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Multiscale oil-stocks dynamics: the case of Visegrad group and Russia

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ABSTRACT

This paper tries to determine the strength of the interdependence between Brent oil market and the stock markets of oil importing Visegrad group countries and oil exporting Russia in different time-horizons. The paper uses several novel and elaborate methodologies – bivariate DCC-EGARCH model, wavelet correlations and phase difference. The results of DCC model show that all dynamic correlations between Brent oil and the selected stock indices are low at daily-frequency level. The magnitude of mutual correlations does not exceed 20% for Visegrad countries, while for Russia it goes little bit over 30%. Wavelet correlations in short-term confirms DCC results, whereby this relatively weak connection is found up to 32 days. However, in midterm and long-term, wavelet correlations strengthen, and go above 50% in midterm and even beyond 80% in long-term for majority of the indices. Slovakian SAX index has stronger wavelet correlation in 32 days than in 64 days, and it goes around 23%. This means that SAX can be coupled with Brent oil for diversification purposes in both short-term and midterm portfolios. Besides, phase-difference methodology provides an evidence that SAX was in anti-phase position in two separate occasions, meaning that SAX can also serve well for hedging purposes.

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1. Introduction

Global economic growth is highly dependent on the consumption of energy resources, such as coal (lignite), natural gas and particularly oil (see Batrancea et al., 2019; Cuestas & Gil-Alana, 2018), but it produces increased oil price turbulence. Therefore, a greater interest has been born among number of global investors, portfolio managers and policy makers towards a better understanding of the interconnection between oil prices and stock markets. Chen, Wenqi Li, and Jin (2018) asserted that it is almost impossible to identify factor that has a greater influence than the oil price on the world economy. Due to the fact that majority of countries are oil dependent,

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the literature on this topic mainly found a negative relationship between the two markets (see e.g. Kurshid & Uludag, 2017; Sodeyfi & Katircioglu, 2016). Theoretically speaking, the mechanism by which the nexus between oil and stocks is explained can be summarised as follows. Direct link is manifested *via* higher transportation and production costs that are caused by increased oil prices. Under this conjecture, firms will not fully embed rising costs of oil into the prices of their final products, hence profits will inevitably decrease due to reducing expected returns, causing stock prices to fall. Indirect connection happens due to the fact that rising oil prices undoubtedly push up an overall inflation, instigating central banks to respond by raising the interest rate, which will in turn affect stock prices.

Due to the various phases of tranquil and crisis periods of world economy in last two decades, it is a well-known fact that the relationship between stock and oil markets exerts heterogeneous behaviour at different time periods. Therefore, numerous recent papers provide an evidence that these markets undergo dynamic interconnections (see e.g. Jouini, 2013; Hosseini & Tang, 2014; Mirović, Živkov, & Njegić, 2017). However, most researchers that investigated the dynamic connection between oil and stock markets, observed this relationship only *via* time dimension, neglecting the frequency dimension features that exist in these time-series. The study of Conlon and Cotter (2012) explained that the sample reduction problem arises when researchers try to match the frequency of data with the different time horizons, thus the multi-scale analysis in this topic has been little studied in general.

According to numerous authors, such as Borys (2011), Lyócsa, Baumöhl, and Výrost (2011), Nițoi and Pochea (2016), Akhvlediani and Śledziwska (2017), the Visegrad group countries are fast growing, but they are highly dependent on oil import.¹ Therefore, the main purpose of this paper is to conduct an in-depth analysis of the dynamic interconnection that exists between Brent oil and stocks indices of four Visegrad group countries. For the purpose of comparison, we also analyse time-varying connection between oil and Russian RTS index, the country that is one of the major global oil exporters. In order to disentangle the complex pattern between these two markets, our study tries to stipulate the time-dimension dynamics as well as multi-horizon nature of the co-movement between the two assets. In that manner, firstly, we apply a bivariate dynamic conditional correlation, i.e. DCC-EGARCH model because variations in correlations and volatilities in higher frequency levels are richer (see Nagayev, Disli, Inghelbrecht, & Ng, 2016). Secondly, we further enhance our DCC findings by employing a wavelet correlation method, which is able to assess the co-movement between the assets on a higher level of comprehension. In particular, this methodology is a powerful signal processing tool capable of gauging the strength of the interdependence across various scales. We gain an idea to utilise wavelet method by referring to the following recent studies, such as Dajčman (2012), Barunik and Vacha (2013), Lee and Lee (2016), Živkov, Balaban, and Đurašković (2018), Tsai and Chang (2018), Poměnková, Klejmová, and Kučerová (2019) and Živkov, Đurašković, and Manić (2019). Unlike traditional methodologies, this technique can simultaneously capture both time and frequency domain, circumventing the problem of sample size reduction, i.e. computation is done without loss of valuable information. According to Altar, Kubinschi, and Barnea (2017), this

characteristic is particularly useful when researchers work with non-stationary signals that contains numerous outliers.

Due to the fact that commodity and equity markets are complex systems of interacting agents with varying term objectives as Nagayev et al. (2016) asserted, DCC model along with wavelet correlations could collectively provide a more profound and robust analysis of the subject matter. In addition, we further analyse the lead-lag relationship between Brent and selected indices *via* three different frequency bands in order to answer which particular market leads and which one lags in different time-horizons. Even though there are a vast number of studies related to this topic, to the best of our knowledge, none of the papers analyses thoroughly and comprehensively the oil-stocks dynamics in the case of Visegrad group countries. This research aims to fill this void.

In summary, this analysis tries to achieve several objectives, which are of interest for global investors who combine Brent with the selected indices. First, we want to assess the level of mutual correlation, regarding different time-horizons, which is an important factor for portfolio designing. Second, we calculate phase difference, which can give us a clue which market is shock transmitter, and which one is the shock recipient. This information is important for portfolio rebalancing purposes. We hypothesise that stock indices from Visegrad countries are better instruments to combine with Brent than Russian RTS index, because Visegrad countries are oil importers, while Russia is oil exporter and heavily dependent on oil revenues.

Besides introduction, the rest of the paper is structured as follows. Second section provides literature review related to the oil-stock topic. Third section explains used methodologies. [Section 4](#) presents used data and preliminary findings. [Section 5](#) reveals empirical results of the bivariate DCC-EGARCH model, wavelet correlations and wavelet phase difference. [Section 6](#) explains possible implications for the global investors, while [Section 7](#) concludes.

