

Wavelet Analysis of the Interdependence between Stocks and Bonds in the Selected East European and Eurasian Emerging Markets

Dejan ŽIVKOV* – Jovan NJEGIĆ* – Marko PEĆANAC**

Abstract

This paper tries to thoroughly investigate the multi-horizon nexus between national stocks and 10Y bonds in six emerging markets (the Czech Republic, Poland, Hungary, Romania, Russia and Turkey). For the computational purposes we use two complementary methodologies – wavelet signal decomposing technique and phase difference. Wavelet coherence results indicate that low coherence areas are overwhelmingly present in WTC plots in all the selected countries, which indicates that these instruments might be useful for diversification and hedging purposes. Additional wavelet correlation approach measures average wavelet correlations across the scale very precisely, revealing that majority of the wavelet correlation coefficients are negative, which imply that these financial instruments are good hedging tools. Phase differences were found dominantly in domains beyond $\pi/2$ and $-\pi/2$ boundaries in midterm and long-term in most of the countries, which also suggests negative coherence. Overall findings are in line with the general perception that stock returns and bond yields of the selected countries move in opposite direction, primarily because interest rate is constituent part in dividend discount model, and due to portfolio rebalancing activities.

Keywords: *stocks and bonds, wavelet coherence, phase difference, emerging markets*

JEL Classification: C63, G12, G15

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Introduction

Stocks and bonds are one of the most important asset classes, and understanding their nexus is of utter interest for various market participants, such as global investors, portfolio managers, financial analysts and policy makers. Many researchers asserted that interest rate risk is among the most important risk factors for international investors (see e.g. Che-Yahya, Abdul-Rahim and Yong, 2014; Higgins, Mishra and Dhole, 2014; Adam, Banbula and Markun, 2015; Kal, Arslaner and Arslaner, 2015). Financial theory postulates that interlink between changes in interest rates and stock returns can be either positive or negative. Nevertheless, general perception in the financial community is that stocks and bonds are group of suitable hedging instruments due to their negative correlation, and several reasons explain this connection (see e.g. Nielsson, 2007; Brannas and Soultanaeva, 2011; Komarkova, Lešánovská and Komarek, 2013; Sensoy, Eraslan and Ertuk, 2016; Liivamägi, 2016). Firstly, according to dividend discount models, interest rates increase the cost of capital, which adversely affects companies' equity prices due to reduction in the present value of future cash flows. Also, Cocriş and Nucu (2013) and Fedorova and Vaihekoski (2009) contended that an interest rate change could convey information about an expected rise in the real interest rate, which would make the future nominal cash flows less valuable to shareholders. Secondly, interest rates increase aggravates debt service payments of firms, which sends negative signals to stock investors, mitigates demand for stocks, and eventually impact share prices negatively (see Ferrer, Bolós and Benítez, 2016). Finally, from the portfolio rebalancing point of view, interest rate decrease may instigate investors to shift their funds into equities in search of higher yields, which increases demand for equities and their prices, and *vice-versa*. These three factors suggest an inverse relationship between interest rate changes and stock returns.

On the other hand, positive stock-bond relation is found less often, and it is mainly related to some specific situations, such as financial crisis and high inflation expectations. However, Yang, Zhou and Wang (2009) researched the stock-bond correlations over the last 150 years and found that this nexus has shifted from sizably positive to predominantly negative over the last two decades. Increased markets uncertainty usually galvanizes flight-to-quality behaviour, whereby investors shift from riskier stocks toward safer investments such as government bonds (see e.g. Abad and Chulia, 2016; Bayraci, Demiralay and Gencer, 2018). Due to increase demand for bonds, it inevitably implies dramatic decrease in the yield on long term government bonds. This type of occurrences, generates a positive correlation between changes in yields on sovereign bonds and stock returns (see e.g. Connolly, Stivers and Sun, 2005; Christiansen, 2008; Engsted and Moller,

2009). Second factor that can spark positive correlation between bond yields and stock returns is expected inflation. According to the Fisher's decomposition,¹ higher (lower) growth and/or inflation expectations lead to higher (lower) bond yields. However, the impact of growth and inflation expectations on stock prices is not straightforward. According to Ilmanen (2003), the effects of rising inflation and/or growth expectations may have no repercussions on stock prices, if the discount rates and expected growth rate of dividends are equally impacted by rising inflation and growth expectations. Nevertheless, the same author also showed that in the case of high inflation expectations, the discount rate effect may outweigh the changes in expected future dividends, which tends to have a negative impact on stock prices. Andersson, Krylova and Vahamaa (2008) added that stock and bond prices tend to move in the same direction (positive correlation) during periods of high inflation expectations, while in periods of lower inflation expectations negative correlation can be found between these assets.

Many emerging countries decided to issue long-term government bonds in last 15 years, due to improvement of their overall economic outlook and the fast growth that they recorded (see e.g. Pellešova, 2004; Nakamura, Olsson and Lönnborg, 2012; Caporale et al., 2014; Kjosevski and Petkovski, 2017). These long-term securities turn out to be very appealing for global investors who welcomed their issuance. The reason for that lies in a fact that emerging markets' sovereign bonds, denominated in local currencies, have several favourable characteristics, such as: 1) relatively high real yields; 2) expected currency appreciation; 3) declining currency volatility; and 4) strengthening credit quality. However, it should be said that extant literature in a field of the stock-bond relations is mainly based upon low frequency data (see e.g. Tetrelova, 2004; Yang, Zhou and Wang, 2009; Baele, Bekaert and Inghelbrecht, 2010; Dauti, 2016). This approach is insufficient for an in-depth analysis, because stock and bond markets comprise thousands of heterogeneous agents, who operate over different time horizons, ranging from days to years. Ferrer, Bolós and Benítez (2016) explained that investors with very short term-horizons (e.g. chartists or day traders) are interested in speculative activities, whereby their decisions are largely based on sporadic events, market sentiment or psychological factors. On the contrary, long-time agents (e.g. fundamentalists or big institutional investors) are keen to understand macroeconomic fundamentals, such as interest rates, because their investment activities are related to long-term developments. Having this in mind, it is reasonable to assume that the degree of connection between interest rates and stock prices may vary across different investment horizons. Besides, Ferrando, Ferrer and Jareno (2017) asserted that vast majority of existing studies, focused only on highly developed financial markets.

