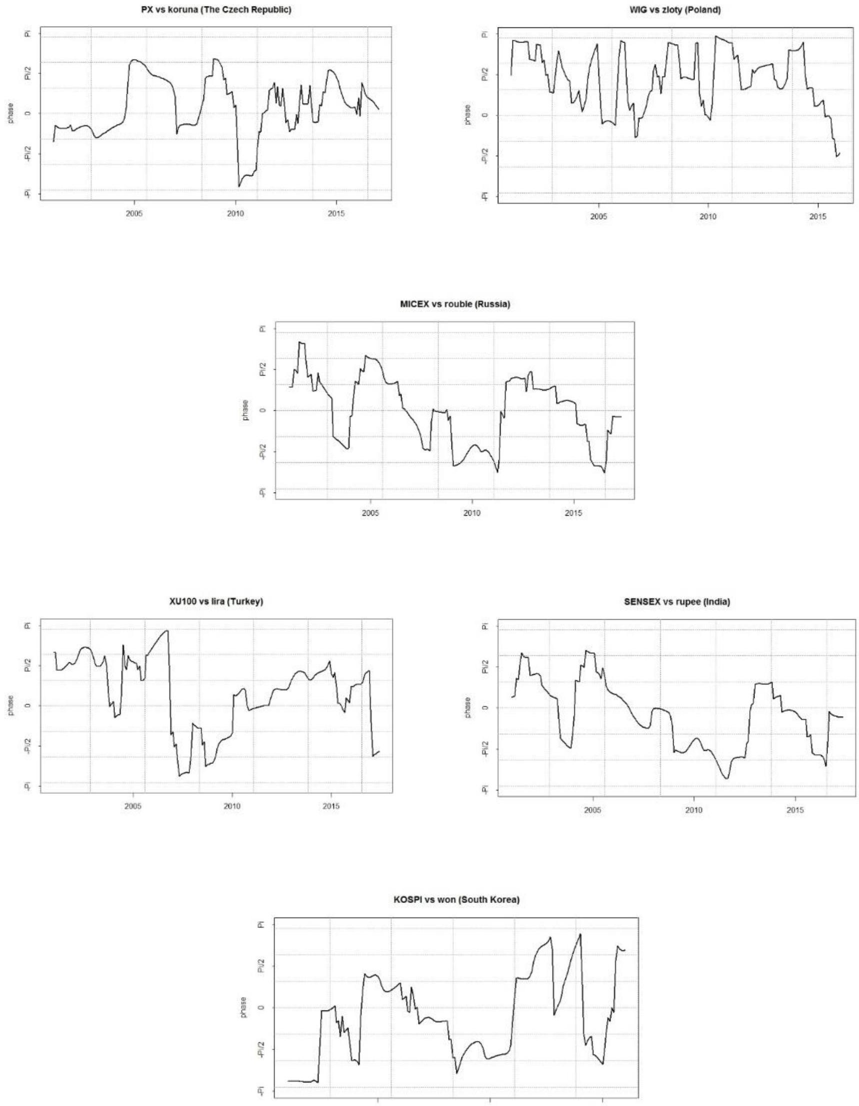


Figure 6 presents phase difference plots of the real assets for 2-8 months frequency band, which we treat as longer time-horizon. Unlike the daily plots in Figure 4, phase difference for real values relatively rarely goes in anti-phase regions (beyond $\pi/2$ and $-\pi/2$ boundaries), except for Poland, which indicates that phase differences are in-phase position for most of the time, supporting, in that way, the flow-oriented model. In other words, the real assets advocate stronger support to the flow-oriented model in longer-run, than the daily nominal counterparts. Figure 6 suggests that the inflation-corrected assets are positively correlated for most of the time in longer time-horizon in all selected emerging markets, except Poland. Differently speaking, the connection between the real assets is achieved most likely via current account, that is, via higher export. In addition, it is important to noticed that lead-lag connection is more persistent and long-lasting for some real assets. For instance, it can be seen that real koruna and real lira have a leading role from 2012 and 2011, respectively, to the end of the sample. MICEX leads from 2007 to 2011 and from 2015, while SENSEX leads from 2007 to 2013, and from 2015 onwards. For Polish case, it is not clear which asset has advantage, since phase difference constantly oscillates between in-phase and anti-phase domains. In Korean cases, phase difference finds itself dominantly in-phase realm, but without long-lasting leading role of particular asset.

8. Conclusion

This paper tries to determine whether the interdependence between the national stock and exchange rate markets is in accordance with the portfolio balance approach or the flow-oriented theory in the major emerging markets of Europe and Asia, whereby we jointly observe time-frequency domain of the analysed nexus. As a benchmark, we use the U.S. economy. For the research purposes, we apply relatively novel methods of wavelet coherence and phase difference. The results from the empirical analysis highlight a number of interesting issues.

Firstly, wavelet coherence reveals that strength of the nexus at lower scales as well as at upper scales is not particularly strong throughout the whole sample, which is in line with the existing literature. However, we find very high coherence at longer time-horizons (between 32-64 days) during WFC and ESDC in all emerging markets as well as in the U.S. economy. High coherence existed in that period due to extreme market occurrences, such as contagion effect, widespread panic and rapid cross-market fund rebalancing. Phase arrows in the Czech Republic, Poland, Turkey and South Korea in high coherence areas point to left, which indicates to an anti-phase position, whereas in India and the U.S, these indicators are directed to right, which is in line with the in-phase situation. Results disclose that global investors abandoned most of the analysed emerging markets' currencies during WFC in fear of loses, whereas it did not happen with Indian rupee. As for USD, it even became a wanted asset that consequently appreciated significantly.

Secondly, in order to stipulate direction of the coherence in short and long horizons, and over the entire sample, we utilize phase difference technique. Calculating short-term phase difference, we learn that phase difference enters anti-phase domain (between $\pi/2$ and π) during WFC and ESDC in Czech Republic, Turkey, Poland, Russia and South Korea. These results suggest that co-movement between exchange rates and stock prices in these emerging markets is generally driven by the capital account balance rather than that of trade during WFC, and that stock market has leading role in short run. Phase difference at longer time-horizon indicate that an anti-phase situation is relatively common occurrence in Poland and South Korea throughout the entire sample. For Turkey, it applies till 2009, whereas for Russia, anti-phase situations can be found from 2012. These results support the portfolio balance model. However, when we apply the same type of calculation on real values, our results suggest that real stock returns and real exchange rate changes overwhelmingly behave in accordance with the flow-oriented model in all emerging markets, except Poland. As for the Czech and Indian cases, real and nominal phase differences find itself dominantly in in-phase realm, which means that interconnection between the major financial markets in the Czech Republic and India behaves predominantly in accordance with the flow-oriented model at long-term horizon. Phase difference of the U.S. goes very rarely in anti-phase domains (beyond $\pi/2$ and $-\pi/2$ boundaries), which indicates that capital mobility is not a major factor that determines stocks-exchange rate nexus in long-run in this country.

The overall results show that the stock-exchange rate nexus in the selected emerging markets in longer-run in tranquil periods is determined by current account rather than capital account, which is a frequent characteristic of developed markets as well. Discrepancy between emerging and developed markets occurs only in crisis periods when emerging markets' currencies depreciate, while developed countries' currencies tend to gain strength.

This study could serve well for global investors who are interested in these countries and who take their investment positions at different time horizons. Also, the results of this paper could help policy makers when they intend to intervene in exchange rate market.

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