2. Brief literature review

Due to the fact that oil represents one of the most important commodities in the world, a growing body of literature considers the empirical relationship between oil price and stocks, suggesting that oil price changes are associated with fluctuations in stock prices, although the results are mixed. Some papers suggested adverse impact of oil price shocks on the financial markets. For instance, Broadstock, Wang, and Zhang (2014) researched how oil price shocks influence energy related stock portfolios in the Asia Pacific region. They showed that oil shocks can affect stocks directly, but also indirectly through general market risk. They asserted that direct effect is not always present, whereas the indirect effect is always existing. They claimed that these effects are positive, which implies that a sudden rise in oil prices leads to positive returns on energy related stocks. Eryiğit (2012) researched the short-term nexus between oil prices and interest rate, stock market index, and exchange rate in Turkey via vector autoregressive (VAR) model. He found that oil price shocks have effect on Istanbul stock exchange market index, because Turkey is an oil importing country

and most of the companies on Istanbul stock exchange are impacted directly or indirectly from oil price and exchange rate changes.

On the contrary, there are researchers who endorsed the notion that positive impacts of oil price movements on stock markets holds for the oil-exporting countries. For example, Bhar and Nikolova (2010) provided a greater understanding of the implications of oil price changes on the equity investment in Russia. They claimed that oil companies are some of the strongest performers on the Russian stock market and are viewed as the main contributors to the booming Russian economy due to increasing oil prices and stronger global oil demand. Arouri and Rault (2012) examined long-run links between oil prices and stock markets in Gulf Cooperation Council (GCC) using recent bootstrap panel cointegration techniques and seemingly unrelated regression (SUR) methods. They found an evidence for cointegration existence between oil prices and stock markets in GCC countries, while the SUR results point to the conclusion that oil price increases have a positive impact on stock prices, except in Saudi Arabia. Shaeri and Katircioğlu (2018), using the DOLS methodology and weekly data, analysed the US case and showed that stocks prices of oil companies are positively affected by rising crude oil prices. They also contended that technology stocks are positively affected by the crude oil prices. They explained that these companies in these occasions lower their energy-related costs and innovate more energy-conserving products. As a result, their financial performances improve.

In addition, there are some studies that provided empirical evidence that oil price changes have little or no effects on stock market returns. Jammazi and Aloui (2010) combined wavelet analysis and Markov Switching VAR approach to explore the impact of the crude oil shocks on the stock market returns for UK, France and Japan. They disclosed that oil shocks do not affect the recession stock market phases (except for Japan). The study of Cong, Wei, Jiao, and Fan (2008) investigates the interactive relationships between oil price shocks and Chinese stock market *via* multivariate VAR model. The results indicated that oil price shocks do not show statistically significant impact on the real stock returns of most Chinese stock market indices, except for manufacturing index and some oil companies.

3. Methodology

3.1. DCC-EGARCH model

The connections between selected stock indices and Brent oil are investigated firstly *via* only time domain, utilising bivariate DCC² model of Engle (2002), because it is very appealing for dynamic connection investigation (see e.g. Dajčman & Festić, 2012; Onay & Ünal, 2012). For univariate specification, we applied EGARCH(1,1) model of Nelson's (1991), where mean equation has first order auto-regressive form. We fit the univariate EGARCH model and estimate standard deviations, $\sqrt{h_t}$. Next, the asset-return residuals are standardised, i.e. $v_t = \varepsilon_t / \sqrt{h_t}$, wherein the v_t is used subsequently to estimate the parameters of the conditional correlation. Accordingly, the multivariate conditional variance is specified as $H_t = D_t C_t D_t$, where $D_t = \text{diag}(\sqrt{h_{11,t}}, \dots, \sqrt{h_{nn,t}})$ and $h_{nm,t}$ represents the conditional variance, which is obtained from the EGARCH model in the first stage. The evolution of correlation in

the DCC model is presented as:

$$Q_t = (1 - a - b)\bar{Q} + av_{t-1}v'_{t-1} + bQ_{t-1}, \tag{1}$$

where a and b are nonnegative scalar parameters of DCC(1,1) model under condition $a + b < 1$, and if $a = b = 0$ the DCC model reduces to constant conditional correlation (CCC) model. These parameters gauge the effects of previous shocks and previous dynamic conditional correlations on current dynamic conditional correlations, respectively. Symbol $Q_t = [q_{nm,t}]$ describes $n \times n$ time-varying covariance matrix of residuals, where $i \neq j$ in our bivariate model, and n equals two. Symbol $\bar{Q} = E[v_t v'_t]$ signifies a $n \times n$ time-invariant variance matrix of v_t . Since Q_t does not have unit elements on the diagonal, it is scaled to obtain proper correlation matrix (C_t) according to the following form:

$$C_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \tag{2}$$

Accordingly, the element of C_t denoted as $\rho_{nm,t}$ can be written for a bivariate case as:

$$\rho_{nm,t} = q_{nm,t} / \sqrt{q_{nn,t} q_{mm,t}} \tag{3}$$

All DCC models were estimated by the quasi-maximum likelihood (QMLE) technique. This procedure allows asymptotically consistent parameter estimates even if the underlying distribution is not normal, as asserted by Bollerslev and Wooldridge (1992).

3.2. Wavelet correlation and phase-difference

In contrast to the DCC-EGARCH approach, the wavelet correlation³ technique allows us to evaluate the connection between stock indices of Visegrad group and Brent oil in various frequency spaces, complementing, in this way, our DCC-EGARCH findings. Wavelet methodology estimates the spectral characteristics of a time-series as a function of time, revealing how the different periodic components of a specific time-series evolve over time (see Dewandaru, Rizvi, Masih, Masih, & Alhabshi, 2014). In particular, we use the maximum overlap discrete wavelet transformation (MODWT) for the decomposition of the empirical time-series. We assume that $\mathbb{Z}_t = (x_t, y_t)$ is a bivariate stochastic process of two time-series, Brent - $x(t)$ and stocks - $y(t)$, whereby $D_{j,t} = (D_{x,j,t}, D_{y,j,t})$ is a scale j wavelet coefficient computed from \mathbb{Z}_t . Decomposition of the empirical time-series in the MODWT process is given by the following way:

$$S_j(t) = \sum_k s_{j,k} \phi_{j,k}(t) \tag{4}$$

$$D_j(t) = \sum_k d_{j,k} \psi_{j,k}(t) \tag{5}$$

where $S_j(t)$ and $D_j(t)$ stand for the fluctuation and scaling coefficients, respectively, at the j -th level, which reconstructs the empirical time-series in terms of a specific frequency (trending and fluctuation components). Symbols $\phi_{J,k}(t)$ and $\psi_{j,k}(t)$ denote two basic wavelet functions – the father wavelet (ϕ) and mother wavelet (ψ). Father wavelets augment the representation of the smooth (low) frequency parts of a signal with an integral equal to 1, while the mother wavelets describe the details of high frequency components with an integral equal to 0. These functions are generated as in Equation (6):

$$\phi_{J,k}(t) = 2^{-\frac{J}{2}}\phi\left(\frac{t-2^Jk}{2^J}\right), \quad \psi_{j,k}(t) = 2^{-\frac{j}{2}}\psi\left(\frac{t-2^jk}{2^j}\right) \quad (6)$$