¹ Nominal bond yield (n) = real interest rate (r) + expected inflation rate (π) + term premium (θ).

According to the aforementioned, the goal of this paper is to thoroughly investigate the interdependence between the national 10Y government bond yields and the domestic stock market returns in four East European economies (the Czech Republic, Poland, Hungary and Romania) and two Eurasian emerging countries (Russia and Turkey), analysing both time and frequency domains of the underlying nexus. In other words, we strive to stipulate whether the stocks and bonds of these countries are suitable hedging instruments, which means that they have negative correlations, or perhaps they are not, which imply that their correlations are positive. This paper goes even further in the analysis, trying to determine the size and direction of their nexus at different time-horizons. All the East European countries and Russia are the major transition countries, while Turkey is considered because it is a regional fast-growing emerging market, and the part of its territory also belongs to the Balkan peninsula. Some stylized facts about the stock and bond markets of the selected countries are given in Table 1.

Table 1

Some Basic Characteristics about the Selected East European and Eurasian Markets

Stocks	Market capitalization ¹	World rank ¹	Trading volume ²	Bonds	Bond ratings ³	Debt/GDP ⁴ in %
Czech SE	40,912.4	50	12,269	Czech bond	AA-	34.6
Polish SE	138,691.0	36	68,002	Polish bond	A-	50.6
Hungarian SE	22,553.36	61	10,383	Hungarian bond	BBB-	73.6
Romanian SE	14,023.92	64	1,618	Romanian bond	BBB-	35.0
Russian SE	622,052.0	18	145,515	Russian bond	BBB-	12.6
Turkish SE	171,765.0	33	377,304	Turkish bond	B+	28.3

Notes: SE stands for stock exchange. Stock market capitalization and trading volume are portrayed in millions of USD in 2016.

Source: ¹ <www.indexmundi.com/facts/indicators/CM.MKT.LCAP.CD/rankings>.

² Source for trading volumes: the World Bank – World Federation of Exchanges database.

³ Credit ratings for sovereign bonds according to Standard & Poor's credit agency.

⁴ Reference year for the Debt/GDP ratio is 2017; <<https://tradingeconomics.com/>>.

It can be seen that the selected stock exchange markets are relatively large according to the world rank, whereas their liquidity levels are also relatively significant, except for Romanian SE, which has the lowest trading volume. In addition, the bond ratings of the selected countries are relatively high, which provides security to the investors in a sense that these countries will meet their obligations. Low percentage of debt/GDP, except for Hungary, contributes to their relatively high bond ratings.

In order to fulfil our research goals, regarding the observation of different time-horizons, we consider wavelet methodology, which is a powerful mathematical tool capable of unravelling the strength of the dynamic interactions between observed variables at different frequency scales and in different time-periods. This model-free approach allows a deeper understanding of a particular issue, while it

circumvents the problem of sample size reduction at the same time. In other words, the computation is done without wastage of valuable information. In particular, we apply wavelet coherence (WTC) and wavelet correlation methods. Many recent studies applied wavelet approach to analyse various economic phenomena at different time-horizons (see e.g. Nikkinen et al., 2011; Dajčman, 2012; Madaleno and Pinho, 2012; Barunik and Vacha, 2013; Dewandaru et al., 2014; Njegić, Živkov and Damnjanović, 2017; Živkov, Đurašković and Manić, 2019). In order to further define the nature of the mutual interlink, as well as the lead(lag) relationship (spillover effect) between national stocks and bonds, we utilize phase difference approach of Aguiar-Conraria and Soares (2011). 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. We follow some papers, such as Altar, Kubinski and Barnea (2017) and Živkov, Balaban and Đurašković (2018) which used this methodology. Dajčman (2013) contended that knowing lead(lag) relationship could be very useful, because empirical movements of leading variable can be utilized to forecast the realizations of lagging time series. To the best of our knowledge, this is the first paper that investigates comprehensively stocks-bond nexus at multiple investment horizons, taking into consideration relatively wide group of emerging markets.

Beside introduction, the rest of the paper is structured as follows. First section introduces methodologies used for computational purposes. Second section presents dataset. Third section explains wavelet coherence results, while fourth section contains phase difference findings for midterm and long-term horizons. Last section concludes.

1. Methodology

Wavelet methodology presents the estimation of the spectral characteristics of a time-series as a function of time, showing how the different periodic components of a particular time-series evolve over time. Following Rua and Nunes (2009), the continuous wavelet transform $W_x(u, s)$ is obtained by projecting a specific wavelet $\psi(\cdot)$ onto the examined time series $x(t) \in L^2(\mathbb{R})$ by the following expression:

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

where u represents the position of the wavelet in the time domain while s portrays the position in the frequency domain. From equation (1), information on time and frequency can be simultaneously acquired by mapping the original time series into a function of u and s in the wavelet transform.

