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ORIGINAL ARTICLE

Assessing volatility transmission between Brent and stocks in the major global oil producers and consumers – the multiscale robust quantile regression

Dejan Živkov[1] · Slavica Manić[2] · Jelena Kovačević[3] · Željana Trbović[4]

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Abstract

This paper investigates the volatility transmission effect between Brent oil futures and stock markets in the major global oil producing and consuming countries – the U.S., Russia, China and Saudi Arabia. In that process, we employ a mixture of novel and elaborate methodologies – wavelet signal decomposing procedure, GARCH model with complex distribution and recently developed robust quantile regression. Our results indicate that the effect is stronger in short-term horizon than in midterm and long-term in most cases. The magnitude is much stronger in turbulent times, whereas in tranquil times, this effect is very weak. We find that Russian RTS index endures the strongest volatility transmission effect from oil market. Surprisingly, Saudi stock market does not suffer heavy spillover effect even in the periods of increased market unrest. In the U.S. and China, the effect is much stronger from stocks to oil than vice-versa, and this particularly applies for the U.S. case.

Keywords Volatility spillover effect · Oil and stock markets · Wavelets · Robust quantile regression

JEL codes C14 · C63 · G12 · Q02

✉ Dejan Živkov
dejanzivkov@gmail.com

Slavica Manić
slavicamanic66@gmail.com

Jelena Kovačević
jelenakovacevic.06@gmail.com

Željana Trbović
zeljanatrbovic5@icloud.com

Extended author information available on the last page of the article

1 Introduction

Conventional wisdom suggests that numerous market participants, such as traders, hedgers, corporate managers, portfolio designers and scholars have risen recently an interest about volatility transmission effect between oil and stocks. The main reason for such activities is the growing disturbance in the energy market in the last two decades, which is sparked by various global developments such as global financial crisis, regional wars, conflicts which affect oil suppliers, frequent changes in the global demand and supply, speculative activities, etc. (see e.g. Grecu et al. 2020). Kirkulak-Uludag and Safarzadeh (2018) and Obadi and Korček (2014) asserted that oil plays a crucial role in the economy and financial markets, since oil shocks impacts companies' revenues directly or indirectly as well as interest rates, which are used in discounting future cash flows. According to the theory of equity valuation, the adverse happenings in the oil market subsequently influence stock prices, because their value is simply a result of the discounted expected future cash-flows and the investors' required rate of return. Arouri et al. (2012) asserted that corporate cash-flows and discount rate are subject to the dynamics of the various economic indicators, such as inflation, interest rates, production costs, income, economic growth, market confidence, etc., and all these variables can be impacted by oil shocks and thus stock prices may react significantly to the oil price changes. Although many papers analysed the interdependence between oil and stocks, relatively few studies researched an important topic of volatility transmissions between these two assets (see Arouri, Arouri et al. 2011a). According to Mun (2007), this topic is crucial for portfolio selection and risk hedging, because if volatility from one financial market transmits to another, then assets from such markets cannot be included in the same portfolio. Ross (1989) contended that synonymous for information transfer is volatility spillover effect, since changes in variance, and not the asset's price change, reflects the arrival of information in the market. He found that the variance of price changes is directly linked to the rate of information flow to the market.

Based on the aforementioned, this paper tries to contribute to the literature by investigating the magnitude of the bidirectional volatility spillover effect between Brent oil futures and the stock indices of four largest global oil producers and consumers, highlighting in that process several different dimensions. First of all, we consider four most important global oil producers and consumers – the U.S., Saudi Arabia, Russia and China. The reason why we consider these four countries is the fact that the United States, Saudi Arabia, and Russia are the world's top three crude oil producers in 2018, according to the U.S. Energy Information Administration (EIA). More specifically, the United States accounts for 18% of global oil production in 2018, while Saudi Arabia and Russia follow with 12% and 11%, respectively. Besides, China is included in the analysis since China is the top oil consumer right after the United States, which consumes about 20% of world oil production. Therefore, even though the U.S. is the largest oil producer in the world, it is net oil importer because it is the largest oil consumer too, according to the EIA. This research is motivated by the lack of related attempts in the extant literature.

In addition, we intend to stipulate the bidirectional volatility transmission effect not only from temporal point of view, but from different time-horizons as well, since global market participants act on different time scales depending on their investment goals.

Conlon and Cotter (2012) claimed that researchers usually do not investigate both time and frequency segments, because the sample reduction problem emerges when they try to combine the frequency of data with different time-horizons. In order to overcome this issue, we apply the wavelet signal-decomposing methodology on our time-series, which is the first stage in our research process. Wavelet methodology is a very useful tool, because it preserves information contained in the empirical data, and at the same time permits researcher to observe different time-horizons (see e.g. Tsai and Chang 2018; Živkov et al. 2019; Poměnková et al. 2019). We refer to different authors who utilized the wavelet methodology in recent years in order to analyse various economic phenomena in different time-horizons (see e.g. Rua and Nunes 2009; Lee and Lee 2016; Rua 2017; Živkov et al. 2018; Portugal and Rua 2020; Fidrmuc et al. 2020).

After wavelet transformation, we put an effort to measure volatilities of the selected time-series as accurate as possible. Therefore, the second stage in our research process involves creation of dynamic volatility series of the selected stock indices and Brent oil. Usually, time-series volatilities are created by the various types of the GARCH models, but the problem may occur in this process when empirical data have no-normal characteristics, such as strong skewness and heavy tails. In order to address this issue, we combine GARCH type model with several traditional and recently developed innovative distribution functions – normal, Student-t, generalized error distribution and generalized asymmetric Student-t (GAT) distribution of Zhu and Galbraith (2010). This approach is in contrast to the abundance of studies that have used only the GARCH model with the traditional normal distribution. Chen et al. (2008) asserted that primary weakness of GARCH-normal type model is that it assumes a specific functional form before any estimations are made, which, as a result, could yield biased coefficient estimates and standard errors. In addition, Lyu et al. (2017) asserted that recently developed distribution function, such as GAT distribution, has theoretical advantages over the more traditional distributions in modelling heavy tails and skewness, which can potentially improve the assessment and avoid biased estimates.

In the last stage, we gauge the magnitude of the bidirectional volatility transmission effect by inserting wavelet-based conditional volatilities into the recently developed sophisticated econometric methodology – robust quantile regression (QR) of Wichitaksorn et al. (2014). In particular, this new quantile regression technique uses a likelihood-based approach for the quantile parameter estimation, considering a new family of skewed distributions – Normal, Student-t, Laplace, contaminated Normal and slash distribution. Studies which use QR approach usually disregard the choice of proper density function, because QR estimate quantile parameters, which makes irrelevant the choice of the best fitting distribution. However, if QR is estimated under the optimal distribution function then it increases robustness of the parameters, which is crucial for the reliability, because it gives us an assurance that the calculated results are unbiased and trustworthy. In other words, the robust QR methodology decreases the length of credible intervals and increases the accurateness of quantile estimates, comparing with the traditional quantile regression approach of Koenker and Bassett (1978).

In addition, by applying robust QR we can measure the volatility transmission effect across the quantiles and wavelet scales, which gives an abundance of information regarding the magnitude of the spillover effect in the states of low, moderate and high volatility in short-, mid- and long-term horizons. Also, we try to be more informative, so we use wavelet cross-correlation methodology as complementary approach, which gives us a review about the lead (lag) interlinks between stock and Brent oil volatilities across the wavelet scales. This method carries an important information at different frequency scales, regarding the direction of volatility shocks. In other words, we can determine from which market the spillover shocks originate and which market is the recipient of the shocks. This type of knowledge is very important for global investors, since it allows a better understanding how they can construct their trading and hedging strategies, enter or leave particular market or rebalance their international portfolios (see Dajčman 2013).

Besides introduction, the rest of the paper is constructed as follows. Second section contains literature review. Third section presents used methodologies – wavelet concept, GARCH model with different density function and the robust quantile regression. Fourth section encompasses dataset and various auxiliary calculations. Fifth section is reserved for the robust quantile regression estimates. Sixth section contains the results of the spillover effect from WTI oil to stocks, whereas seventh section reveal the results of wavelet cross-correlation. The last section concludes.

2 Literature review

The extant literature already harbours numerous papers about the nexus between oil and stocks, but relatively limited number of papers address the subject of volatility transmission between the markets. In the following, we listed some of them chronologically. For instance, Malik and Hammoudeh (2007) researched the volatility and shock transmission mechanism among US equity, WTI crude oil market, and equity markets of Saudi Arabia, Kuwait, and Bahrain. Their results indicated significant transmission among second moments. They reported that Gulf equity markets receive volatility from the oil market in all the cases, but only in the case of Saudi Arabia they found a significant volatility spillover from the Saudi market to the oil market. Tsuji (2008) researched return transmission and volatility spillovers between oil futures and international oil and gas sector equity returns in North America, Latin America, developed Europe, emerging Europe, the Far East, and BRIC. He reported unidirectional asymmetric volatility spillover effects from all the six oil equities to oil futures except for the Far East, where the findings indicated bidirectional asymmetric volatility spillover effect. The study of Arouri, Arouri et al. (2011b) researched the extent of volatility transmission between oil and stock markets in Europe and the United States at the sector-level. They disclosed the existence of significant volatility spillover between oil and sector stock returns, but this effect is usually unidirectional from oil markets to stock markets in Europe and bidirectional in the United States. Lin et al. (2014) examined the dynamic volatility and volatility transmission between oil and stock market returns in Ghana and Nigeria. They found significant existence of volatility spillover and interdependence between oil and the two stock market returns, but they asserted that the spillover effects are stronger for Nigeria. In addition, they claimed that the transmission of volatility is much more apparent from oil to stock than from stock to oil in the case of Ghana.