After MODWT decomposition, we calculate the time-dependent wavelet variance for scale j of each time series as $Var(D_{x,j,t})$ and $Var(D_{y,j,t})$, while the time-dependent wavelet covariance for scale j is $COV(D_{x,j,t}, D_{y,j,t})$. Accordingly, wavelet correlation coefficient ($\rho_{x,y,j,t}$) can be computed as follows:

$$\rho_{x,y,j,t} = \frac{COV(\hat{D}_{x,j,t}, \hat{D}_{y,j,t})}{\left(Var(\hat{D}_{x,j,t})Var(\hat{D}_{y,j,t})\right)^{1/2}}. \quad (7)$$

In order to determine the lead (lag) relationship between the assets, we follow Aguiar-Conraria, Azevedo, and Soares (2008) and calculate phase difference.⁴ According to these authors, phase difference of zero indicates that the time series move together (analogous to positive covariance) at the specified frequency. If $\phi_{xy} \in (0, \pi/2)$ then the series move in phase, with the time-series y leading x . On the other hand, 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 $-\pi$), 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 $\phi_{xy} \in (-\pi, -\pi/2)$.

4. Data and the stylised facts

Daily data are used for the research of mutual interlink between stock indices and Brent oil, since shock impacts are very fast and die out after a few days, and so correlation could vanish in a matter of days (see Gallegati, 2012). The following spot closing price indices are selected – PX (the Czech Republic), WIG (Poland), BUX (Hungary, SAX (Slovakia), RTS (Russia) and Brent oil. We opt for Brent oil because the Brent basket composes the main price benchmarks on the basis of which 70% of international trade in oil is directly or indirectly priced. All daily stock 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 index or Brent oil at time (t). The sample covers the period from January 1, 2003 to June 30, 2019 and all data were obtained from Yahoo finance.com and quandl.com. Besides, employing wavelet correlation methodology, we investigate dynamic nexus in seven frequency levels.

Table 1. Summary statistics.

	Mean	St. dev.	Skewness	Kurtosis	JB	DF-GLS	KPSS
Brent	0.018	1.651	-0.069	6.836	2611.2	-4.307	0.202
PX	0.018	1.315	-0.597	20.264	51473.4	-6.653	0.216
WIG	0.034	1.182	-0.440	6.837	2664.4	-2.857	0.092
BUX	0.039	1.470	-0.121	10.386	9348.1	-5.454	0.108
SAX	0.023	1.135	-0.954	21.364	57280.5	-7.911	0.311
RTS	0.028	2.069	-0.499	14.545	22743.5	-6.556	0.299

Notes: JB stands for the value of Jarque-Bera coefficients of normality. 1% and 5% critical values for DF-GLS test with 10 lags assuming only constant are -2.566 and -1.941, respectively. 1% and 5% critical values for KPSS test are 0.739 and 0.463, respectively. Source: Authors' calculations.

This allows us to observe interdependence in different time horizons, which corresponds 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 days). The first five scales observe short term dynamics, midterm is represented by the sixth scale, while the seventh scale correspond to the long-term dynamics.

Due to the unavailability of some empirical data in stock and Brent oil markets, because of national holidays and non-working days, the daily dates are synchronised between two markets according to the existing observations. The concise descriptive statistics accounts first four moments, Jarque-Bera test, DF-GLS unit root test and KPSS test of stationarity. All the values are summarised in Table 1. It can be seen that all stock indices report relatively high average returns, except PX index, which makes these assets an alluring opportunity for investment. Standard deviations indicate that there is relatively equable risk among Visegrad group, while Brent oil and RTS index have somewhat higher risk. Left skewness, kurtosis and JB test confirm their non-normality characteristic. In addition, DF-GLS test suggests that none of the selected series contains unit root, while KPSS test proposes that all series are stationary. According to Table 1, all the selected assets have high kurtosis, which signals the presence of outliers. High kurtosis values justify the usage of the wavelet decomposing technique, because this methodology successfully deals with extreme movements and numerous outliers in empirical signals.

5. Empirical findings

5.1. Results of dynamic conditional correlations

This subsection briefly explains the findings based on the estimated results of bivariate DCC-EGARCH model, which is capable of assessing the time-varying volatility and correlation between the selected assets. Table 2 presents the results of DCC parameters (a and b), which show whether evaluated dynamic correlations are statistically significant or not, while Figure 1 presents time varying DCC plots estimated with this model. As can be seen, all a and b coefficients are statistically significant and nonnegative, also satisfying the condition $a + b < 1$, which is a sign that all DCCs are reliable. The highly significant parameter of Student t distribution (v) indicates the adequacy of this distribution. Table 2 reveals average correlations, at one-day scale, between Brent and selected indices, while Figure 1 displays the evidence of their time-varying nature.

Table 2. Estimated DCC parameters.

	Brent-PX	Brent-WIG	Brent-BUX	Brent-SAX	Brent-RTS
a	0.019***	0.015***	0.012**	0.014*	0.019***
b	0.973***	0.980***	0.982***	0.787***	0.970***
v	9.37***	10.13***	12.02***	4.39***	8.23***
Average ρ	0.193	0.202	0.148	0.023	0.337

Note: ***, **, * represent statistical significance at the 1%, 5% and 10% level, respectively. Source: Authors' calculations.