The concepts of a bivariate framework called wavelet coherence and wavelet phase-difference are natural generalizations of the basic wavelet analysis tools and it determines the time-frequency dependencies between two time-series. Particularly, WTC is needed to be applied in order to investigate the interaction between two time-series on how closely X and Y are related by a linear transformation (see Rahim and Masih, 2016). According to Vacha and Barunik (2012), the 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 the linear regression. Referring to Torrence and Webster (1999), WTC is defined as the 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 $W_{xy}(u, s) = W_x(u, s)\overline{W_y(u, s)}$, wherein W_x and W_y are the wavelet transforms of x and y , respectively. The squared wavelet coherence coefficient is given as follows:

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

where $S(\cdot)$ stands for a smoothing operator and s is a wavelet scale. The squared wavelet coherence coefficient ranges $0 \leq R^2(u, s) \leq 1$, where values near zero point to weak correlation, while values near one indicate strong correlation. WTC is estimated by applying the Monte Carlo simulation methods. WTC methodology is unable to stipulate whether dependence between two time-series is positive or negative because the wavelet coherence is squared. Thus, we also consider wavelet coherence phase differences, which describes details about the delays in the oscillation (cycles) between the two time-series under study. Following Torrence and Webster (1999), the wavelet coherence phase difference is defined as follows:

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

Phase difference between two series (x, y) is indicated by arrows on the wavelet coherence plots. As Vacha and Barunik (2012) asserted, 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.

Additionally, we apply phase difference method of Aguiar-Conraria and Soares (2011), which can determine average phase-position at specific frequency band. Phase-arrows in WTC plots frequently change direction in lower coherence areas, preventing in that way researchers to properly determine the direction of the coherence throughout observed sample. Aguiar-Conraria and Soares (2011) technique bypasses these deficiencies. According to these authors, if $\phi_{xy} \in (\pi/2, 0) \cup (0, -\pi/2)$ then the series move in phase. If phase difference is in realm $(\pi/2, 0)$ then the time-series y leads x . The time-series x leads y if $\phi_{xy} \in (-\pi/2, 0)$. An anti-phase situation, that is, negative correlation, happens if we have a phase difference in an area $\phi_{xy} \in (-\pi/2, \pi) \cup (-\pi, \pi/2)$. If $\phi_{xy} \in (\pi/2, \pi)$ then x is leading. Otherwise, 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 correlation, at the specified frequency.

CWT plots are not so accurate when it comes to the strength of the correlation, because it is portrayed via black and white palette. In order to be more precise in that matter, we introduce another wavelet tool, called wavelet correlations. It can produce exact numbers of wavelet correlations across the scales. Firstly, we imply a bivariate stochastic process $\mathbb{Z}_t = (x_t, y_t)$ of two time-series, $x(t)$ and $y(t)$, which are in our case index and 10Y bond yield. Expression $\widehat{D}_{j,t} = (\widehat{D}_{x,j,t}, \widehat{D}_{y,j,t})$ represents a scale J wavelet coefficient computed from \mathbb{Z}_t . Secondly, each wavelet correlation coefficient is obtained by applying the Maximum overlap discrete wavelet transformation (MODWT) process in \mathbb{Z}_t . Subsequently, the time-dependent wavelet variance for scale J of each time-series is then presented as $\sigma_{x,j,t}^2 = \text{Var}(\widehat{D}_{x,j,t})$ and $\sigma_{y,j,t}^2 = \text{Var}(\widehat{D}_{y,j,t})$, whereas time-dependent wavelet covariance for scale J is $\gamma_{x,y,j,t} = \text{COV}(\widehat{D}_{x,j,t}, \widehat{D}_{y,j,t})$. Combining wavelet variances and wavelet covariance, we can calculate the wavelet correlation² coefficients as follows:

$$\rho_{x,y,j,t} = \frac{\text{COV}(\widehat{D}_{x,j,t}, \widehat{D}_{y,j,t})}{\left(\text{Var}(\widehat{D}_{x,j,t})\text{Var}(\widehat{D}_{y,j,t})\right)^{1/2}} \quad (4)$$

2. Dataset

Our dataset consists of daily yields on 10-year government bonds and daily closing stock market prices of four East European and two Eurasian emerging markets (the Czech Republic, Poland, Hungary, Romania, Russia and Turkey). We consider following stock indices – Czech PX, Polish WIG, Hungarian BUX,

Romanian BET, Russian MICEX and Turkish XU100. We opt for the 10-year government bond yield as a proxy of long-term interest rates because these securities incorporate market expectations about future prospects for the economy and determine to a large extent the cost of borrowing funds (see Ballester, Ferrer and González, 2011; Soudis, 2017). According to this, long-term interest rates have a critical effect on companies' investment decisions, their profitability, and eventually on their stock market performance. Also, it should be mentioned that long-term government bonds are often perceived as closest maturity substitute to stocks, which presumably may enhance the degree of connection between both financial assets.²

The length of our sample is determined by the availability of the data. Therefore, starting point of the data for the Czech Republic, Poland, Hungary and Russia is November 28, 2005, while for Romania and Turkey it is August 20, 2007 and January 29, 2010, respectively. All time-series range to October 20, 2018. Taking into account the unavailability of some data, due to national holidays and non-working days in the selected stock and bond markets, the daily dates are synchronized between two markets according to the existing observations. All time-series are collected from Investing.com. Stock returns (r) are calculated as the first log difference of closing stock price indices (P), according to $r_{t,i} = 100 \times \log(P_{t,i} / P_{t-1,i})$. Also, we perform first difference in the level of bond yields between two consecutive observations in order to obtain changes in 10-year sovereign bond yields. Descriptive statistics for these series is presented in Table 2, while Figure 1 presents their empirical movements. We observe seven wavelet scales, which can provide an insight about stock-bond nexus at different time horizons. These horizons correspond to: 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), scale 6 (64 – 128 days) and scale 7 (128 – 256). We treat first four scales as short-term dynamics, midterm is represented by fifth and sixth scales, while seventh scale portrays long term dynamics.