Gomes and Chaibi (2014) used a bivariate BEKK-GARCH(1,1) model to simultaneously estimate the mean and conditional variance between equity stock markets of twenty one national frontier stock indices and two broad indices (the MSCI Frontier Markets and the MSCI World) and oil prices. They reported significant transmission of shocks and volatility between oil prices and some of the examined markets, whereas this spillover effect is sometimes bidirectional. The paper of Khalfaoui et al. (2015) examined the mean and volatility linkage between crude oil market (WTI) and stock markets of the G-7 countries over various time horizons. They applied both multivariate GARCH models and wavelet analysis. Their results showed strong evidence of significant volatility spillovers between oil and stock markets, as well as time-varying correlations for various market pairs. Wang and Liu (2016) investigated volatility spillovers and dynamic correlations between crude oil and stock markets using GARCH-class models. They focus on seven major oil-exporting countries and nine oil-importing countries. Their findings suggested that the volatility spillovers and dynamic correlations between global crude oil market and a country's stock market depend on the net position of oil imports and exports of this country in the world market. Kirkulak-Uludag and Safarzadeh (2018) also considered the volatility spillover effect between OPEC oil price and the Chinese sectoral stock returns, which includes construction, machinery, automobile, military, agriculture, and financial indices. Their results showed significant volatility spillover between OPEC oil prices and the Chinese sectoral stock returns, but the determine that this effect is unidirectional from oil to stock returns. Xu et al. (2019) investigated volatility spillover effect, using high-frequency data, between WTI future prices and the S&P500, SSEC index during the period between 2007 and 2016. They reported that the volatility spillovers between the oil and stock markets are time-varying, and this interdependence strengthens during financial crisis. Also, they found the asymmetric spillover effect between oil and stock markets, whereby bad volatility spillovers dominate good volatility spillovers.

Wang and Wang (2019) studied the frequency dynamics of volatility spillovers between crude oil and the Chinese stock market using sectoral stock indices data. They disclosed that the total spillover evolves over time, while it is mainly driven by short term spillovers before 2016 and by long-term spillovers in the most recent two years. Besides, net spillovers of WTI futures are almost all significantly positive and caused by short-term components. Ashfaq et al. (2019) studied the volatility spillovers between stocks of leading Asian oil exporting and oil importing countries stock exchanges and crude oil returns. Their results suggested that the bidirectional spillover effect exists for the correlation of two oil exporting countries (Saudi Arabia and Iraq). They contended that oil exporting and oil importing countries demonstrate a different level of significant correlation with oil, but oil shock are more influential on oil exporting countries. Kondoz et al. (2019) studied the volatility transmission between the West Texas Intermediate (WTI) crude oil price returns and the U.S. stock market (S&P500 index) returns, employing univariate GARCH and multivariate GARCH (BEKK-GARCH) models. The results of GARCH methods revealed that volatility spillover effect of S&P500 index returns on the crude oil returns is more significant than vice-versa. Also, they found a one-way volatility spillover effect that runs from S&P500 index returns to crude oil returns when multivariate BEKK-GARCH model is applied.

3 Methodology

3.1 Wavelet signal decomposing technique

The first step in our computation process involves the transformation of stock indices and Brent oil returns in the several wavelet time-frequency components. Wavelets can provide an appropriate trade-off between resolution in the time and frequency domains, which traditional Fourier analysis cannot do, since it deals only with the frequency domain (see Dewandaru et al. 2014). Two basic wavelet functions exist in the wavelet theory – the father wavelet (ϕ) and the mother wavelet (ψ). Father wavelets augment the representation of 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. In other words, father wavelet outlines the long-term trend over the scale of the time-series, while the mother wavelet delineates fluctuations in the trend. The functions of father wavelet $\phi_{J,\,k}(t)$ and mother wavelet $\psi_{j,\,k}(t)$ ca be presented in the following way:

$$\phi_{J,k}(t) = 2^{-J/2}\phi\left(\frac{t-2^J k}{2^J}\right),\quad \psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t-2^j k}{2^j}\right) \tag{1}$$

According to expression (1), j is typically referred to as 'level', while the scale or dilation factor is 2^j, whereas the translation or location parameter is $2^j k$. As much as j grows, so does the scale factor 2^j, which is a measure of the width of the functions $\phi_{J,\,k}(t)$ and $\psi_{j,\,k}(t)$, and it affects the underlying functions to get shorter and more dilated.

In this study, we apply the maximum overlap discrete wavelet transformation (MODWT) algorithm, which is based on a highly redundant non-orthogonal transformation. Accordingly, signal-decomposing procedure in MODWT can be presented in the following way:

$$S_J(t) = \sum_k S_{J,k}\phi_{J,k}(t), \tag{2}$$

$$D_j(t) = \sum_k D_{j,k}\psi_{j,k}(t) \quad j = 1, 2, \ldots, J \tag{3}$$

where symbols $S_J(t)$ and $D_j(t)$ stand for the smooth and detail coefficients, respectively, at the *j-th* level wavelet that reconstructs the signal in terms of a specific frequency (trending and fluctuation components). Consequently, an empirical time series $y(t)$ can be expressed in terms of those signals as:

$$y(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \ldots + D_1(t). \tag{4}$$

In addition, as a complementary analysis we calculate wavelet cross-correlation,[1] which corresponds basically to the standard correlation coefficient between the detail components of the series. By using this wavelet tool,[2] we can determine the lead-lag relationship between the assets on a scale-by-scale basis. Cross-correlation can indicate which return innovations is leading and which one is lagging, giving an answer from which market shocks originate and which market is a recipient of the shocks. Heaving an information about which variable leads can be of great help to forecast the realizations of lagging time series, which is useful information for global investors (see Dajčman 2013). Wavelet cross-correlation take into account two time series, which are generated on the basis of a synchronous information flow, for scale j and lag τ, whereby ρ_τ is lagged correlation function. In that regard, wavelet cross-correlation have a symmetric lagged correlation function, $\rho_\tau = \rho - \tau$. However, this symmetry is interrupted when deviations between ρ_τ and $\rho - \tau$ become significant, creating in this way an asymmetry in the information flow. From the perspective of this asymmetry, a conclusion can be drawn that the leading variable has predictive power on the lagging time variable. Referring to Dajčman (2013), the MODWT cross-correlation expression, for scale j and lag τ can be written as follows:

$$\rho_{x,y,j,t} = \frac{COV\left(\widehat{D}_{x,j,t}, \widehat{D}_{y,j,t}\right)}{\left(Var\left(\widehat{D}_{x,j,t}\right) Var\left(\widehat{D}_{y,j,t}\right)\right)^{1/2}}, \tag{5}$$

where the time-dependent wavelet variance for scale j of each time series is $Var(D_{x, j, t})$ and $Var(D_{y, j, t})$, while the time-dependent wavelet covariance for scale j is $COV(D_{x, j, t}, D_{y, j, t})$. Cross-correlation takes value $-1 \le \rho_{x, y, j, t, \tau} \le 1$.

3.2 Creation of the conditional volatilities

After we decompose the empirical time-series into several wavelet scale signals, the second stage of our computational process refer to the creation of wavelet-based conditional variances, which will be embedded eventually in the robust quantile regression model. In order to accurately recognize conditional volatilities, we utilize GARCH specification with several traditional and novel distributions – normal $\varepsilon \sim N(0, h_t)$, Student-t $\varepsilon \sim St(0, h_t, \nu)$, generalized error distribution $\varepsilon \sim GED(0, h_t, k)$, and generalized asymmetric Student-t (GAT) distribution.[3] Spurious regression in the mean process, which can be caused by autocorrelation, is avoided by considering AR(1) specification for all the selected time-series. The mean equation and the GARCH process are presented as in eqs. (6) and (7):

$$r_t = a_0 + a_1 r_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim i.i.d.(0, h_t) \tag{6}$$

[1] Construction of wavelet details via MODWT and wavelet cross-correlations are calculated by using an original code in the 'waveslim' package in 'R' software.

[2] Besides wavelet cross-corelation, there are other similar concepts in wavelet analysis, as for example coherency or the wavelet correlation (see e.g. Rua 2010).

[3] Estimation of GARCH-normal, GARCH-st, GARCH-ged and GARCH-gat models was done via 'GEVStableGarch' package in 'R' software.

$$h_t = \omega_0 + \omega_1 \varepsilon_{t-1}^2 + \omega_2 h_{t-1} \tag{7}$$

where r_t is either stock index returns or Brent oil returns, computed as first difference of logarithm of their prices. Since we work with wavelet series, r_t stands for wavelet details created via MODWT algorithm. h_t is the conditional variance with the conditions $\omega_0 \geq 0$, $\omega_1 \geq 0$ and $\omega_2 \geq 0$.