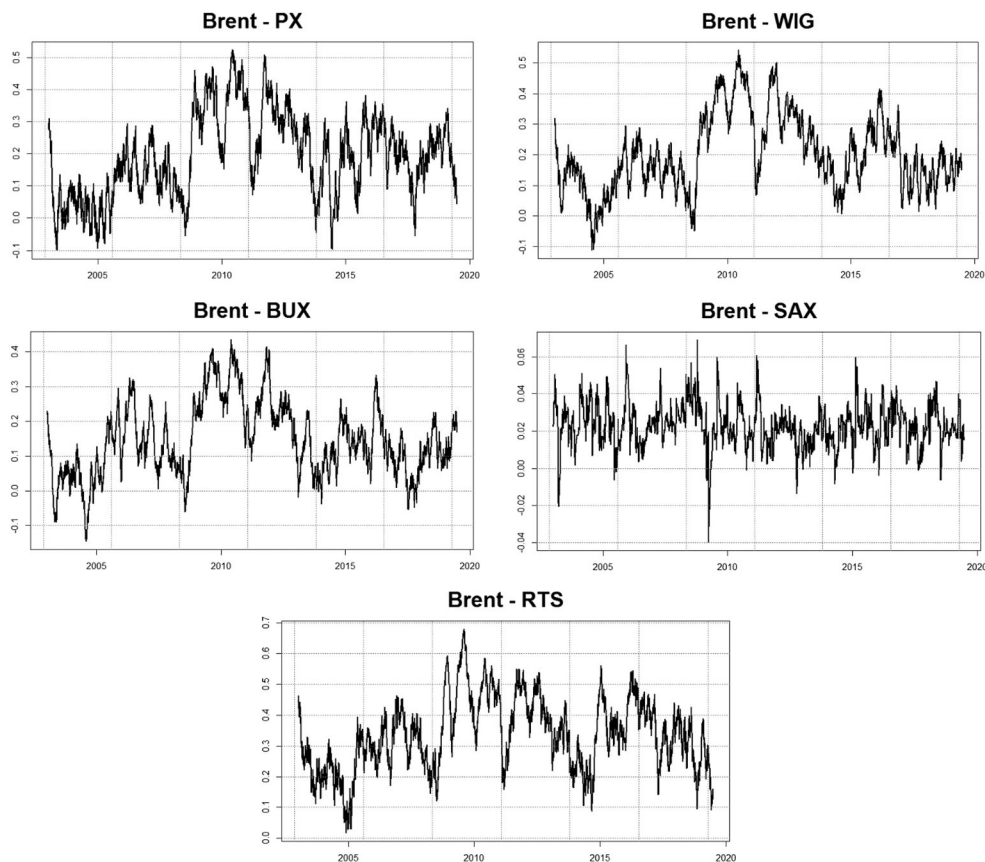


Figure 1. Dynamic correlations plots of Brent oil and five stock indices. Source: Authors' calculations.

It is obvious that in almost all DCC plots similar pattern can be observed. PX, WIG, BUX and RTS indices generally exhibited low correlations with Brent oil prior to 2008, while during and after the world financial crisis (WFC) these correlations increased. The reason probably lies in the fact that these indices had a steady increase from 2004, while price of world oil commenced dramatic rise sometime later, at the beginning of 2007 (see e.g. Choi & Hammoudeh, 2010; Koseoglu & Cevik, 2013). Because of that, we record relatively low dynamic correlations prior to WFC. On the contrary, the rise in DCCs, in almost all examined pairs, happened during the 2008 global financial crisis, where correlations continued to be high up to 2012. These findings coincide with the results of Delatte and Lopez (2013) who reported the exact

same pattern, but they analysed dynamic correlations between 21 commodities and four developed markets. As for Slovakian SAX index, DCCs are very low in general, where dynamic correlation just reached 5% even during WFC. Nagayev et al. (2016) contended that steep rise of correlation between equities and oil in this period can be attributed to the several plausible macroeconomic and behavioural factors coalescing from 2008 to 2012. Some of the key factors they mentioned are widespread panic that was caused by world crisis which instigated a negative sentiment at the global scale that affected most markets in similar ways. Also, they explained that financial actors have been buying large amounts of commodity futures contracts between 2004 and 2008, while they temporarily left those markets during the crisis, which caused a steep fall in prices. Investment sentiment changed from mid-2009, when investors became bullish again.

Visegrad stock markets and Russian stock market commenced to recover in early 2009, but not long after, they started to fall again in late 2011 which is probably linked with the European sovereign debt crisis (ESDC). During that time, the price of oil maintained high value – above 100\$/barrel, which reflected in our DCC plots as abrupt decrease of dynamic correlations in all Brent-CEEC plots. From the mid-2015, all CEEC stock markets entered modest growth-mode, while at the same time oil prices started to recover slowly at the begging of 2016. These events induced the increase of dynamic correlations in 2016, which can be noticed in Figure 1. The largest rise of DCCs occurred between Russian RTS index and Brent in 2016, i.e. Russian market reacted most positively on the slight oil price recovery. This is not surprising having in mind that eleven oil and gas companies accounted for approximately 55% of the total Russian market capitalisation in 2008, according to Bhar and Nikolova (2010).

Table 3. Wavelet correlations between Brent oil and the selected sock indices.

Wavelet scales	Brent vs PX			Brent vs WIG			Brent vs BUX		
	Lower	Wcorr	Upper	Lower	Wcorr	Upper	Lower	Wcorr	Upper
Raw data – 1 day	0.188	0.229	0.270	0.122	0.163	0.205	0.145	0.187	0.228
D1 – 2 days	0.233	0.290	0.345	0.173	0.231	0.287	0.183	0.242	0.298
D2 – 4 days	0.215	0.296	0.373	0.153	0.235	0.314	0.158	0.241	0.321
D3 – 8 days	0.237	0.349	0.452	0.128	0.245	0.355	0.193	0.309	0.416
D4 – 16 days	0.068	0.239	0.396	0.050	0.219	0.375	0.060	0.231	0.389
D5 – 32 days	-0.022	0.225	0.446	-0.021	0.222	0.440	0.052	0.294	0.504
D6 – 64 days	0.196	0.510	0.729	0.141	0.462	0.695	0.283	0.575	0.769
D7 – 128 days	0.506	0.801	0.928	0.383	0.738	0.903	0.589	0.839	0.943

Wavelet scales	Brent vs SAX			Brent vs RTS		
	Lower	Wcorr	Upper	Lower	Wcorr	Upper
Raw data – 1 day	-0.019	0.024	0.068	0.275	0.315	0.353
D1 – 2 days	-0.051	0.011	0.072	0.350	0.403	0.453
D2 – 4 days	-0.086	0.001	0.088	0.351	0.425	0.494
D3 – 8 days	-0.112	0.012	0.135	0.342	0.446	0.540
D4 – 16 days	0.003	0.178	0.342	0.301	0.451	0.580
D5 – 32 days	0.187	0.415	0.601	0.371	0.567	0.714
D6 – 64 days	-0.137	0.228	0.539	0.578	0.774	0.885
D7 – 128 days	0.130	0.602	0.852	0.748	0.911	0.970

Note: Wcorr stands for wavelet correlations. Source: Authors' calculations.