Table 2 indicates that yields on 10-year bonds have lower volatility than stock returns for all countries. The sign of skewness tends to be negative for equity returns and positive for 10-year bond rate fluctuations, while all time-series have positive kurtosis coefficients in excess of three, suggesting the existence of heavy tails compared to a normal distribution. Kurtosis of Russian bond is particularly high. Due to detected heavy tails and extreme values, the wavelet approach is appropriate, because wavelet method is suitable for finding extreme movements and for non-stationary signals that contains numerous outliers (see e.g. Jammazi, 2012). The Jarque-Bera test statistics rejects the null hypothesis of normality for all selected time-series. We do not perform unit-root tests because we work with wavelet series, which are stationary by default.

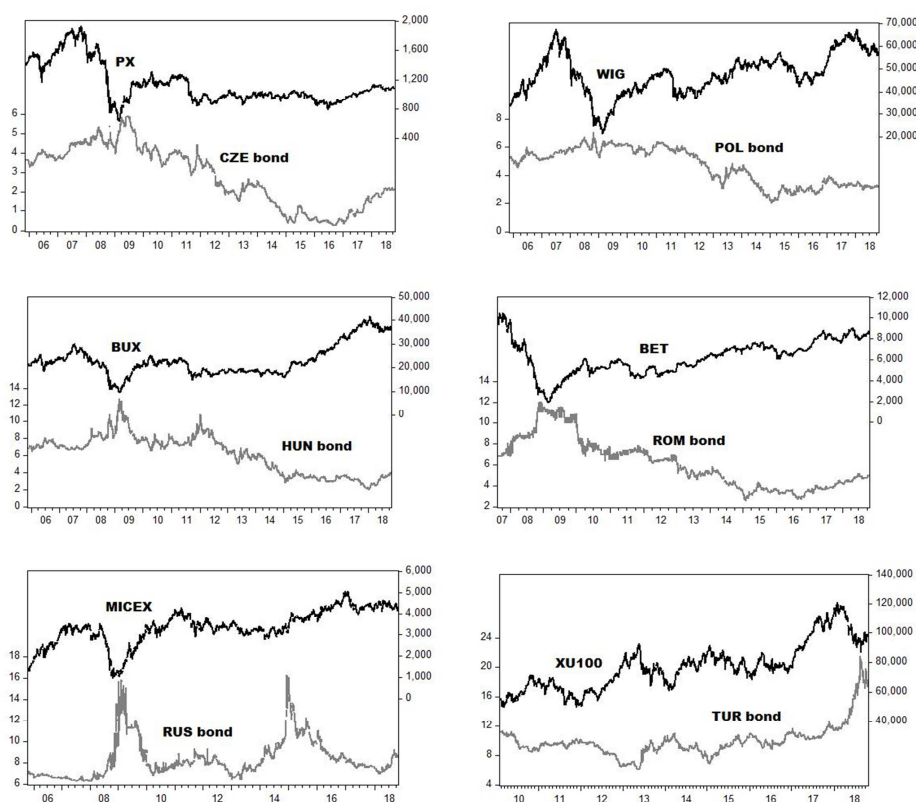
² Wavelet correlations are calculated via 'waveslim' package in 'R' software.

Table 2
Descriptive Statistics of the Selected Series

	Mean	St. dev.	Skewness	Kurtosis	JB
Panel A: Indices					
PX	-0.012	1.428	-0.550	19.354	33 872
WIG	0.022	1.247	-0.487	6.978	2 114
BUX	0.019	1.563	-0.092	10.588	7 233
BET	0.031	0.826	-0.808	9.140	2 447
MICEX	0.019	1.149	-0.626	10.490	3 501
XU100	0.037	1.363	-0.585	8.195	1 721
Panel B: 10Y Bond yields					
Czech bond	-0.001	0.047	0.984	23.511	53 532
Polish bond	-0.001	0.053	0.729	18.409	30 198
Hungarian bond	-0.002	0.117	0.089	18.871	31 627
Romanian bond	-0.002	0.079	0.007	6.532	757
Russian bond	-0.000	0.159	1.653	155.107	1 405 253
Turkish bond	0.002	0.122	0.435	7.760	1 421

Source: Authors' calculation.

Figure 1
Empirical Dynamics of Stock Prices and Yields on 10-year Government Bonds



Note: Black and grey lines denote empirical movements of stock indices and yields on 10-year government bonds, respectively.

Source: Authors' calculation.

3. Wavelet Coherence Results

This section contains the results of wavelet coherence³ between stock indices and yields on 10-year government bonds of the selected emerging markets. Technically speaking, horizontal axis depicts time component in WTC plots, while the left vertical axis represents frequency component, which goes up to 128 days (seventh scale).

The strength of the co-movement between each of the selected assets can be seen via black and white colours, whereby lighter shades indicate to low coherence, while darker shades suggest higher coherence. The black and white palette is depicted at right Y-axis and it ranges from 0 to 1. The cone of influence marks the area of statistical significance at 5% level. This curved boundary delimits the region of the wavelet spectrum, which is influenced by the edge effects, hence these values should be interpreted with great caution. Theoretical distribution of the wavelet coherence is not known, which means that the statistical significance is usually assessed by using Monte Carlo simulation methods (see Torrence and Webster, 1999).