In order to be concise as much as possible, we only explain in more detail the innovative heavy tailed generalized asymmetric Student-t (GAT) distribution, whereas eq. (8) presents its mathematical expression. Zhu and Galbraith (2010) claimed that GAT distribution uses one skewness parameter and two tail parameters, which offers the potential to better describe the tail phenomena. GAT distribution mathematically can be described in the following manner:

$$f_{gat}(y;\alpha,\upsilon_1,\upsilon_2,\mu,\sigma) = \begin{cases} \frac{1}{\sigma}\left[1+\frac{1}{\upsilon_1}\left(\frac{y-\mu}{2\alpha\sigma K(\upsilon_1)}\right)^2\right]^{-(\upsilon_1+1)/2} & ,y\leq\mu \\ \frac{1}{\sigma}\left[1+\frac{1}{\upsilon_2}\left(\frac{y-\mu}{2(1-\alpha)\sigma K(\upsilon_2)}\right)^2\right]^{-(\upsilon_2+1)/2} & ,y>\mu \end{cases} \tag{8}$$

where μ is the location parameter, while σ is the scale parameter. α is the skewness parameter with the condition $\alpha \in (0, 1)$, whereas υ_1 and υ_2 are the left and right tails, respectively, conditioned by $\upsilon_1 > 0$ and $\upsilon_2 > 0$. $K(\upsilon) = \Gamma((\upsilon+1)\frac{/2)}{\sqrt{a}\Gamma(\upsilon/2)}$ and $\Gamma(\cdot)$ is the Gamma function.

3.3 Robust quantile regression methodology

Starting with the general quantile regression, Yu and Moyeed (2001) introduced a Bayesian modelling approach by using the asymmetric Laplace distribution (ALD). However, albeit ALD has the zero-quantile property and a useful stochastic representation, ALD is not differentiable at zero, which could cause problems of numerical instability, according to Morales et al. (2017). Therefore, the Laplace density is a pretty strong assumption in order to set a quantile regression model through the classical or Bayesian framework. In order to overcome this setback, Wichitaksorn et al. (2014) developed a generalized class of skew densities (SKD) for the analysis of QR that provides competing solutions to the ALD-based formulation. In particular, the procedure of the robust skew density class distributions construction involves mixing a skew-normal distribution of Fernandez and Steel (1998) and the symmetric class of scale mixture of normal distributions of Andrews and Mallows (1974). According to Morales et al. (2017), y has a skewed distribution (SKD) with location parameter μ, scale parameter σ, skewness parameter p and weight function $\kappa(\cdot)$, if y can be presented stochastically as $y = \mu + \sigma\kappa(U)^{1/2}Z$, where Z follows skewed normal distribution (SKN), $Z \sim SKN(0, 1, p)$. If U is integrated out, then the marginal probability density function (*pdf*), of y is given in the following manner:

$$\int_0^\infty \frac{4p(1-p)}{\sqrt{2\pi k(u)\sigma^2}} exp\left\{-2p_p^2\left(\frac{y-\mu}{k^{\frac{1}{2}}(u)\sigma}\right)\right\} dH(u|\nu) \tag{9}$$

Table 1 Mathematical presentation of skewed distributions

Distribution	$f(y\|\mu, \sigma, p, \nu)$
Skewed Student t (SKT)	$\frac{4p(1-p)\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{2\pi\sigma^2}}\left\{\frac{4}{\nu}p_p^2\left(\frac{y-\mu}{\sigma}\right)+1\right\}^{\frac{-\nu+1}{2}}$
Skewed Laplace (SKL)	$\frac{2p(1-p)}{\sigma}exp\left\{-2\rho_p\left(\frac{y-\mu}{\sigma}\right)\right\}$
Skewed slash (SKS)	$\nu\int_0^1 u^{\nu-1}\phi_{skd}\left(y\|\mu, u^{-\frac{1}{2}}\sigma, p\right)du$
Skewed contaminated normal (SKCN)	$\nu\phi_{skd}\left(y\|\mu, \gamma^{-\frac{1}{2}}\sigma, p\right)+(1-\nu)\phi_{skd}(y\|\mu.\sigma, p)$

From the expression (9), several skewed and thick-tailed distributions can be obtained, regarding different specifications of the weight function $\kappa(\cdot)$ and *pdf* $h(u|\nu)$. These functions are Student-t, Laplace, slash distribution and contaminated Normal distribution. Their mathematical presentations are given in Table 1.

We intend to measure the complex dependence structure between volatilities of stocks and Brent futures, using robust quantile regression[4] approach, thus the conditional quantile function of y at quantile τ, given regressor x and some form of distribution function (F_u) of the errors, can be defined as in expression (10):

$$Q_y(\tau|x) = \beta_0 + \beta_1 \mathrm{x} + F_u^{-1}(\tau) \tag{10}$$

where β_0 and β_1 are the parameters to be estimated. In our case, we investigate bidirectional volatility spillover effect, thus when y stands for stock volatility, then x denotes Brent oil volatility, and vice-versa. The quantile regression estimation of the particular quantile parameter β_τ can be achieved by minimization of eq. (11):

$$\widehat{\beta}(\tau) = \mathrm{argmin}\sum_{i=1}^{n}\rho_\tau(y_i - x_i'\beta); \quad \beta \in \Re \tag{11}$$

where $\tau \in (0, 1)$ is any quantile of interest, while $\rho_\tau(z) = z(\tau - I(z < 0))$ and $I(\cdot)$ stands for the indicator function. It is very important to emphasize that connection between the minimization of the sum in (11) and the maximum likelihood theory exists. In other words, minimization of eq. (11) is equivalent to maximize the likelihood when data follows some form of distribution function, observed in the family of zero conditional quantile SKD, as presented in Table 1.

4 Dataset and auxiliary calculations

This study uses daily closing prices of four indices and Brent oil futures. The following indices are considered – S&P500 (the U.S.), RTS (Russia), SSEC (China) and TADAWUL (Saudi Arabia). The sample covers the period between January 2004 and September 2019, whereby all time-series are collected from the *investing.com*

[4] Estimation of robust quantile regression was done via 'lqr' package in 'R' software.

website. We transform the empirical closing prices (P) of stock indices and Brent oil futures into log returns (r) according to the expression $r_{i,\ t} = 100 \times \log(P_{i,\ t}/P_{i,\ t-1})$, where i stands for particular stock indices or Brent. Some empirical data are unavailable, so we synchronize all stock indices with Brent oil futures according to the existing observations. Brent oil futures prices are considered rather than spot prices, because futures are richer in information. They incorporate both available information known up to present date as well as predictions and expectations about incoming events (see Natanelov et al. 2011).

We strive to gauge volatility spillover effect in different time-horizons, but we also want to be parsimonious as much as possible in order to save space. In that regard, we only consider three time-horizons – very short, midterm and long-term. In order to do that, we transform the empirical time-series in three wavelet decomposed signals, which correspond to these time-horizons. More specifically, we create wavelet details of scale 1, which describes very short time-horizon (2–4 days), while scales 5 and 6 represent midterm (32–64 days) and long-term (64–124 days), respectively. In the process of time-horizon determination, there is always a good deal of arbitrariness, since someone else could consider other wavelet scales. As for this paper, we observe three time-horizons in the aforementioned way.

Table 2 gives concise descriptive statistics of three decomposed wavelet time-series. It shows first four moments and the Jarque-Bera test. It is obvious that all time-series in three wavelet scales have high kurtosis value, suggesting that extreme movements are present, which in turn implies that increased volatility is present as well. Also, it is evident that almost all time-series are heavily skewed, while none of the time-series fulfils normality conjecture. According to the Table 2 results, it can be concluded that our method – robust quantile regression based on wavelets is a suitable choice due to the following reasons. First, the wavelet technique can deal successfully with extreme movements and numerous outliers in empirical signals (see e.g. Nikkinen et al. 2011). Second, the robust quantile regression estimators are powerful in recognizing the deviations from normality and it gives reliable estimates in the extreme value environment.

Table 2 could give us an indication that GARCH model with normal distribution does not fit the best to any of the wavelet time-series. In order to find out which GARCH model is the best fitting, we estimate several GARCH models with different density functions – normal, Student-t, GED and GAT, for every wavelet time-series that has been created. Table 3 presents the AIC values for the estimated wavelet-based GARCH models with different distribution functions, while greyed numbers signal the lowest AIC value. The GARCH model with the lowest AIC value fits the best to the particular wavelet time-series, and is used consequently for the creation of the conditional volatilities. Results in Table 3 indicate that innovative GAT distribution of Zhu and Galbraith (2010) is the optimal choice in most cases, regarding all time-series and all wavelet scales.

In order to be parsimonious as much as possible, Fig. 1 presents created wavelet-based conditional volatilities for the S&P500 index, while all other volatilities can be obtained by request.