5.2. Results of wavelet correlations

High-level frequency results of DCC model are rich in details, but this methodology lacks the ability to efficiently identify more persistent and pronounced time-varying correlations, as Aloui and Jammazi (2015) explained. They also asserted that traditional models often fail to accurately recognise the co-movements of financial time series due to the complex structure and irregularities of the underlying data. Contrary to the traditional DCC approach, the wavelet technique can assess interdependence in different frequency scales, which complements our DCC findings. Table 3 contains actual levels of correlations across the scales along with the upper and lower boundaries, while Figure 2 presents wavelet correlation plots.

Looking at Table 3, it can be seen that in the short-run (up to fourth scale), the wavelet correlations are relatively equable and low for the Visegrad group countries. This coincides very well with our DCC findings. For oil-exporting Russia, we find wavelet correlation in D4 scale (16-days) that is almost double in size of Visegrad group counterparts, which is not surprising since Russia is heavily dependent on oil

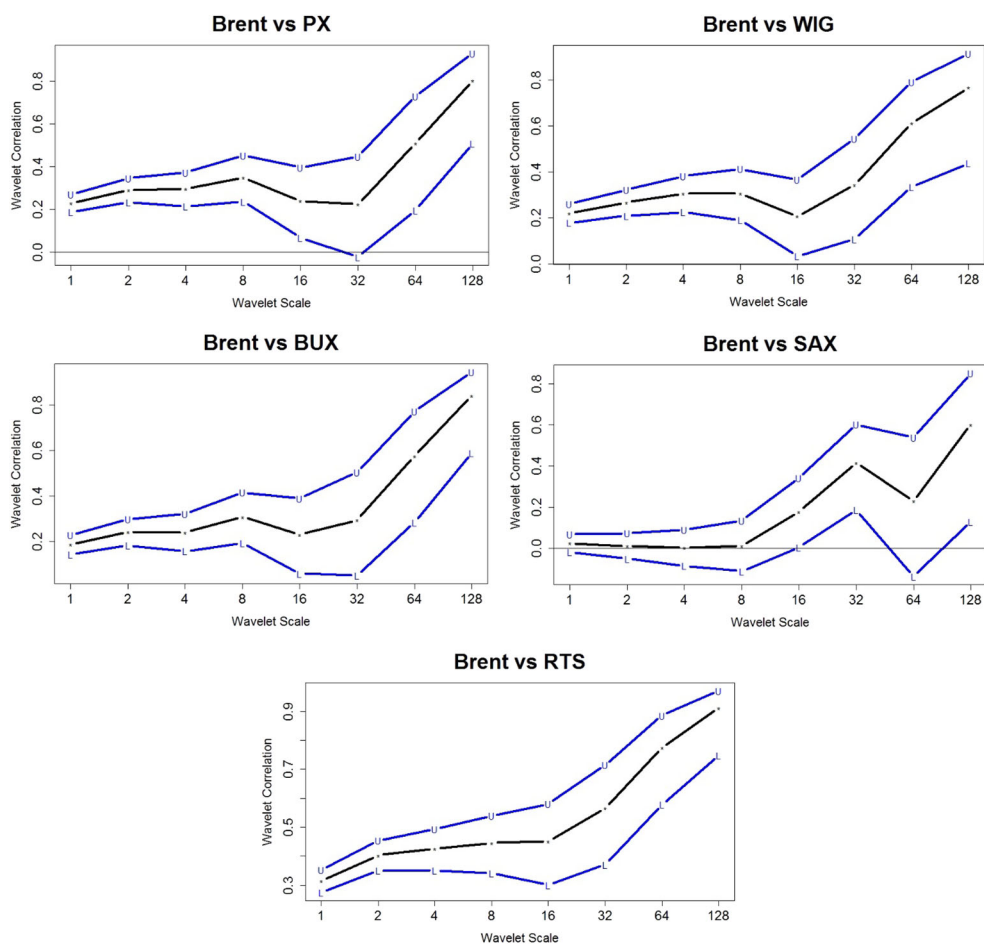


Figure 2. Wavelet correlation plots between Brent oil and the selected stock indices. Note: Blue lines denote upper and lower boundaries of wavelet correlations. *Source:* Authors' calculations.

revenues, as has been said. It is interesting to note that wavelet correlations of Visegrad group slowly grow till some point in time, then subsides and eventually grows again. The PX index reach low point in 32 days, for WIG and BUX it is 16 days, while for SAX it is 64 days (midterm). Slovakian SAX index has the lowest wavelet correlation of 23% in midterm horizon. As for Russia, this is not the case. Russian wavelet correlation constantly grows with the flow of time. In addition, we find that wavelet correlations rise significantly in the long-term for all the countries.

Also, by applying wavelet correlation approach, we are able to identify whether fundamental interdependence and market contagion exist between oil and the indices. Jokipii and Lucey (2007) and Jung and Maderitsch (2014) explained that interdependence is a state of stable period relationships that are driven by fundamentals, which underline real linkage for shock transmission between two markets in both crisis and non-crisis periods. On the other hand, Forbes and Rigobon (2002) contended that contagion represents a significant increase in cross-market linkages after the occurrence of a shock in one country. Wavelet correlations could be helpful methodology in this context, because strong wavelet correlation at the higher frequencies (up to fifth scale) are regarded as contagion, whereas strong wavelet coherence at the lower frequencies (6-th and 7-th scales) can be recognised as interdependence (see Bodart & Candelon, 2009).

Table 3 suggests that in the very shorts-term (up to D4 scale), all wavelet correlations of Visegrad group are relatively low (below 30%), while only in the case of Russian RTS index, wavelet correlations exceed 45%, which could be referred as contagion. This is evidence that contagion effect between Brent and stocks in oil importing countries of Visegrad group do not exist whatsoever. Owing to the fact that the wavelet correlation results and DCC findings do not show strong correlation between Brent oil and the selected stock indices of Visegrad group, it seems that combination between these stocks and Brent oil could be suitable for short-term international investors. These conclusions particularly apply for the Slovakian SAX index, because according to both DCC and wavelet correlation results, mutual nexus between SAX and Brent oil does not go beyond 2.3% in very short time-horizon (8 days) which is very low.

If we recall the DCC results, we can see that dynamic correlation between Brent and RTS reached its maximum (almost $\rho = 0.7$) during the global financial crisis, and this is a clear indication of contagion. Our results are in line with the study of Bhar and Nikolova (2009), who asserted that Russian equity returns and the conditional volatility of returns are largely determined by the oil return spillovers. The second very important event was the oil price plunge in 2015, which influenced profoundly and very negatively RTS index. In both cases, we find very strong DCCs, which concur with the wavelet correlations at very high frequencies. The explanation for these findings lies in the fact that Russian economy is highly energy-export oriented, where the share of oil in primary energy exports is approximately 50%, according to Bhar and Nikolova (2010).