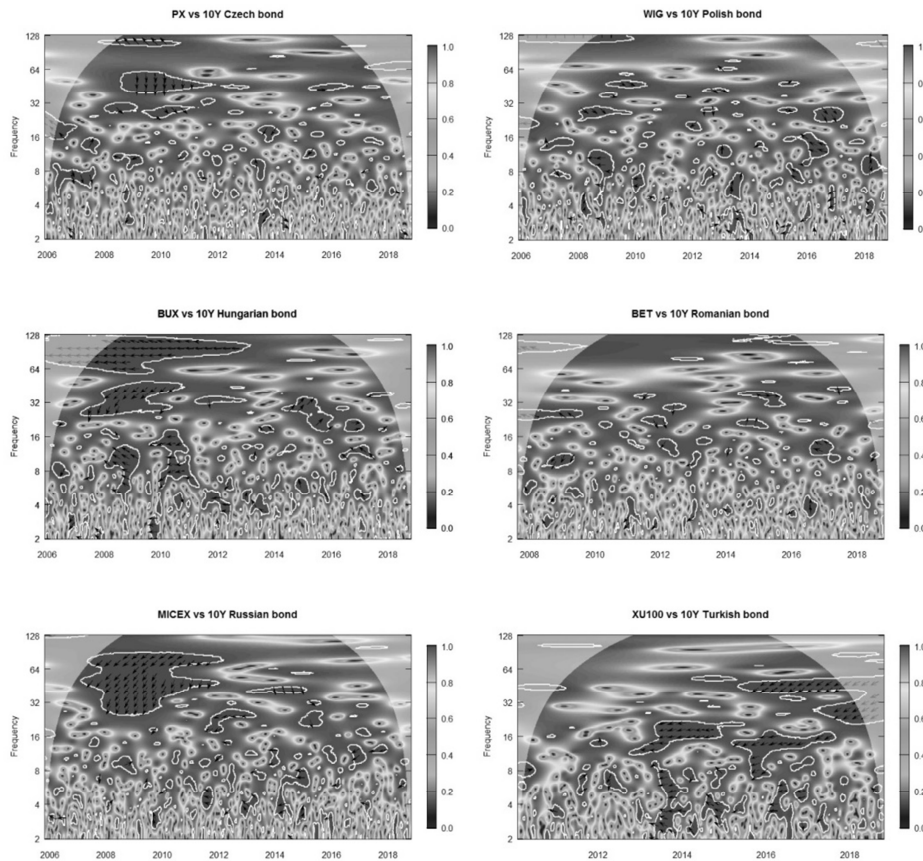
Figure 2 shows that correlation strength between national stocks and bonds varies widely over time and across wavelet scales, which justifies the usage of this methodology. It can be seen that lighter shades dominates at short-term horizons (up to eight days), whereas darker shades have predominance at higher wavelet scales, and this pattern is relatively common for all countries.

Our results coincide with the findings of Ferrer, Bolós and Benítez (2016), who claimed that shorter investment horizons are more influenced by noise and idiosyncratic market performances, whereas investors with long-term horizons are more likely to follow macroeconomic fundamentals such as long-term interest rates. Also, since data-sample for all the countries, except Turkey, covers the World financial crisis (WFC), we can evaluate how this extreme market event affected the stock-bond nexus. It can be noticed that widest dark-delineated areas are found between 2008 and 2010 in the cases of Hungary, Russia and Turkey, whereas in the cases of Poland, Romania and the Czech Republic the dark areas are very modest during WFC. These very dark surfaces suggest pretty strong coherence between stocks and bonds during WFC.

Our results coincide with the claim of Ferrando, Ferrer and Jareno (2017), who contended that in times of market stress, investors frequently exhibit herding behavior, which may lead to a disproportionate response to stock markets as well as to changes in equity fundamentals such as interest rates, which in turn enhances their mutual nexus.

³ All WTC calculations were done via 'R' software, using 'WaveletComp' package.

Figure 2
Wavelet Coherence between Stock Prices and Yields on 10-year Government Bonds



Source: Authors' calculation.

In addition, phase arrows, which can be found in the dark areas, suggest the direction of the coherency and the lead-lag relationship between stocks and bonds. Left-pointing arrows indicate an anti-phase situation in the cases of Hungary, Russia and Turkey in high coherence areas, which suggests that stock prices and bond yields move in opposite directions in the longer time-horizons. This means that tactical asset allocation did not hold in these countries during WFC and at these particular time-horizons. As for the Czech case, it can be noticed that phase arrows point to right-down between 16 and 32 days, which indicates to positive coherence, whereby 10Y bond yield has leading role. This may indicate that flight-to-quality episode from stocks into less risky government bonds happened in the Czech Republic during WFC in 16 – 32 days horizon.

However, the lack of phase arrows at lower coherence areas does not give a clue about the direction of the nexus in the largest part of WTC plots. Therefore, making a conclusion solely based on WTC plots could be misleading. In order to dispel any doubt on the question whether these instruments are suitable hedging instruments or not, we calculate wavelet correlations, which provides average levels of correlations across the scales, and Table 3 contains these results. It can be seen that wavelet correlations take negative values across all the scales in the cases of Hungary, Romania, Russia and Turkey. In the case of Poland this is the case in the first five wavelet scales, while for the Czech case, negative correlations are present in time-horizon between 4 – 32 days. These results indicate that Hungarian, Romanian, Russian and Turkish stocks and bond could serve well for hedging purposes in the all observed time-horizons. Particularly strong bond is detected at higher wavelet scales in the case of Turkey, while in the cases of Hungary, Poland and the Czech Republic, strong connections are found at D5 scale. As for Romania, it applies for D6 and D7 scales. It should be said that investors which invest in longer time-horizon (64 – 28 days) can use Czech and Polish instruments only for diversification, but not for hedging, since these instruments at longer time-horizons have positive nexus.