After the creation of optimal wavelet-based conditional volatilities, we intend to determine which SKD fits the best to the particular dependent variable in the robust QR model. Due to the fact that all indices are synchronized with Brent, the length of Brent time-series differentiates, depending on with which index Brent is paired. Therefore, Table 4 contains AIC values for robust QR models with different distributions and for every pair considered,

Table 2 Descriptive statistics of the empirical time-series

	Mean	St. dev.	Skewness	Kurtosis	JB
Panel A: D1 wavelet scale					
Brent oil	0.000	1.549	0.017	6.183	1634.7
S&P500	0.000	0.858	0.309	15.087	24,094.4
RTS	0.000	1.365	0.136	11.089	10,571.4
SSEC	0.000	1.139	−0.043	6.521	1955.9
TADAWUL	0.000	0.919	0.205	12.449	10,316.0
Panel B: D5 wavelet scale					
Brent oil	0.000	0.336	0.000	3.417	28.1
S&P500	0.000	0.166	−0.110	6.173	1664.1
RTS	0.000	0.350	−0.336	4.599	485.1
SSEC	0.000	0.296	−0.149	4.498	367.8
TADAWUL	0.000	0.252	−0.357	5.672	882.4
Panel C: D6 wavelet scale					
Brent oil	0.000	0.244	−0.296	3.582	111.2
S&P500	0.000	0.123	−0.082	6.090	1575.3
RTS	0.000	0.255	−0.291	3.330	72.1
SSEC	0.000	0.209	−0.051	3.286	14.6
TADAWUL	0.000	0.156	0.105	3.703	62.1

JB stands for the Jarque-Bera coefficients of normality

Table 3 Estimated AIC values for different GARCH specifications

	Brent	S&P500	RTS	SSEC	TADAWUL
Panel A: D1 wavelet scale					
GARCH-norm	13,383.5	7212.8	11,663.1	10,320.4	5308.6
GARCH-std	13,365.5	7181.1	11,624.5	10,266.9	5169.9
GARCH-ged	13,378.4	7194.5	11,642.6	10,282.0	5204.5
GARCH-gat	13,359.8	7179.7	11,619.7	10,267.2	5169.8
Panel B: D5 wavelet scale					
GARCH-norm	−1205.9	−8044.1	−1419.4	−2904.1	−3384.4
GARCH-std	−1176.7	−8016.7	−1391.8	−2876.8	−3365.1
GARCH-ged	−2504.9	−9005.4	−2512.8	−3955.2	−4101.1
GARCH-gat	−2059.1	−9177.8	−2650.8	−4155.6	−4216.9
Panel C: D6 wavelet scale					
GARCH-norm	−5143.6	−10,950.8	−3921.2	−5744.8	−6378.0
GARCH-std	−5111.1	−10,917.7	−3887.9	−5711.4	−6355.0
GARCH-ged	−6724.9	−12,805.0	−6010.1	−7888.9	−7599.8
GARCH-gat	−7240.1	−13,318.6	−6246.7	−7911.1	−7767.4

Greyed numbers denote the lowest AIC value

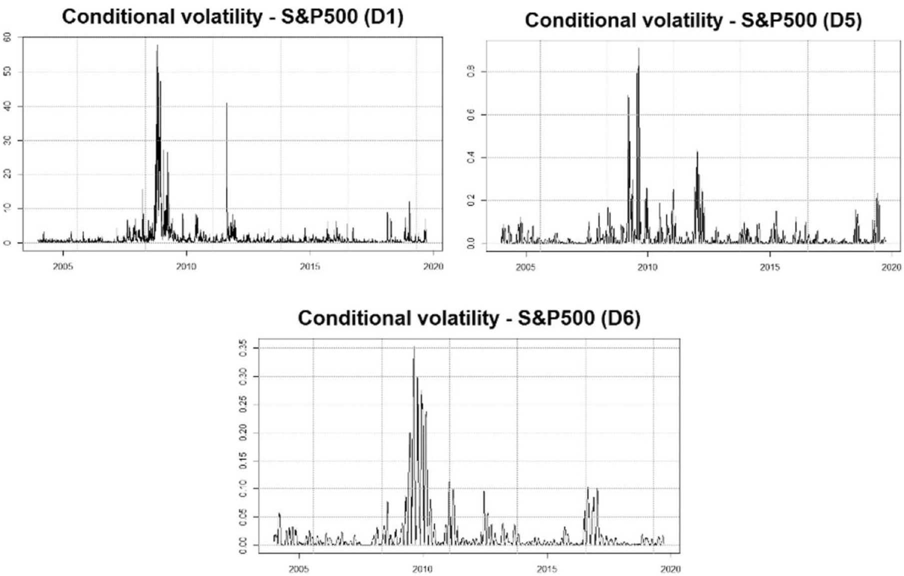

Fig. 1 Wavelet-based conditional volatilities for S&P500 index

taking into account both directions of volatility transmission. We fit five models with different distribution functions, performing a median regression ($\tau^{0.5}$). According to AIC measures, it can be concluded that the best model is with the skewed slash distribution for all time-series examined, and this density function is just a little bit better than robust QR with skew Student-t distribution. Figure 2 presents model residuals with the theoretical shape of every distribution function for model in which S&P500 index is dependent variable. Visually, it also can be confirmed that skewed slash distributions match the best to the estimated residuals. Therefore, all quantile parameters are assessed with the slash robust QR, and the results are presented in the next section.

5 Empirical results

This section presents the results of the estimated robust quintile parameters that range from 0.05 to 0.95. Table 5 contains the findings, while Figs. 3 and 4 presents the plots. We inspect the level of volatility transmission between Brent and stock indices of four major global oil producers and consumers. In addition, by applying wavelet concept, we can assess the magnitude of this effect in different time-horizons – short-term, midterm and long-term. Several interesting findings can be highlighted from the results. First of all, it can be seen that most of the estimated parameters are highly statistically significant, whereby this pattern particularly applies for the higher quantile coefficients, taking into account both directions. These results suggest that volatility transmission between the markets is more intense in periods of increased market turmoil, which is not unknown fact. Numerous authors reported increased shock and volatility spillover effect between the financial and commodity markets in the periods of enhanced market turbulence (see e.g. Lee et al. 2014; Kirkulak-Uludag and Lkhamazhapov 2017). As

Table 4 Estimated AIC values for quantile regression under different SKD

	norm	Std	Lap	sla	c.norm	norm	Std	Lap	sla	c.norm
	From Brent oil to stock indices					From stock indices to Brent oil				
	Panel A: D1 wavelet scale									
USA	32,772.4	23,582.0	24,364.1	23,540.9	26,031.8	31,605.2	20,962.3	22,289.1	20,641.3	24,626.7
RUS	31,147.2	17,184.4	19,547.5	16,793.4	23,558.8	31,184.6	20,500.1	21,912.0	20,189.9	24,341.9
CHN	21,863.3	11,201.7	12,763.5	10,757.6	15,224.4	31,034.2	20,445.3	21,871.8	20,122.3	24,273.5
SAU	19,122.2	7988.1	10,642.5	7041.4	13,884.6	23,127.6	14,902.1	16,036.4	14,720.9	18,003.2
	Panel B: D5 wavelet scale									
USA	−553.0	−8869.0	−8511.2	−9011.8	−6722.3	−1746.4	−10,382.7	−9606.3	−10,749.5	−8065.0
RUS	5826.5	−4771.5	−3211.9	−5235.9	−794.4	−1325.8	−9620.4	−8895.7	−9911.9	−7443.5
CHN	3295.7	−6946.7	−5408.4	−7815.1	−3038.9	−2235.6	−10,805.7	−9969.7	−11,030.6	−8496.9
SAU	1585.9	−6961.9	−5490.4	−7777.1	−3334.2	−471.2	−6566.4	−5980.5	−6819.9	−4984.8
	Panel C: D6 wavelet scale									
USA	−56.3	−8190.9	−8028.2	−8557.4	−6134.4	−1186.2	−9518.9	−8723.8	−9894.2	−7360.9
RUS	−195.5	−9011.6	−8316.9	−9053.3	−6775.9	−775.6	−9255.4	−8375.7	−9592.6	−6767.6
CHN	−3311.2	−11,217.5	−10,469.1	−11,678.8	−9095.5	−971.1	−9504.4	−8602.0	−10,016.6	−7043.7
SAU	−5033.2	−11,248.1	−10,553.6	−11,776.2	−9365.1	−1393.5	−7012.3	−6538.1	−7231.9	−5596.3