The picture is somewhat different when we observe the higher wavelet scales (mid-term and long-term). It is obvious that wavelet correlations grow strongly in the longer time-horizons, and this applies for all the selected countries, while the Slovakian

case is somewhat peculiar. In the cases of the Czech Republic, Hungary and Russia, we find wavelet correlations which exceed 50% in midterm horizon, while in the long-term these values go even beyond 80% (the Czech and Hungarian cases). These results could be the sign of strong fundamental interdependence between the indices and Brent oil. However, Slovakian SAX index reaches relatively low point in midterm (23%) and then grows stronger in long-term horizon, exceeding 60%. Based on these findings, this implies that SAX index could be coupled with Brent oil for diversification purposes even during the crisis periods in midterm.

5.3. Results of phase-difference

Previous section provides insight about the strength of the scale correlations and their direction, but these results cannot provide information about the lead-lag relationship between analysed time-series. In order to be more informative, this section presents wavelet phase-difference plots of different frequency bands that uncover average dynamic lead-lag relationship throughout entire sample-period. This information is useful for international investors since if they know empirically that one time series leads the other one, then its realizations may be used to forecast the realizations of the lagging time series, as Dajčman (2013) stated. We present phase difference plots for short-term (32–64 days), midterm (64–128 days) and long-term horizons (128–256 days). Time-horizons below 32 days are not considered, because phase difference line at lower scales are too erratic and do not provide clear-cut conclusions. Figures 3–7 present phase difference plots between Brent oil and the selected indices of CEECs. In order to identify lead-lag relationship properly, we need to know which

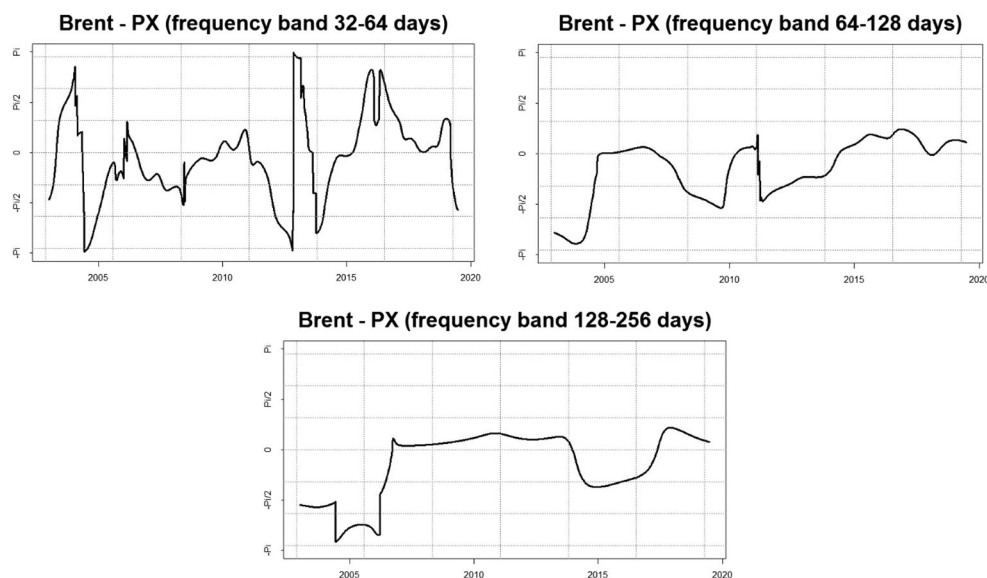


Figure 3. Phase difference between Brent oil and PX index. Note: This figure depicts phase difference between Brent and PX index for various frequency bands – 32–64 frequency band (upper-left plot), 64–128 frequency band (upper-right plot) and 128–256 frequency band (lower plot). Source: Authors' calculations.

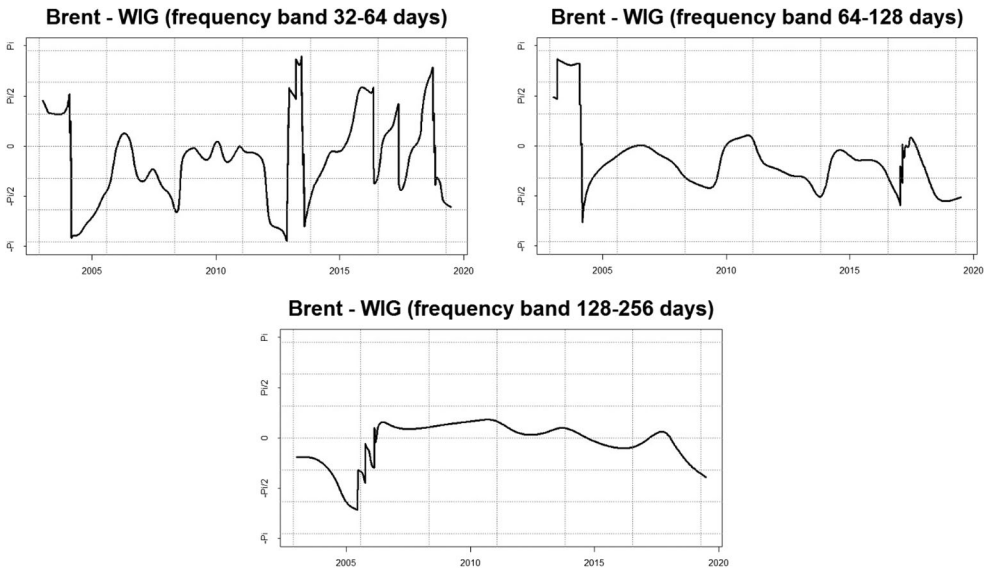


Figure 4. Phase difference between Brent oil and WIG index. Note: This figure depicts phase difference between Brent and WIG index for various frequency bands – 32–64 frequency band (upper-left plot), 64–128 frequency band (upper-right plot) and 128–256 frequency band (lower plot). *Source:* Authors' calculations.

