Assessing Permanent and Transitory Volatility Spillover Effect from Oil to Stocks in Baltic and Visegrad Countries

Dejan ŽIVKOV – Marina GAJIĆ-GLAMOČLIJA** – Jasmina ĐURAŠKOVIĆ*** – Mirela MOMČILOVIĆ**

Abstract

This paper researches the size of volatility transmission from Brent oil market to six stock markets of Central and Eastern European countries, with a distinction between the short-term and long-term effect. We create the transitory and permanent parts of volatilities by using the component GARCH model with the optimal density function and inserted dummy variables. Created volatilities are subsequently embedded in the robust quantile regression framework. The results indicate that the transitory volatility shocks are higher than the permanent ones, which means that investors who operate in the short-term horizons need to be more careful for volatility spillovers from oil market than long-term investors. We find that Polish and Czech stock markets receive the strongest volatility impact from oil. On the other hand, Hungarian and Lithuanian stock markets suffer the lowest volatility effect, in both short and long terms, which favors combining these indices with oil. All the findings can be explained very well by the weight of industry sector in GDP and the net-import of oil. Results of weekly data serve as robustness check for the main findings.

Keywords: *transitory and permanent volatility transmission, Brent oil, stock indices, CGARCH, robust quantile regression*

JEL Classification: C22, C52, G12, Q02

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Introduction

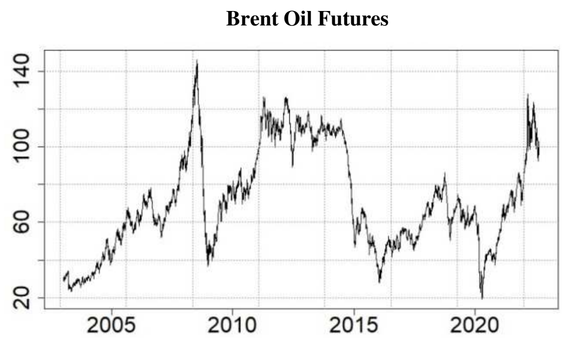
Due to large fluctuations of oil prices in the last two decades, there is a widespread concern among policymakers, researchers and market participants about the effect of oil price on stocks. Sarwar et al. (2019) asserted that oil stands as a very important global macroeconomic factor, while its unstable dynamics inevitably effects stock prices in higher or lesser extent. In the conditions of erratic oil price fluctuations, corporations have adverse consequences on production costs, corporate gains, market confidence and cash-flows (see e.g. Arouri and Rault, 2011; Wen et al., 2019; Baruník and Kočenda, 2019). Taking into account that stock prices are practically the sum of the discounted values of expected future cash flows at different investment horizons, it implies that oil shocks can impact stock prices profoundly. Regarding the subject of spillovers, it is important to make a difference between the first and second moments because volatility rise in both periods of price increase and decrease. Živkov et al. (2020b) contended that oil volatility impacts expectations of companies regarding current production and investment decisions. In addition, oil volatility can affect GDP growth because companies postpone their investment decisions in the uncertain conditions of the future cost of oil, whereas households delay their present consumption for precautionary savings reasons (Punzi, 2019). Mun (2007) added that this topic is important 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. However, despite its relevance, relatively few studies investigated volatility transmissions between these two assets according to Khalfaoui et al. (2019), and this is where we find a motive for this research.

In particular, the goal of this paper is to examine the magnitude of the volatility spillover effect from Brent oil futures market to six stock indices of the Central and Eastern European countries (CEEC) – the Czech Republic, Poland, Hungary, Lithuania, Latvia and Estonia. We exclude the Slovakian SAX index from the analysis, although Slovakia is the member of the Visegrad group, because Bratislava stock exchange (SE) is very illiquid market, with very small daily trading volumes.[1] This means that external volatility shocks hit very small number of stocks on the Bratislava SE, rather to dissipate throughout the market. This might cause biased measures of the spillover effect and serious lack of credibility, and this is why Slovakia is removed from the sample.

[1] Observing 2019, the year before COVID-19, average daily trading volume in Slovakian stock exchange was 377. In Prague SE it was 2,127,563, in Warsaw SE it was 46,000,789, in Budapest SE it was, 2,664,020, in Vilnius SE it was 472,567, in Riga SE it was 16,851 and in Tallinn SE it was 443,168. *Source*: <stooq.com website>.