Table 3
Wavelet Correlations for the Selected Pairs of Assets

	PX vs Czech bond	WIG vs Polish bond	BUX vs Hungarian bond	BET vs Romanian bond	MICEX vs Russian bond	XU100 vs Turkish bond
D1 – 2 days	0.076	-0.140	-0.332	-0.005	-0.078	-0.114
D2 – 4 days	-0.068	-0.227	-0.399	-0.096	-0.057	-0.114
D3 – 8 days	-0.076	-0.307	-0.370	-0.116	-0.096	-0.213
D4 – 16 days	-0.091	-0.199	-0.419	-0.200	-0.198	-0.190
D5 – 32 days	-0.386	-0.561	-0.621	-0.296	-0.209	-0.564
D6 – 64 days	0.213	0.021	-0.171	-0.369	-0.185	-0.761
D7 – 128 days	0.050	0.353	-0.401	-0.471	-0.079	-0.821

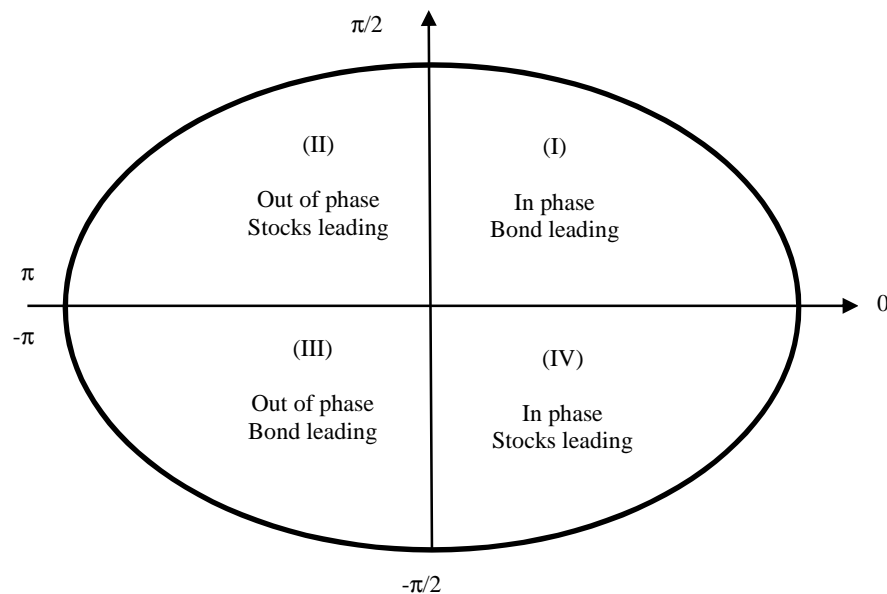
Source: Authors' calculation.

4. Phase Difference Findings

Phase arrows within WTC framework bear some information regarding the lead-lag relationship between observed series. However, as have been said, this information is relatively limited, since phase arrows can be seen only in high-power areas, while in other, low-power regions, phase arrows shift direction constantly, without a common and stable behaviour. In such circumstances, it is very difficult to precisely determine which variable lagging (leading) the other

one. Therefore, we apply phase difference method⁴ of Aguiar-Conraria and Soares (2011), which is a suitable tool for providing an information regarding the direction of coherence as well as the leading(lagging) role of particular variable, throughout the observed sample and at specific frequency band. At the same time, this analysis will serve as a robustness test for the previous findings. Concise lead (lag) relationship between stocks and bond are presented visually via phase difference circle in Figure 3.

Figure 3
Phase Difference Circle



Source: Authors' presentation.

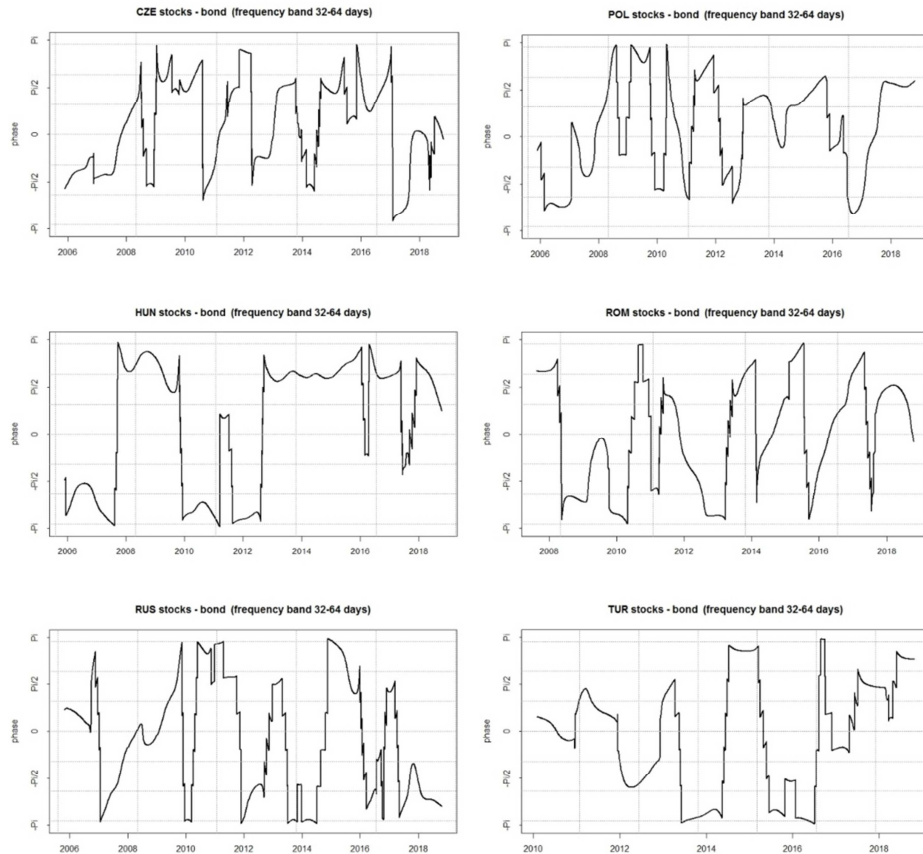
Phase difference at high frequencies has pretty chaotic dynamics, so we calculate phase difference only in midterm and long-term, and results are presented in the next two subsections.