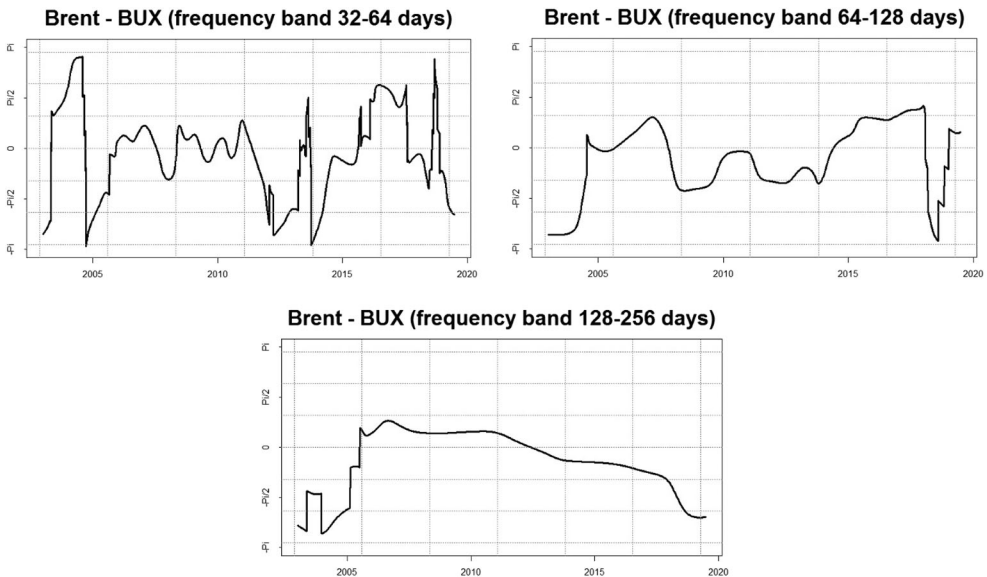


Figure 5. Phase difference between Brent oil and BUX index. Note: This figure depicts phase difference between Brent and BUX index for various frequency bands – 32–64 frequency band (upper-left plot), 64–128 frequency band (upper-right plot) and 128–256 frequency band (lower plot). *Source:* Authors' calculations.

of the time series is processed first in phase difference calculations. The caption of phase-difference plots indicates which time-series is used first and which one is the second. In other words, Brent is always the first variable.

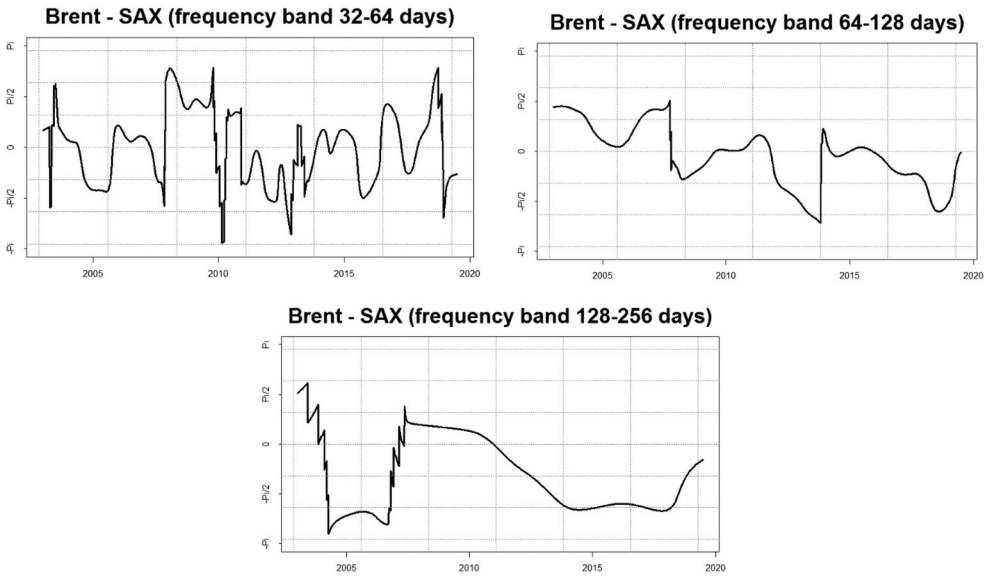


Figure 6. Phase difference between Brent oil and SAX index. Note: This figure depicts phase difference between Brent and SAX index for various frequency bands – 32–64 frequency band (upper-left plot), 64–128 frequency band (upper-right plot) and 128–256 frequency band (lower plot). Source: Authors’ calculations.

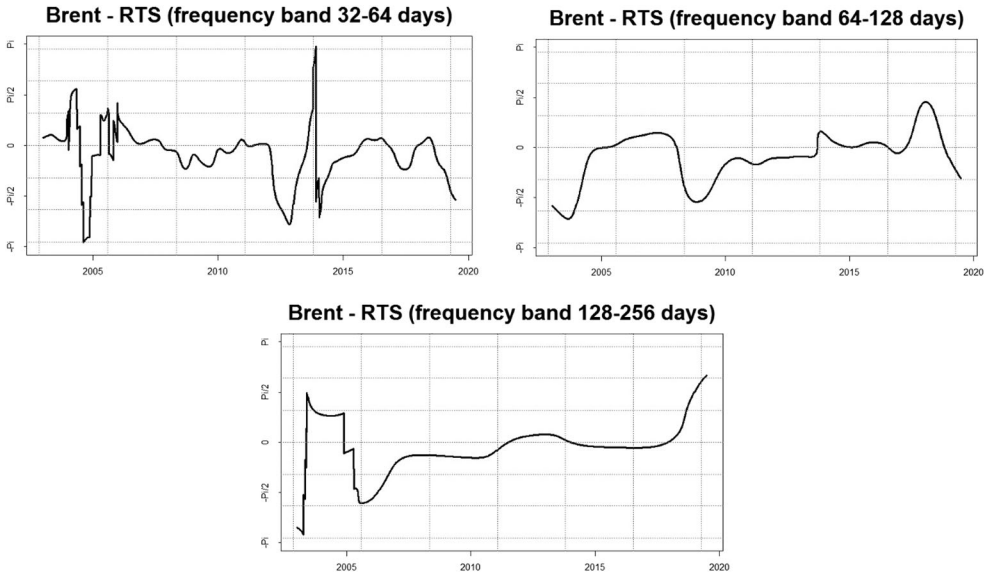


Figure 7. Phase difference between Brent oil and RTS index. Note: This figure depicts phase difference between Brent and RTS index for various frequency bands – 32–64 frequency band (upper-left plot), 64–128 frequency band (upper-right plot) and 128–256 frequency band (lower plot). Source: Authors’ calculations.

Looking at the [Figures 3–7](#), we can see that relatively similar patterns emerge in all Visegrad group countries and Russia as well, throughout the observed period. It can be assumed that phase difference findings were influenced by various world events.