The focal point of our research is the volatility transmission, and not the return spillovers, since volatility in equity markets is more sensitive to crisis, comparing to the returns, as Diebold and Yilmaz (2009) pointed out. The analysis covers the period of 20 years, which is riddled with significant ups and downs in the oil prices (see Figure 1), and this could indicate that oil volatility spills over to the selected CEEC stock markets. We only estimate unidirectional volatility spillover effect from oil to stocks and not *vice-versa*, because all the selected countries are net oil-importers, while their relatively modest oil consumption has no effect on the global oil price. We decide to take this approach referring to Arouri et al. (2012), who researched 18 developed European countries and reported that volatility spillovers from European stock to oil are insignificant.

Figure 1
Empirical Dynamics of the Brent Oil Futures



Source: Authors' calculation.

This study uses several complex methodological approaches that help us to thoroughly investigate the unidirectional volatility spillover effect. In other words, we estimate the size of the volatility transmission effect in both short-run and long-run, applying the component GARCH (CGARCH) model that can decompose the conditional time-varying volatility in the two parts – transitory (short run) and permanent (long run). According to our knowledge, relatively few papers used the CGARCH model to study the transitory and permanent volatility spillover effect. For instance, Morales-Zumaquero and Sosvilla-Rivero (2018) and Wong (2019) utilized the CGARCH model to investigate the permanent and transitory volatility transmission effect, but their investigations considered stock and exchange rate markets. On the other hand, Živkov et al. (2020a) researched volatility transmission between oil and agricultural commodities, using the CGARCH model. However, none of the papers researched the permanent and transitory volatility spillover effects between oil and stock markets in

CEECs, which leaves a room to contribute to the international literature. This is an important segment of the research because observing the persistent and transitory risk independently, one can tell whether uncertainty is driven by long-term macroeconomic fundamentals or short-term market sentiment. As it is known, unpredicted oil price oscillation can cause a lot of systemic problems in the economy, such as rising inflation, unstable exchange rate, decreasing industrial production, which inevitably affect all companies in greater or lesser extent. On the other hand, market sentiment is related to the behaviour of investors on stock markets, where the anticipation of future price developments, the prevailing attitude of investors, psychological and contagion effects, last relatively short and implement quickly.

In order to obtain reliable results, we try to estimate dynamic volatility time-series with great precision because a problem may arise if empirical time-series have high skewness and heavy tails. In order to address this potential problem, we couple CGARCH model with the six conventional and non-conventional distribution functions – normal (*N*), Student-t (*St*), generalized error distribution (*GED*), normal inverse Gaussian distribution (*NIG*), generalized hyperbolic distribution (*GHYP*) and Johnson SU distribution (*JSU*). Chen et al. (2008) asserted that major weakness of the ordinary GARCH-normal type model is that it assumes a specific functional form before any estimations are made, which could be a crucial estimation error that can generate biased coefficients and standard errors. Therefore, besides the three classical distributions, we also consider the three non-traditional density functions that undoubtedly have theoretical advantage over the ordinary Gaussian distribution in fitting the tail of the oil and stocks. In addition, since the sample covers relatively long period, it is very likely that structural breaks are present in the time-series, and this could also be an issue in the CGARCH estimation. In other words, Kramer and Azamo (2007) reported that volatility persistence might be overestimated if deterministic regime shifts is neglected. Therefore, we add dummy variables in every conditional variance equation of the CGARCH model, which represent detected structural breaks. In all the time-series, structural breaks are determined by the modified Iterative Cumulative Sum of Squares (ICSS) algorithm of Sansó et al. (2004).

Following the construction of the transitory and permanent part of the conditional volatilities, we embed these time-series into the recently developed methodology – robust quantile regression (RQR) of Wichitaksorn et al. (2014). This particular method uses a likelihood-based technique for the quantile parameter estimation, but unlike the traditional QR approach of Koenker and Bassett (1978), this methodology considers several newly developed skewed distributions – Normal, Student-t, Laplace, contaminated Normal and slash distribution.