Greyed numbers denote the lowest AIC value

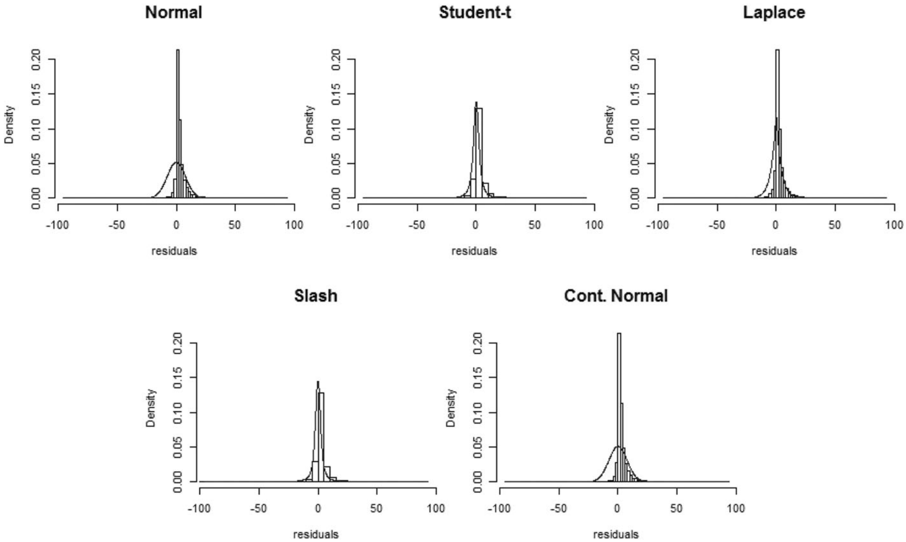

Fig. 2 Theoretical densities and the estimated S&P500 residuals

for the volatility transmission between oil and stock markets, Arouri, Arouri et al. (2011a) investigated the return links and volatility transmission between oil and stock markets in the Gulf Cooperation Council (GCC) countries, and their results indicated a significant intensification of volatility spillovers from oil to GCC stock markets during the crisis period. On the other hand, most of the left-tail quantile parameters ($\tau^{0.05}$ and $\tau^{0.25}$) are either very small or statistically insignificant, which signals that volatility transmission hardly exists between the markets in tranquil periods.

In addition, observing different wavelet details (D1, D5 and D6), which portrays diverse time spans, it is apparent that, in most cases, the volatility transmission effect is stronger in the short-term horizon (2–4 days), while it gradually subsides in longer run. This is particularly true when the transmission effect is observed from stock market toward oil market. This is not unusual, since we research the volatility spillover effect that represents the arrival of information in the markets. According to common knowledge, new information appears fast, but it quickly becomes irrelevant once everyone obtains it. This claim coincides well with the contention of Ross (1989), who explained that changes in variance, and not the asset's price change, reflects the arrival of information in the market. These results are also supported by the findings of Wang and Wang (2019), who found an evidence that total volatility spillover between stocks and oil is driven mainly by short-term spillovers.

In cases of Russia and China and somewhat Saudi Arabia we find that the effect is stronger in midterm and long-term, when spillovers go from Brent to stocks. As for the case of China, the probable reason for such findings lies in the fact that China's oil consumption has tripled in the period from 1990 to 2015, primarily owing to the rapid development of transportation, industries, and powerplants as well as the expansion of foreign trade (see Wen et al. 2019). Also, Shao et al. (2017) contended that China's share of global oil consumption has risen from 3.57% in 1990 to 12.92% in 2015. Therefore, due to Chinese high oil dependence, it is not hard to assume that any

Table 5 Bidirectional wavelet-based volatility transmission effects between Brent oil and stocks

	From Brent oil to stock indices					From stock index to Brent oil				
	Estimated quantiles					Estimated quantiles				
	0.05-th	0.25-th	0.5-th	0.75-th	0.95-th	0.05-th	0.25-th	0.5-th	0.75-th	0.95-th
	USA					USA				
D1	0.002*	0.005**	0.014***	0.029***	0.171***	0.090***	0.185***	0.291***	0.827***	1.345***
D5	0.000	0.001	0.003	0.016***	0.159***	0.002	0.027**	0.184***	0.361***	0.408***
D6	0.000	0.001	0.004**	0.011***	0.003	0.002	0.007	0.021	−0.024	0.819***
	Russia					Russia				
D1	0.012***	0.033***	0.061***	0.161***	0.333***	0.030***	0.086***	0.190***	0.288***	0.670***
D5	0.001	0.023	0.083***	0.234***	0.829***	0.000	0.004	0.022***	0.089***	0.176***
D6	0.001	0.071***	0.386***	0.446***	0.757***	0.000	0.011*	0.059***	0.176***	0.888***
	China					China				
D1	0.001	0.012***	0.019***	0.037***	0.054***	0.009	0.077***	0.226***	0.341***	0.575***
D5	0.004	0.018*	0.048***	0.079***	0.167***	0.000	0.001	0.006	0.018**	0.064***
D6	0.000	−0.002	−0.003	0.040***	0.224***	0.000	0.000	0.003	0.105***	0.082***
	Saudi Arabia					Saudi Arabia				
D1	0.003***	0.009***	0.016***	0.025***	0.078***	0.026***	0.038***	0.102***	0.136***	0.197***
D5	0.000	0.002	0.014*	0.070***	0.144***	0.001	0.004	0.009	0.015	0.052***
D6	0.000	0.001	0.002	0.015**	0.031***	−0.001	−0.002	−0.023	−0.069	0.000

***, **, * represent statistical significance at the 1%, 5% and 10% level, respectively

increased turbulence in the oil market sends reverberating shocks to the Chinese economy in an extended period of time, which inevitably hit Chinese stock market. However, although the oil volatility shocks toward stocks is relatively high, it should be emphasized that risk transmission from Chinese stock market towards Brent futures market is even stronger. This effect amounts 57.5%, in short-term horizon, regarding $\tau^{0.95}$ quantile, while the impact from oil to Chinese stocks is 22.4% in long-term horizon. Some explanation why Chinese stocks experience relatively low spillover effect from oil could lie in the nature of Chinese stock markets. According to Kirkulak-Uludag and Safarzadeh (2018), Chinese stock markets are subject to several regulations including the restriction on stock purchases by foreign investors, whereby these restrictions affect the degree of market openness and diminish the volatility spillover effects from other markets. Also, these results could indicate that large and well diversified economies, such as Chinese, suffers less impact from oil market, but turbulences from the second largest global economy, could inflict serious shocks to the global oil market, due to its importance as a major global oil consumer.

On the other hand, Russia faces other type of problems. Russian economy is highly dependent on oil export and oil revenues, since Russia receives most of the income from oil sales. Pavlova et al. (2017) asserted that the percentage of budget revenues from oil sales in the USA is only 1% to 2%, while in Russia this share amounts around 50%. Besides, significant portion of the Russian market capitalization is composed of oil companies. For instance, Bhar and Nikolova (2010) presented the data that approximately 19% of the total stock market capitalization in 2008 goes to five oil companies.

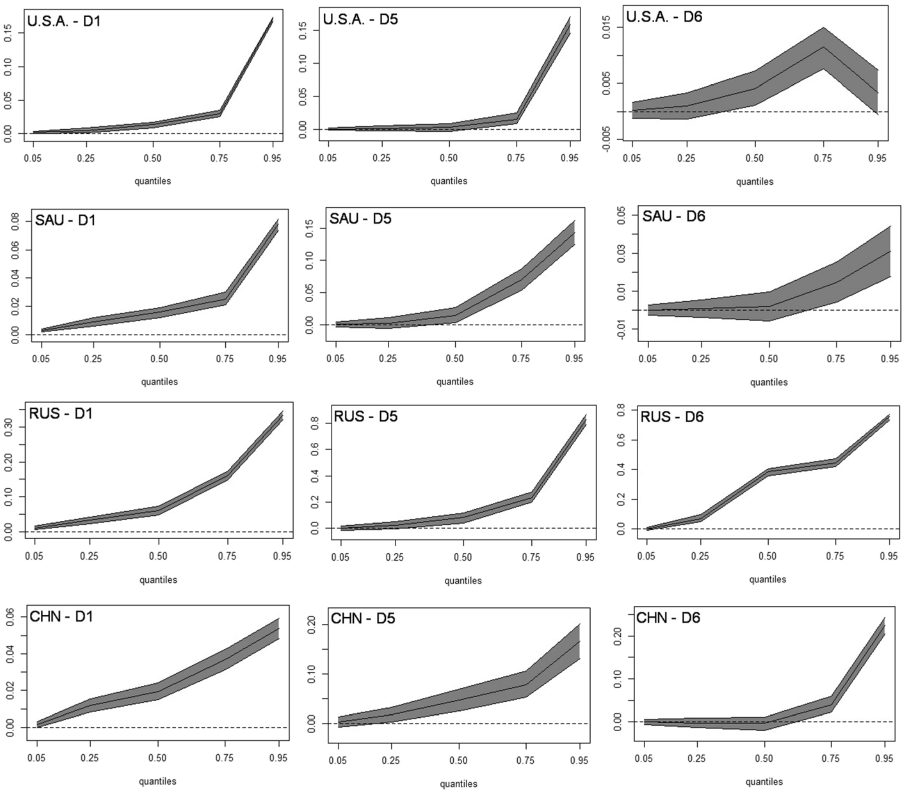

Fig. 3 Estimated robust quantiles – from Brent oil futures to stock index. **Note:** The shaded area gives the adjusted credible intervals at 95% probability

Since Russian rouble is practically an oil currency, it means that oil price drop, automatically imply huge currency depreciation, which is immediately followed by budget deficit, rising inflation, rising unemployment and declining production. Therefore, this could be probable reason why volatility shocks from the oil market have deep and prolonged effect on the Russian stock market. We report that our results concur well with the findings of Nasit et al. (2018) who studied the implications of oil prices shocks on the BRICS economies. They asserted that between the major BRICS oil exporters, i.e. Russia and Brazil, the former's economy is rather more intensively influenced by oil prices shocks. In addition, it should be said that Russia is among top 3 global oil producers for decades, and as such, Russian oil production has very important influence on global supply oil market. Arguably, this could be the reason why we find relatively large volatility spillover effect in the highest quantile ($\tau^{0.95} = 0.670$) that goes from Russian stock market towards Brent futures market.