As for the 32–64 days' frequency interval, we can see that phase differences constantly shifts between phase and anti-phase areas during Iraqi war, and it particularly applies for Visegrad group countries. It is also obvious that lead-lag relationship alters during that period. More specifically, in 32–64 days' frequency band, an anti-phase happened around 2003, where Visegrad stock indices led Brent oil, while Brent oil took over leading role in 2004 in another anti-phase situation. In period around WFC and ESDC, Brent and Visegrad stock indices were in phase, where the leading role had Brent during WFC, while during ESDC that situation reversed. Around 2012 and 2015 we detect some anti-phase situations in the cases of PX, WIG and BUX indices, and these findings could be attributed to the dynamics of Brent oil. In other words, Brent recorded fall in price during 2012 but quickly recovered, but since the end of 2014, price of Brent oil started to decline significantly and lost 2/3 of its original price that was in 2014. Meanwhile, PX, WIG and BUX realised slow growth or in the worst case they stagnated, and that is way we find an anti-phase behaviour.

Unlike oil-importing Visegrad group countries, Russian RTS index and Brent oil was in phase during Iraqi war, during WFC and ESDC and particularly during the oil price breakdown in 2014 and 2015 in 32–64 days' frequency band. We recorded a short anti-phase segment at the end of 2004 and 2012. This kind of findings are expected since Russian RTS index heavily depends on the oil price movements.

Observing midterm phase difference plots (64–128 days), we can see that phase-difference line is more smoothed and with more conspicuous trend-segments. It signals that certain situation remained unchanged for longer period of time, which leaves more room for investors to draw some helpful conclusions. In particular, we can see that Visegrad indices and Brent oil was constantly in-phase from 2004, where leading role had Brent for most of the time. This type of findings also applies for the Brent-RTS pair.

As for the long-term analysis (128–256 days), we find that WIG and SAX indices have very pronounced anti-phase situations, i.e. WIG had anti-phase nexus with Brent in the period 2000–2004, while SAX was in that kind of relation during 2005–2006 and 2014–2018. In these periods, WIG and SAX were leading. In all other instances, selected indices were in-phase with Brent oil, particularly from 2005 to 2014, where leading role had PX, WIG and BUX indices, while RTS index also showed leading dominance during that time. From 2014, the reverse happened in the cases of PX, WIG and BUX.

6. Implications of the results

This section concisely explains how the results can be utilised by the investors who combine Brent oil with the East European stock indices. DCCs and high-frequency wavelet correlations detect relatively low correlations between Brent and all the selected indices in short-term, thus all the indices, from that point of view, could be used for diversification purposes in combination with Brent. From the perspective of midterm and long-term international investors (64–128 and 128–256 days), we can provide additional indication *via* phase difference in a sense how investors can rebalance their portfolios, regarding the developments in the oil and stock markets. In

particular, according to the wavelet correlations, the mutual nexus increases with the increase of time-horizons, which is characteristic for all the selected countries, while it is less obvious for Slovakia. In the cases of the Czech Republic, Hungary, Poland and Russia, we find that wavelet correlations exceed 50% in midterm horizon, while in the long-term, these values go even beyond 80%. These results clearly indicate that strong fundamental interdependence exists between the indices and Brent oil, which is a sign that Brent oil and the selected indices are not particularly good combination for diversification in longer time-horizons.

However, even in these occasions, Brent oil and the indices can be combined in a single portfolio, because more important factor in portfolio construction is risk of a particular asset in the portfolio. Khalfaoui, Boutahar, and Boubaker (2015) asserted that if auxiliary asset has significantly higher level of risk than primary asset, than such asset should be excluded from a portfolio. According to Table 1, all indices, except Russian RTS index, have lower risk *vis-à-vis* Brent, and from this perspective, they can be suitable to combine with Brent. In addition, since our phase difference results suggest that shocks spill over from oil to the indices for the majority of time in midterm and long-term, it means that rising volatility in the oil market will be followed by the rising volatility in the stock markets. Therefore, in the periods of increased oil volatility, stock indices, as an auxiliary asset, can be removed from the portfolio and replaced with some other asset which is not so susceptible to shocks from the oil market. In that manner, the risk of portfolio will be diminished.

It should be highlighted that Slovakian SAX index is the most suitable for combination with Brent, because SAX index has three good characteristics. The first one is low correlation with Brent even in the midterm. The second one is the lowest risk, comparing to all other indices. This means that portfolio combined with Brent and SAX will have the lowest risk in comparison to all other portfolios, regardless of time-horizons that is observed. In addition, phase-difference findings reveal that SAX index also has excellent hedging possibilities, since SAX often finds itself in anti-phase position *vis-à-vis* Brent oil, so in these situations SAX can serve very well for hedging purposes, which means that portfolio risk is lowered even further in these occasions.

7. Summary and conclusion

This paper thoroughly investigates dynamic nexus between Brent oil market and stock markets of Visegrad group countries and Russia by applying several sophisticated methodological approaches – bivariate DCC-EGARCH model, wavelet correlation and phase difference. Firstly, we calculated dynamic correlations *via* DCC model, which provides detail information regarding the daily-frequency scale. Secondly, we expand our research scope by using wavelet correlation technique, which is very handy in providing the answer – how dynamic correlation behaves at different frequency levels. At the end, we explain the leading (lagging) role at different frequency scales by applying the wavelet phase-difference method.

The results of DCC model show that all averaged dynamic correlations between Brent oil and Visegrad stock indices are low or very low, while in the case of Brent-

RTS, average dynamic correlation is somewhat higher. We find that dynamic correlations between Brent and PX, WIG, BUX and RTS notably increased during WFC, while for Brent-SAX pair it is not the case.

Wavelet correlations indicate the strength of the interdependence, but at different frequency levels. It is particularly evident that strong correlations area exists in higher scales in the cases of PX, WIG, BUX and RTS. However, in the case of SAX, wavelet correlation is relatively moderate even in midterm horizons.

Within the meaning of conclusion, our DCCs, wavelet correlations and phase-difference findings could serve very well for international investors who implement their portfolio strategies at different investment horizons. Our results, from different aspects, suggest that investors should combine the SAX index with Brent, because SAX has low correlation with Brent even in the midterm, it has the lowest risk and often finds itself in anti-phase position *vis-à-vis* Brent oil. We believe that various portfolio managers, market analysts and investors who consider the oil market and East European stock indices as part of their portfolio could find the results useful. Our findings could also be valuable for market participants who act at various investment horizons, and who could benefit by knowing which is the best instrument for the combination with Brent oil.

Notes

1. According to Energy supply security report from 2014, the Czech Republic, Poland, Hungary and Slovakia depended on oil import in 2012 by 97.6%, 96.2%, 82.3% and 92.9%, respectively.
2. DCC-GARCH calculations are done via 'rmgarch' package in 'R' software.
3. Wavelet correlations are calculated via 'waveslim' package in 'R' software.
4. Phase difference results were obtained by applying ASToolbox of Aguiar-Conraria and Soares (2011) in 'R'.

Disclosure statement

No potential conflict of interest was reported by the authors.

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