In the traditional QR model, researchers have no option to choose a proper density function, and this issue usually do not bother them too much, because QR assesses quantile parameters, which makes irrelevant the choice of the best fitting distribution. However, the crucial advantage of the RQR methodology is the fact that optimal distribution function enhances the robustness of estimated quantile parameters, which is of utmost importance for the results' reliability. In other words, the robust QR shrinks credible intervals and enlarges accurateness of quantile estimates. This is a pivotal advantage of RQR compared to the traditional QR approach. Therefore, combining the CGARCH model with the robust quantile regression can give us a comprehensive insight about the magnitude of the spillover effect in the states of low, moderate and high volatility in both the short- and long-term horizons. At the same time, this combination of the techniques ensures trustworthiness of the obtained results. Many researchers used quantile regression for their investigations (see e.g. Chen, 2015; Lee et al., 2020; Ozcelebi, 2021; Das et al., 2022), but very few used RQR (see Živkov et al., 2020a).

Besides introduction, the rest of the paper is structured as follows. Second section contains brief literature review. Third section explains used methodologies. Fourth section presents dataset and creates the transitory and permanent volatilities. Fifth section contains the research results of daily data. Sixth section serves for the robustness check, while the last section concludes.

1. Brief Literature Review

Despite the fact that every oil price shock induces new wave of research about the nexus between oil and stocks, relatively little studies have focused on the time-varying volatility spillover phenomenon, as Xu et al. (2019) contended. For instance, Malik and Hammoudeh (2007) investigate the volatility transmission in Gulf stock markets and oil market, using the BEKK GARCH model. They found the spillover from oil market to all stock markets, whereas Saudi Arabia is the only country that supported volatility transmission from stock market to oil market. Sarwar et al. (2019) researched the volatility spillover effect between stock market returns and crude oil returns in the top three Asian oil-importing countries – China, Japan and India. They used several multivariate GARCH models – BEKK-GARCH, DCC-GARCH, cDCC-GARCH and GO-GARCH and reported that conditional volatility in its own market have more important role than volatility spillover. They found a bidirectional spillover effect between Nikkei stock return and oil returns, unidirectional spillover from Indian stock returns to oil returns, while no evidence of volatility spillover was found in the case of China. The paper of An et al. (2020) investigated the volatility spillover among multiple energy stocks in different periods and clusters (the period of similar fluctuation) by employing the Toeplitz inverse covariance-based clustering method (TICC) and network method. They disclosed that the volatility of energy stocks clearly varies in different periods and clusters from several aspects. They asserted that despite energy stocks have similar fluctuations in the same clusters, the spillover effects on other stocks are distinct.

Khalfaoui et al. (2019) analysed the volatility spillover between the oil market and the stock market of oil-importing and oil exporting countries. They reported that oil-importing countries are severely affected by lagged oil price shocks, while the lagged volatility in the oil market and stock market has a statistically significant impact on the current volatility in its respective markets. Wang and Wu (2018) examined asymmetric volatility spillovers between oil and international stock markets in a vector autoregression framework and found an evidence that bad total volatility spillovers dominate the system and change over time. This implies that a pessimistic mood and uninformed traders who tend to increase volatility dominate in markets. Kirkulak-Uludag and Safarzadeh (2018) studied the volatility spillover between OPEC oil price and the Chinese sectoral stock returns, using the VAR-GARCH model. They found a significant unidirectional volatility spillover between OPEC oil prices and the Chinese sectoral stock returns, underlying that past oil shocks have negative and significant impact on the conditional volatility of Construction, Machinery, Automobile, Military and Agriculture stock indices.

2. Research Methodologies

2.1. Component GARCH Model

In order to evaluate the size of the short- and long-term volatility transmission effect from the Brent oil market to the selected CEEC stock markets, we decompose conditional volatility into the transitory and permanent segments, using the component GARCH model.[2] Equations (1) – (3) define specifications of mean and GARCH processes. In order to avoid autocorrelation bias, we assume AR(1) lag-order in the conditional mean of all the examined assets, while particular characteristics of the empirical time-series are recognized by using the some form of identical and independent distribution function $\varepsilon_t \sim i.i.d.\left(0,\ \sigma_t^2\right)$. More specifically, we take into account the three well-known distribution functions –

[2] Estimation of the component GARCH model with different alternative distributions and structural breaks was done via the 'rugarch' package in the 'R' software.