As for the Saudi case, our results indicate that the volatility spillover effect is not as pronounced as in the case of Russia, regarding the transmission direction from Brent futures to stocks, albeit Saudi Arabia is even more dependent on oil than Russia is. According to IMF,[5] Saudi's oil revenues account for around 85% of exports and almost

[5] http://www.imf.org/external/pubs/cat/longres.aspx?sk=43343.01.

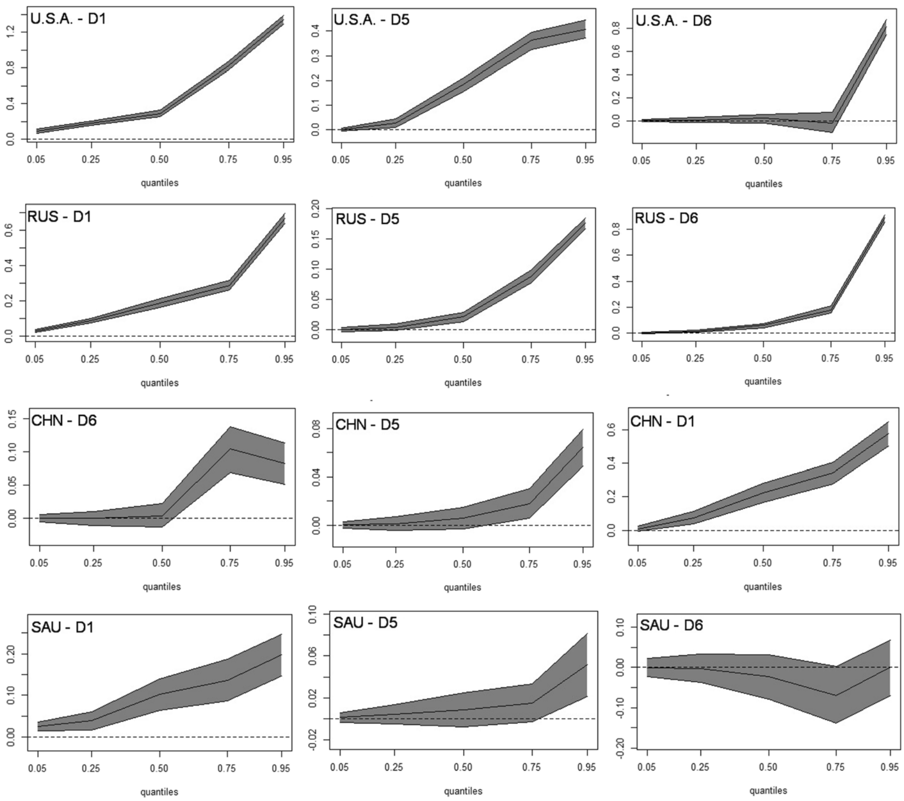

Fig. 4 Estimated robust quantiles – from stock index to Brent oil futures. **Note:** The shaded area gives the adjusted credible intervals at 95% probability

90% of fiscal revenue, while the oil sector makes over 40% of overall GDP. Comparing these figures and our relatively low quantile estimates, it is a bit perplexing that the volatility transmission effect is not higher in the case of Saudi Arabia. The probable explanation lies in the fact that Saudi stock market is largely segmented from international markets, while only investors of the GCC region owning up to the one-fourth of listed firms are allowed to access to Saudi stock market (see Jouini 2013). In addition, the access of global investors to Saudi market is restricted, and they can enter this market only through mutual funds. Therefore, we find a weaker spillover effect in turbulent times in short-term horizon, observing the direction from Brent futures to stocks ($\tau^{0.95} = 0.078$) than from Saudi stocks to Brent futures ($\tau^{0.95} = 0.197$). Our results are very well in line with the findings of Jouini (2013), who investigated volatility transmission between Saudi stocks and oil via VAR-GARCH model and reported the existence of significant transmission between oil price and Saudi stock sectors with more apparent spillover effects from stock sector markets to oil price. This author found one important implication from these results. He asserted that policy makers of the oil dependent countries (especially neighbouring GCC countries) can realize benefits by monitoring the Saudi stock market for eventual oil price fluctuations, due to the fact that shocks on Saudi equity sectors impact the volatility of the oil market strongly than vice-versa.

Regarding the U.S. case, Table 5 discloses that volatility transmission effect is the strongest in short-term horizon and in the periods when markets are under increased turmoil, which is expected. This finding applies for both directions, and it is in line with the paper of Arouri, Arouri et al. (2011b), who documented bidirectional volatility spillover effect between the U.S. stocks and oil. They investigated volatility transmission between oil and stock markets in Europe and the United States at the sector-level, and revealed that the spillover is unidirectional from oil markets to stock markets in Europe, but bidirectional in the United States. In addition, our results undoubtedly indicate that this effect is many times higher when the direction goes from the U.S. stocks to the Brent market ($\tau^{0.95} = 1.345$), than other way around ($\tau^{0.95} = 0.171$). In other words, volatilities that come from oil market affect the U.S. stock market much weaker than vice-versa. These results coincide with the findings of Alsalman (2016), who reported via GARCH-in-Mean model that there is no statistically significant effect of oil price volatility on the U.S. stock returns. We seek the possible explanation for our drastic difference in the transmission effect in the paper of Thorbecke (2019). He asserted that the conventional view, which tells that oil price increases harm the overall U.S. stock, no longer holds. According to this author, this shift happened because the U.S. oil shale-based production has soared in the past decade, whereby the consumer-oriented stocks are struck less by oil price increases after the shale revolution than they were before. On the other hand, our robust quantile estimates suggest that the U.S. stock market has very strong effect on the oil market, and this particularly applies for the upper quantiles ($\tau^{0.75} = 0.827$ and $\tau^{0.95} = 1.345$) in short-term, whereby this heavy impact is also present in the midterm ($\tau^{0.95} = 0.408$) and the long-term ($\tau^{0.95} = 0.819$). The explanation for such findings could be the fact that the U.S stock market is the largest on the world, and any disturbance that occur in this market in crisis periods inevitably hit all the markets worldwide in a greater or lesser extent, including the oil market. The other conduit could be the indirect effect via financialization phenomenon, which imply that the price of an oil commodity is not only determined by its fundamental supply and demand factors, but also by investors' activities. The activities of market participants are most intense in turbulent times, and they involve asset reallocation and risk diversification of portfolios that combines both oil and stock. These actions unequivocally provoke the transmission of risk between the markets, and hence our quantile parameter indicates that 100% increase in volatility in the U.S market causes 135% increase in volatility in the oil futures market.

6 Robustness check via WTI oil

This section presents the results of volatility spillover effect between the stock indices and WTI oil[6] (West Texas Intermediate). We conduct this analysis for robustness purposes, because different prices of oil are more relevant for some of the analysed

[6] For the construction of conditional volatilities for WTI, we apply the same procedure as in the case of Brent. Acording to AIC values, the optimal model for D1 and D2 scales is GARCH-gat, and for D3 scale it is GARCH-ged.

countries. In particular, Brent is used for the pricing index for crude from Europe, Africa and other regions. On the other hand, WTI is usually referred as the price of the New York Mercantile Exchange (NYMEX) WTI Crude Oil futures contract, but it is also known as Texas light sweet oil. In addition, it should be said that due to the development of WTI spot and futures markets, many crude oil producers around the world started to use assessed WTI prices as a benchmark in oil pricing. For instance, Saudi Arabia, Kuwait, Iraq, Colombia, and Ecuador based their crude oil selling prices on WTI oil since 2008. Besides, Fig. 5 indicates that Brent and WTI futures prices are not perfectly synchronized, thus it is an additional reason to analyse WTI oil.

Table 6 contains the results of the estimated wavelet-based robust quantile parameters for WTI oil. Comparing Tables 5 and 6, it can be seen that estimated quantile parameters are relatively equable in magnitude across quantiles, which means that there are no significant deviations in volatility transmission between the stock indices and two oil markets, which particularly applies for lower quantiles. However, we can also report some discrepancies between the results in two Tables. For instance, in the case of USA, it can be seen that 75th and 95th quantile parameters in D5 and D6 scales are significantly higher in the case of WTI when spillover effect goes from stocks to oil. In other words, 75th and 95th quantile parameters for Brent are 0.361 and 0.408 in D5 scale, while for WTI they are 1.066 and 1.400. As for D6 scale, 75th quantile parameter for Brent is insignificant, and 95th quantile parameter amounts 0.819, whereas for WTI, these parameters are 0.242 and 1.421, respectively.