4.1. Phase Difference Findings in the Midterm

Figure 4 presents results of phase difference in the midterm. It can be seen that Czech and Polish phase difference plots are more erratic in comparison to the four other counterparts. In other words, Czech and Polish phase differences indicate that stocks and bond frequently change leading (lagging) role, while in other four countries, these relations are more stable and relatively long-lasting.

⁴ The results were obtained by applying ASToolbox of Aguiar-Conraria and Soares (2011).

Figure 4
Phase Difference at 32-64 Frequency Band



Source: Authors' calculation.

It is obvious that phase differences in all plots are dominantly in domains beyond $\pi/2$ and $-\pi/2$ boundaries, which indicates negative coherence, that is, stocks return rise is accompanied by bond yield fall, and *vice-versa*. This finding is in line with general perception that stock returns and bond yields move in opposite direction, primarily because interest rate is constituent part in dividend discount model, and due to portfolio rebalancing activities. Also, it should be said that phase difference more frequently takes positions in realm between $\pi/2$ and π in all the cases, except the Turkish case. It signals that stocks have leading role for most of the time in the majority of the countries in the midterm horizon. Practically, it means that, depending on the level of stock market returns, investors decide whether to enter or leave bond markets, which eventually affect the level of bond yields.

In addition, some interesting pattern can be noticed in Czech and Polish plots around WFC. In particular, phase differences find itself in in-phase position (between $\pi/2$ and $-\pi/2$) at the onset of WFC in these countries, whereby stocks have leading role. It means that investors rebalanced their portfolios in these countries in midterm, that is, capital funds were shifted from stock to bond markets during WFC. Comparing with our previous WTC results, phase difference findings are in line with the Czech case, because Czech phase arrows signals in-phase situation in 16 – 32 frequency scale. However, Polish WTC results lack this information, because phase arrows are not visible at higher wavelet scales in WTC plot. On the contrary, in the Hungarian, Romanian and Russian cases, we do not find positive phase difference during WFC, whatsoever. In other words, phase difference is constantly beyond $\pi/2$ boundary which imply an anti-phase situation, whereby stocks have a leading role. It means that investors did not see bonds of these countries as an appropriate opportunity to invest during WFC.

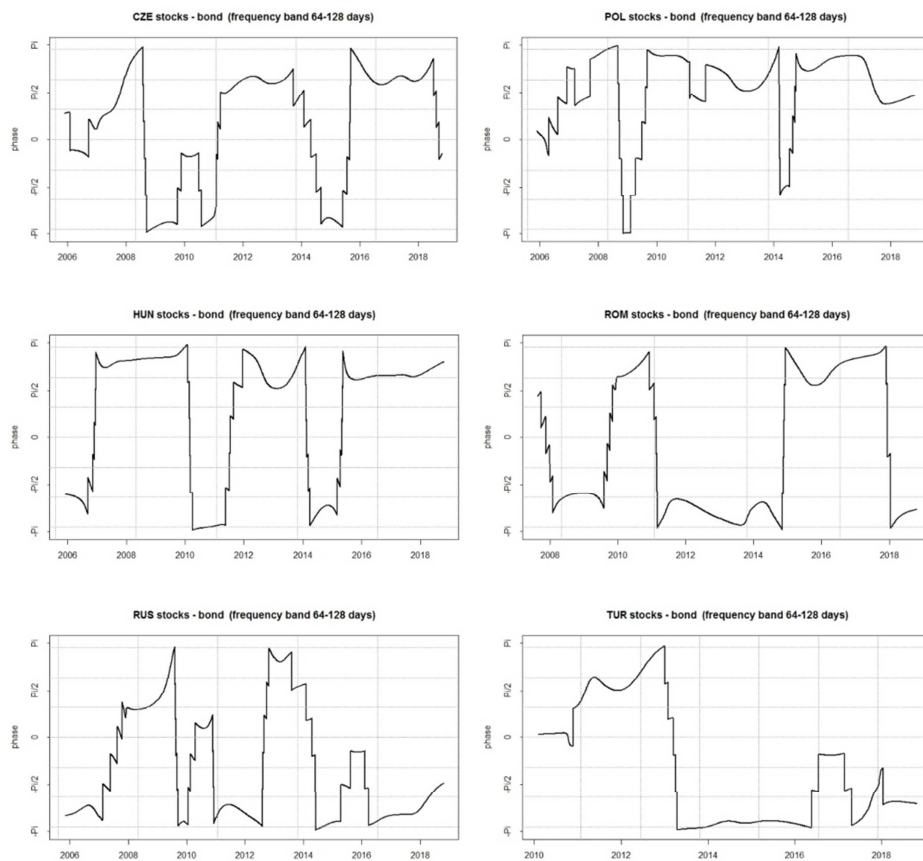
4.2. Phase Difference Findings in the Long-term

This subsection explains phase difference results in the long-term. It is obvious that phase difference dynamics in the long-term is more stable and smoother in comparison with the midterm phase differences, and it particularly applies for the Czech and Polish cases. Unlike the midterm, we find an anti-phase situation in the long-term horizons in the Czech and Polish plots during WFC. In both cases, stock market has leading role in 2008, and later, it reverses and then bond market took advantage in 2009. As for the Hungarian case, stock market constantly leading in an anti-phase situation throughout the WFC period. In Romania, bond leads around WFC and in the period 2011 – 2014, while around 2010 and in the period between 2015 – 2018 it is stocks that is leading. In the Russian case, bond predominantly leads throughout the sample. Turkish phase difference shows constant anti-phase position, whereby bond has dominant role since 2014, whereas, in the period 2011 – 2013, stocks have the leading role. We find a very consistent anti-phase pattern in all the countries, which coincide with assertion of Ferrer, Bolós and Benítez (2016), who argued that long-term investors are keen to understand macroeconomic fundamentals, such as interest rates, thus they are not prone to impulsive capital funds shifting from one market to another. Also, this confirms that stocks and bond of these countries are good hedging instruments in the long-term.