normal $\varepsilon \sim N(0,\ h_t)$, Student-t $\varepsilon \sim St(0,\ h_t,\ \nu)$ and generalized error distribution $\varepsilon \sim GED(0,\ h_t,\ \nu)$, and the three relatively complex and unconventional heavy tailed distributions – normal inverse Gaussian distribution $\varepsilon \sim NIG(0,\ h_t,\ \nu,\ \kappa)$ of Barndorff-Nielsen (1997), generalized hyperbolic distribution $\varepsilon \sim GHYP(0,\ h_t,\ \nu,\ \kappa)$ of Barndorff-Nielsen (1977) and Johnson SU distribution $\varepsilon \sim JSU(0,\ h_t,\ \nu,\ \kappa)$ of Johnson (1949). ν and κ are shape and skew parameters, respectively. Structural breaks are taken into account by adding dummy variables in the transitory component of the conditional variance.

$$r_t = a_0 + a_1 r_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim i.i.d.\left(0,\ \sigma_t^2\right) \tag{1}$$

$$q_t = \phi_1 + \phi_2\left(q_{t-1} - \phi_1\right) + \phi_3\left(\varepsilon_t^2 - \sigma_t^2\right) \tag{2}$$

$$\sigma_t^2 = q_t + \phi_4\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \phi_5\left(\sigma_{t-1}^2 - q_{t-1}\right) + \sum_{i=1}^{k}\omega_i DUM_i \tag{3}$$

where r_t denotes log-returns of Brent oil and the selected CEECs stock indices. Symbol q_t depicts the long-run part of the conditional variance, and it can indicate the effect of fundamental shocks. In addition, q_t also describes the long-run persistence of the variance. It gravitates to the long-run time-invariable volatility level ϕ_1 with a magnitude of ϕ_2. The CGARCH model can be regarded as stable if coefficient ϕ_2 of permanent volatility is larger than the sum of coefficients ($\phi_4 + \phi_5$) in the transitory part. Subsequently, this means that short-run volatility converges faster in comparison with the long-run volatility. If ϕ_2 parameter is close to one, then q_t parameter approaches to ϕ_1 at slower pace. Conversely, if ϕ_2 parameter is closer to zero, q_t parameter approaches to ϕ_1 faster. Speaking differently, parameter ϕ_2 can give an insight about the long-run persistence. The coefficient ϕ_3 shows how shocks impact the permanent component of volatility. Term $\sigma_{t-1}^2 - q_{t-1}$ explains the short-run part of conditional volatility and suggests the degree of memory in transitory component. Expression $\varepsilon_{t-1}^2 - q_{t-1}$ gauges the initial impact of a shock to the transitory component. ω is parameter of the inserted dummy variables (*DUM*) in the CGARCH model.

2.2. Robust Quantile Regression

According to Morales et al. (2017), assumption of Laplace distribution (ALD) in the process of Bayesian quantile regression is pretty strong because it could cause problems of numerical instability. Wichitaksorn et al. (2014) addressed this issue by introducing a generalized class of skew densities (SKD) for the analysis of QR that provides elegant solutions to the ALD-based formulation. In particular, the construction of the robust skew density class distributions implies combining the skew-normal distribution of Fernandez and Steel (1998) and the symmetric class of scale mixture of normal distributions of Andrews and Mallows (1974). Taking into account different weight function $\kappa(\cdot)$ and probability density functions, $pdf\ h(u\,|\,\nu)$, Wichitaksorn et al. (2014) constructed several skewed and thick-tailed distributions – normal, Student-t, Laplace, slash distribution and contaminated Normal distribution. The mathematical presentations of these distributions are presented in Table 1.

Table 1

Mathematical Formulations of the Skewed Distributions

Distribution	$(y\|\mu,\ \sigma,\ p,\ \nu)$
Skewed normal distribution (SKN)	$\int_0^\infty \frac{4p(1-p)}{\sqrt{2\pi k(u)\sigma^2}} exp\left\{-2p_p^2\left(\frac{y-\mu}{k^{\frac{1}{2}}(u)\sigma}\right)\right\} dH(u\,\|\,\nu)$
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)	$\nu\phi_{skd}\left(y\,\|\,\mu,\ \gamma^{-\frac{1}{2}}\sigma,\ p\right)+(1-\nu)\phi_{skd}(y\,\|\,\mu.\sigma,\ p)$

Source: Morales et al. (2017).