These results indicate that in longer time-horizons, volatility from the American stock index impacts WTI oil much stronger, than Brent oil. This is expected, because WTI oil is associated and primarily used by the American market. It is usually said that oilfield production and refineries around Midland, Texas and Cushing, Oklahoma define WTI crude oil. Therefore, when Brent and WTI oils are under increased volatility, volatility shocks that came from the USA hit harder WTI oil, than Brent oil. These results are in line with Khalfaoui et al. (2015) who researched the mean and volatility linkage between WTI oil and stock markets of the G-7 countries over various time horizons. They demonstrated strong evidence of significant volatility spillovers between WTI oil and stock markets. Also, Xu et al. (2019) investigated volatility spillover effect between WTI future prices and the S&P500 and SSEC indices. They found that the volatility spillovers between the oil and stock markets are time-varying, and this interdependence strengthens during financial crisis, which coincide with our results. Kondoz et al. (2019) asserted that volatility spillover effect of S&P500 index on the WTI crude oil returns is more significant

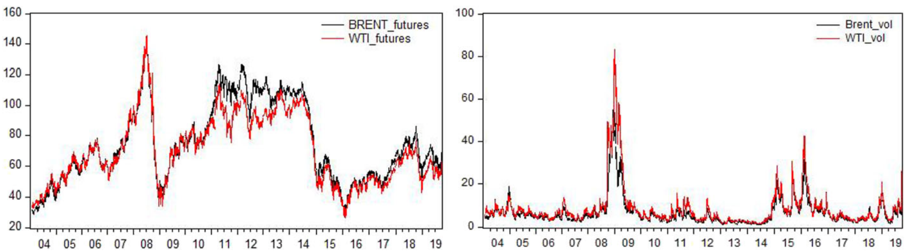

Fig. 5 Parallel dynamics of Brent and WTI futures oil in terms of prices and volatility. **Note:** Left graph shows Brent and WTI futures prices, whereas right graph depicts their conditional volatilities

Table 6 Bidirectional wavelet-based volatility transmission effects between WTI oil and stocks

	From WTI oil to stock indices					From stock index to WTI oil				
	Estimated quantiles					Estimated quantiles				
	0.05-th	0.25-th	0.5-th	0.75-th	0.95-th	0.05-th	0.25-th	0.5-th	0.75-th	0.95-th
	USA					**USA**				
D1	0.001	0.005***	0.017***	0.030***	0.155***	0.094***	0.226***	0.416***	0.887***	1.364***
D5	0.000	0.002	0.007***	0.016***	0.048***	0.012	0.057**	0.483***	1.066***	1.400***
D6	0.000	0.001	0.003	0.008***	0.006***	0.006	0.082***	0.214***	0.242***	1.421***
	Russia					**Russia**				
D1	0.008***	0.037***	0.071***	0.113***	0.342***	0.019***	0.047***	0.147***	0.323***	1.216***
D5	0.000	−0.000	−0.006	−0.016	0.196***	0.000	0.004	0.027**	0.105***	0.292***
D6	0.001	0.008	0.015	0.045**	0.069***	0.000	0.008	0.009	0.045***	0.164***
	China					**China**				
D1	0.002**	0.010***	0.019***	0.033***	0.055***	0.014*	0.086***	0.149***	0.270***	0.552***
D5	0.001	0.006	0.010*	0.014**	0.074***	0.001	0.018*	0.048***	0.069***	0.140***
D6	0.001	0.003	0.007	0.042***	−0.022	0.000	0.004	0.004	0.016	0.049**
	Saudi Arabia					**Saudi Arabia**				
D1	0.002**	0.006***	0.010***	0.025***	0.107***	−0.000	0.034*	0.039*	0.069**	0.622***
D5	0.001	0.004	0.010**	0.043***	0.058***	−0.000	−0.006	−0.015	−0.018	−0.049
D6	0.000	0.002	0.006	0.022	0.018*	0.002	0.049*	0.126***	0.168***	0.709***

Note: ***, **, * represent statistical significance at the 1%, 5% and 10% level, respectively

than the reversed effect, which perfectly concur with our findings. On the other hand, we find that volatility shocks from WTI oil market impact Russian stock index significantly weaker than in the case of Brent oil. This finding is also expected, since Russia, as heavily dependent oil producing country, produces oil of type Brent. This is the primary reason why Brent, rather than WTI, has much stronger effect on Russian RTS index.

At the end, we comment the Saudi case. More specifically, we find that 95th quantile parameters in D1 and D6 scales are higher in Table 6, than their counterparts in Table 5, when transmission is observed from stocks to oil. It means that volatilities from Saudi stock market affect stronger WTI oil, than Brent oil. Saudi Arabia is currently the second largest global oil producer, but for many years it was the largest one, and having in mind that Saudi Arabia refers their crude oil selling prices on WTI oil since 2008, it is reasonable to expect that increased volatility in Saudi stock market could have higher impact on WTI oil, than on Brent oil. In particular, our results suggest that significant transfer of volatility from Saudi stocks to WTI oil happens in very short and long time-horizons in 95th quantile, i.e. when WTI oil market is under increased turbulence, which is not the case with Brent oil. Our results concur very well with the findings of Malik and Hammoudeh (2007), who researched the volatility and shock transmission mechanism among US equity, WTI crude oil market, and equity markets of Saudi Arabia, Kuwait, and Bahrain. They found significant transmission among second moments. They reported that only in the case of Saudi Arabia a significant volatility spillover exists from the Saudi market to the oil market, which is in line with our findings.

Table 7 Wavelet cross-correlations between volatilities of Brent and the selected stock indices

Observed pairs	Wavelet details	Negative lagged correlations				Positive lagged correlations			
		−20	−15	−10	−5	5	10	15	20
Brent vs S&P500	D1	−0.005	0.014	0.035	0.002	0.141	0.008	−0.010	−0.023
	D5	−0.253	−0.213	−0.086	0.093	0.329	0.303	0.215	0.131
	D6	−0.266	−0.126	0.033	0.195	0.472	0.558	0.601	0.597
Brent vs RTS	D1	0.002	0.008	0.032	0.118	−0.038	−0.032	0.039	0.010
	D5	−0.134	−0.079	−0.020	0.032	0.082	0.085	0.098	0.138
	D6	−0.269	−0.176	−0.064	0.059	0.299	0.398	0.471	0.510
Brent vs SSEC	D1	0.015	0.045	−0.017	0.009	0.036	0.012	0.018	−0.017
	D5	−0.157	−0.148	−0.079	0.042	0.242	0.232	0.159	0.077
	D6	−0.251	−0.130	0.003	0.138	0.369	0.442	0.481	0.484
Brent vs TADAWUL	D1	0.013	−0.020	0.011	0.017	0.053	−0.033	−0.089	−0.040
	D5	−0.173	−0.258	−0.275	−0.197	0.110	0.216	0.261	0.273
	D6	−0.374	−0.322	−0.228	−0.097	0.211	0.353	0.461	0.522

7 Complementary analysis via wavelet cross-correlation

In order to be more informative about the nexus between volatilities of stocks and Brent oil markets, we do an additional analysis via wavelet cross-correlation. This particular methodology can give us an insight from which market volatility shocks originate, and which market is the recipient of these shocks. In other words, wavelet cross-correlation, based on wavelets, helps us to better understand the lead-lag relationship between the observed assets in different time-horizons. This type of knowledge can be used by various market participants, such as traders, portfolio managers, hedgers, to make a decision how to rebalance their investments or whether they should enter or leave particular market. Before we have initiated the wavelet cross-correlation process, we created an optimal daily conditional volatility time-series, using GARCH model with aforementioned density functions. AIC values give us a clue which GARCH model is the optimal one. According to this indicator, GARCH-GAT model fits the best to all daily empirical time-series.[7] Table 7 presents exact cross-correlation values for three wavelet scales, whereas Fig. 6 depicts wavelet cross-correlation plots also for three wavelet scales, with the corresponding approximate 95% confidence intervals.

We consider 20 daily lags in wavelet cross-correlation procedure, regarding the same linear combination at each of the wavelet scales. In this way, we can see whether there exists any pulling effect between volatilities of the selected stock indices and Brent futures markets at contrasting time lags. In our computational process, Brent futures is the first variable, therefore the left side of the wavelet cross-correlation plots depicts lagged correlation for Brent oil, while the right part of the plots portrays lagged correlation for the selected indices. It should be said that the lead-lag interlink is determined via skewness of cross-correlation curve. In other words, if this curve is

[7] These AIC results can be obtained by request.