Turkish and Russian long-term phase differences indicate that 10Y bonds take a leading role from 2014, which is different from the cases in other countries. However, it should be said that Turkey also stands out in one other characteristic, and that is the average annual inflation, which amounts 8.86% since

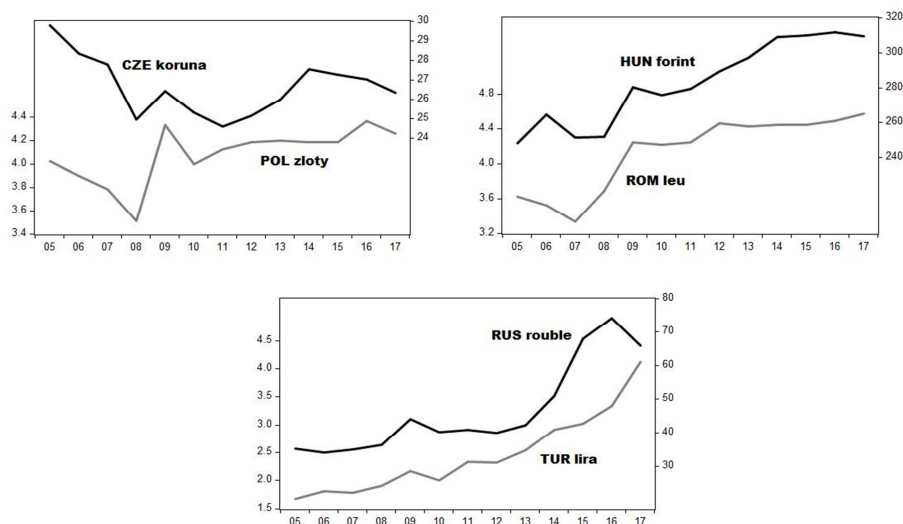
2014. Turkey has a long-lasting problem with relatively high inflation, and one reason why this is the case is the existence of twin deficits (see Catik, Gok and Akseki, 2015). These deficits affect depreciation of Turkish lira, which inevitably spill overs to Turkish inflation. Figure 6 shows that Turkish lira depreciate approximately 100% in the last 10 years. Russian rouble also significantly depreciated in the last 5 years, and that is the case predominantly due to the huge oil price drop in 2014. It effected Russian inflation, which amounts on average 8.52% since 2014. All other countries have relatively stable currencies and low inflations. Therefore, in the Turkish and Russian cases, if long-term investors perceive that inflation expectations will exceed future bond yields, they will abandon bond market and transfer their capital funds to stock market. This is possible reason why bond market leads in these economies since 2014.

Figure 5
Phase Difference at 64-6128 Frequency Band



Source: Authors' calculation.

Figure 6
Empirical Dynamics of the Selected Currencies



Source: Authors' calculation.

Conclusion

This paper investigates the stock vs 10Y bond yield interdependence in six emerging markets of East Europe and Eurasia, trying to understand whether this nexus varies over time and across different investment horizons. For the research purposes we utilize two innovative methodologies – wavelet signal decomposing method and phase difference.

Wavelet coherence results revealed that low coherence areas dominate throughout WTC plots in all the selected countries, which indicates that these instruments might be good for diversification and hedging. However, since the phase arrows are not present at low coherence areas, this methodology is not so accurate in determining a direction of the coherence. Thus, we utilized also the wavelet correlations approach, which can gauge average wavelet correlations across the scales very precisely. Wavelet correlation findings disclosed that majority of the wavelet correlation coefficients are negative, which imply that these financial instruments are good hedging tools. The highest correlation coefficients are found in the Turkish case in the longer time-horizon.

Beside wavelet coherence, we also compute phase difference, which added to the robustness of the overall results. Phase differences were found dominantly in domains beyond $\pi/2$ and $-\pi/2$ boundaries in midterm and long-term in most of the countries, which suggests negative coherence, that is, stocks return rise is accompanied by bond yield fall, and *vice-versa*. This finding is in line with general

perception that stock returns and bond yields move in opposite direction, primarily because interest rate is constituent part in dividend discount model, and due to the portfolio rebalancing activities. However, in the Czech and Polish cases during WFC, phase differences were in an in-phase position (between $\pi/2$ and $-\pi/2$), which could mean that tactical asset allocation took place in these countries in the midterm. Also, we found evidence that existence of high inflation in Turkey and Russia since 2014 could be the probable reason for predominantly leading role of 10Y bond in that period.

This study could have various important practical implications for global investors, portfolio managers and financial market analysts, which invest in these emerging markets at different time-horizons. Knowing the strength and direction of coherence between stocks and bonds as well as their led (lag) relationship at different time-horizons, investors can make optimal decisions regarding their diversification efforts and risk management strategies. Our results suggest that investors will not make a mistake if they combine stocks and bonds of these countries in their portfolios, regarding all the time-horizons, since they can achieve good hedging benefits. Also, for the rebalancing purposes, investors can gain an insight how stock and bond market interact between each other, and from which market spillover shocks primarily come from.

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