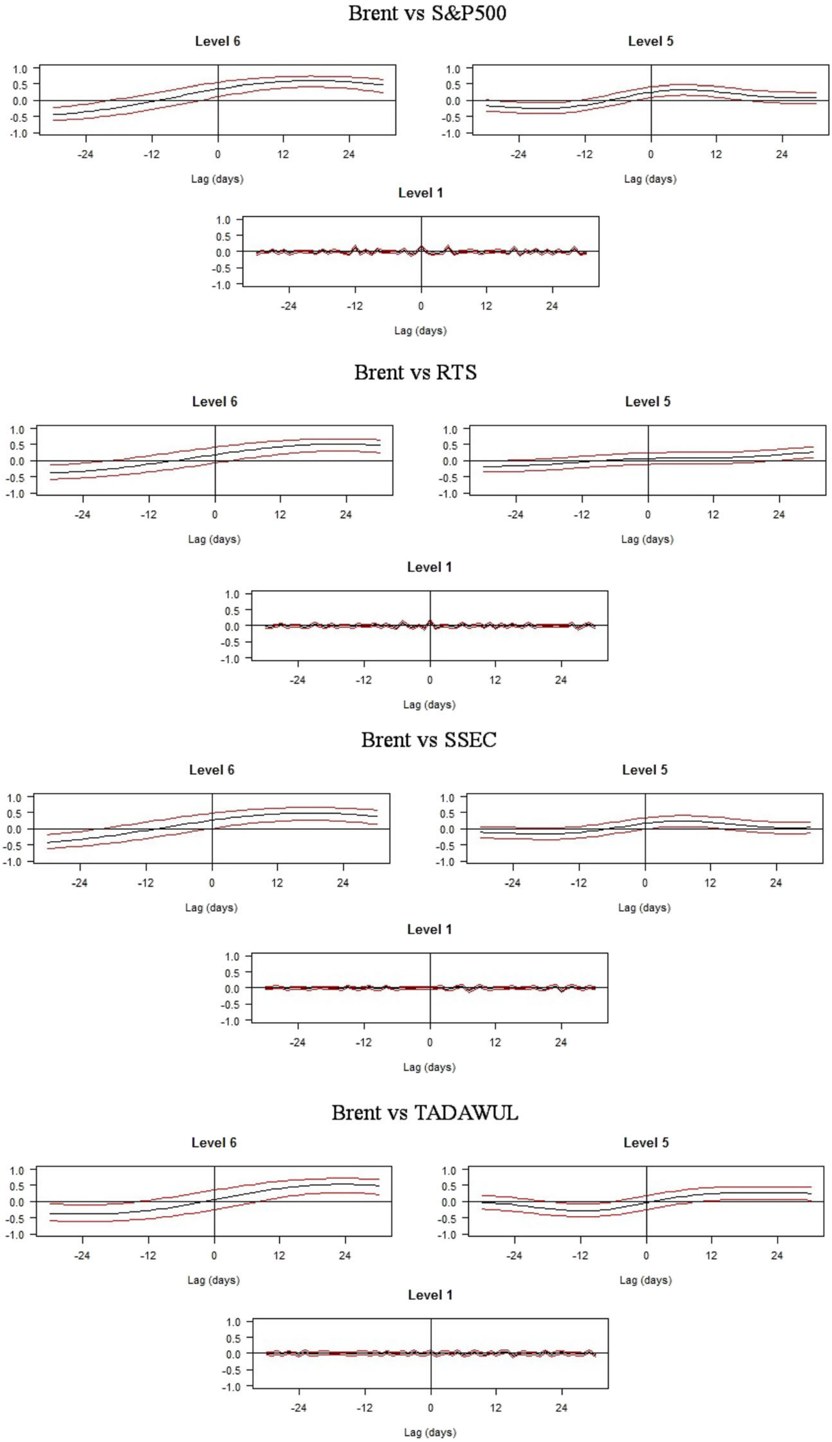

Fig. 6 Wavelet cross-correlation plots between volatilities of the selected pairs

skewed significantly in the left side of the graph, then it implies that first time-series leads the second one, and vice-versa (see Živkov et al. in press). The skewness of the cross-correlation curve is not so obvious in lower frequency plots. Thus, Table 7 would be of great help.

In the previous section, we have seen that volatility shocks are more intense from stock markets to Brent, than other way around in the case of the U.S, and it happens in short-term horizon. The probable reason for such findings lies in the fact that the U.S. is the biggest global oil producer and consumer. Based on these results, it could be assumed that most likely transfer of volatilities goes from stocks to Brent, and not vice-versa. Wavelet cross-correlation results could confirm/refute this contention, but also can serve as robustness check for the results of all examined countries. According to Table 7 and up to 5 lags, we can see that skewness goes overwhelmingly in favour of the S&P500 index in D1, D5 and D6 scales. These results indicate that Brent always lags S&P500 index in volatility transmission, which can give valuable signals to market participants who invest in Brent market. In other words, investors should simply monitor the U.S. stock market and shape their positions in the Brent market accordingly, in order to adjust their actions in Brent market and prevent contagion risks.

As for the Brent vs RTS pair, it can be seen that skewness favours Brent market in the short-term horizon (2–4 days), which means that Brent futures leads Russian RTS index in short run. This is not unexpected, since we also have found via robust quantile estimates that RTS endures major spillover volatility shocks from Brent market in all three time-horizons. On the other hand, the situation changes in midterm and long-term, in a sense that RTS takes over a leading position in these time-horizons. These results cannot be classified as peculiar, since our quantile estimates have suggested that Russia, as a major oil producer, has significant influence on Brent oil market, particularly in turbulent times and in all three time-horizons.

China is currently the second larger global oil consumer, with the tendency to become the largest one. Therefore, we have found significantly higher transmission effect in short run from SSCE index towards Brent, than vice-versa. Wavelet cross-correlation results stand in line with these findings in short-run. However, although we have not found an intense spillover effect from the Chinese stock towards Brent in midterm and long-term, Table 7 suggests that the SSCE index has dominantly leading role in all three time-horizons.

In the Saudi case, we find that TADAWUL has leading position in higher frequency scale (D1), which perfectly concur with the robust quantile estimates that have suggested stronger volatility transmission effect from Saudi stocks towards Brent. In midterm, the leading position has Brent futures, which is also in line with the robust quantile parameters. In the long-term scale, wavelet cross-correlation suggests that the Saudi stock index has a leading role, while the results of quantile estimates are inconclusive, since they are either very low or statistically insignificant, across all the quantiles.

8 Conclusion

This paper does thorough analysis regarding the volatility interdependence between Brent oil futures and stock markets in the major global oil producers and consumers – the U.S., Russia, China and Saudi Arabia. In that process, we employ a mixture of novel and elaborate methodologies – wavelet signal decomposing procedure, GARCH model with traditional and exotic distributions and recently developed robust quantile regression. By combining several complex methodological approaches, we can assert that obtained results are unbiased and trustworthy.

Based on the results, we have several noteworthy findings to report. First, the results indicate that the volatility spillover effect is stronger in short-term horizon than in midterm and long-term in most cases, which happens due to fast information transfer between the markets. Second, robust quantile estimates suggest that the transmission effect is much stronger in turbulent times, whereas in tranquil times, this effect is very weak, almost negligible. This finding applies for all examined countries and both spillover directions. Third, we find that Russia, as major oil exporter, and its RTS index endures the strongest volatility transmission effect from oil market, and this applies for all three time-horizons. On the other hand, Saudi Arabia is even bigger oil exporter, but we find that Saudi stock market does not suffer heavy spillover effect even in the periods of increased market unrest. These findings can be attributed to the peculiarities of the markets. In other words, Russian economy is highly dependent on oil export, while the major share in Russian stock markets has energy companies, thus it is not surprising that Russian stocks are subject to volatility shocks from the oil market. On the other hand, Saudi stock market is largely segmented from international markets, while only investors of the GCC region owning up to the one-fourth of listed firms are allowed to access to Saudi stock market. This could be the probable reason for relatively weak spillover effect that we have found in Saudi case. As for the major oil consumers (the U.S. and China), we reveal that the spillover effect is much stronger from stocks to oil than vice-versa, and this particularly applies for the U.S. case. Forth, the wavelet cross-correlation findings are in line with the estimated quantile parameters, and these results can indicate to global investors which market leads and which one lags. This type of knowledge is crucial for hedging purposes and portfolio construction, particularly in the periods of increased market turmoil.

In summary, this study provides a better understanding of the volatility linkages between Brent oil futures and stock markets of the key global oil producers and consumers, while sophisticated econometric methodologies can ensure reliability of the results for both academic researchers and practitioners. By knowing between which markets strong volatility links exists, market participants can avoid combination of these assets in a single portfolio, and in such way can enhance the diversification benefits. Consequently, the results from quantile parameters and wavelet cross-correlations could be very useful for investors in a sense that they can build profitable and accurate hedging and arbitrage strategies, and diversify and rebalance their portfolios.

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Affiliations

Dejan Živkov[1] · Slavica Manić[2] · Jelena Kovačević[3] · Željana Trbović[4]

1 Novi Sad school of business, University of Novi Sad, Vladimira Perića Valtera 4, Novi Sad 21000, Serbia

2 Faculty of economics in Belgrade, University of Belgrade, Kamenička 6, Beograd 11000, Serbia

3 'LEMIT' company, Futoška 11, Novi Sad 21000, Serbia

4 Business economics, EDUKONS University, Vojvode Putnika 87, Sremska Kamenica 21208, Serbia