This study tries to reveal the true nature of the complex volatility spillover effect between Brent oil and the selected CEEC indices, assuming different time horizons (short- and long-term) and different market conditions. As have been said, for that purpose we utilize the robust quantile regression[3] methodology. Therefore, the conditional quantile function (y) at quantile τ can be defined as in equation (4), assuming regressor x and some form of distribution function (F_u) of the errors:

$$Q_y(\tau|x) = \beta_0 + \beta_1 x + F_u^{-1}(\tau) \tag{4}$$

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

where β_0 and β_1 are parameters that need to be estimated. In this research, *y* stands for either permanent or transitory component of the volatility of particular stock index, while *x* denotes the permanent or transitory component of Brent oil volatility. The quantile regression estimation of the particular quantile parameter β_τ can be achieved by minimizing equation (5):

$$\hat{\beta}(\tau) = \operatorname{argmin} \sum_{i=1}^{n} \rho_\tau (y_i - x_i^{'}\beta); \quad \beta \in \Re \tag{5}$$

where $\tau \in (0, 1)$ is any quantile of interest, while $\rho_\tau(z) = z(\tau - I(z < 0))$ and $I(\cdot)$ stands for indicator function.

3. Dataset and the Construction of the Transitory and Permanent Volatilities

This study uses the daily closing prices of near-maturity Brent oil futures and the six stock indices of CEECs – PX (the Czech Republic), WIG (Poland), BUX (Hungary), OMXV (Lithuania), OMXR (Latvia) and OMXT (Estonia). We use Brent futures rather than Brent spot prices because, by definition, futures markets reflect various global information more accurately than spot prices. All closing prices are transformed into log-returns according to the expression: $r_{i,t} = 100 \times log(P_{i,t} / P_{i,t-1})$. All samples range from January 2003 to August 2022, and all the time-series are collected from the *stooq.com* website. After transformation of the time-series into log-returns, we synchronize separately all the stock indices with Brent oil according to the existing observations. The basic statistics in Table 2 shows that mean value of all the assets is positive, which means that their prices rise on average in the observed period. Brent oil has the highest average risk, while all the indices have significantly lower standard deviation than Brent. The majority of the selected assets are left-asymmetric, while all assets report fat-tails, which violates the Gaussian distribution assumption. High kurtosis values indicate outliers, which also might be the sign of structural breaks presence. Figure 2 shows precisely when structural breaks occurred, and all the breaks are detected *via* the modified ICSS algorithm. Table 3 contains the numbers of the detected structural breaks in every time-series, and they all are embedded in the CGARCH model. Autocorrelation and heteroscedasticity are present in all the empirical time-series, according to the LB(Q) and LB(Q^2) tests. These issues can be resolved with the AR(1)-CGARCH(1,1) specification. The unit root DF-GSL test indicates that all the assets are stationary, which means they can be used in the CGARCH process.

Table 2

Descriptive Statistics of the Selected Assets

	Mean	St. dev.	Skew.	Kurt.	JB	LB(Q)	LB(Q^2)	DF-GLS
Brent oil	0.010	1.009	–0.647	15.285	32183.6	0.079	0.000	–3.232
PX	0.008	0.561	–0.671	19.644	57322.3	0.000	0.000	–11.178
WIG	0.011	0.538	–0.747	10.673	12538.9	0.000	0.000	–2.855
BUX	0.015	0.648	–0.415	11.319	14309.2	0.000	0.000	–11.884
OMXV	0.021	0.425	–0.680	27.008	118005.7	0.000	0.000	–3.348
OMXR	0.015	0.522	0.077	21.100	67083.4	0.000	0.000	–6.613
OMXT	0.019	0.445	–0.324	17.171	41418.7	0.000	0.000	–2.947

Notes: JB indicates Jarque-Bera coefficients of normality, LB(Q) and LB(Q^2) tests show p-values of Ljung-Box Q-statistics of level and squared residuals for 10 lags. DF-GLS is Dickey-Fuller generalized lest squares test with 5 lags, while 1% and 5% critical values of this test are –2.566 and –1.941, respectively.

Source: Authors' calculation.

Table 3

Number of Structural Breaks in the Selected Time-series

	Brent	PX	WIG	BUX	OMXV	OMXR	OMXT
Structural breaks	6	6	7	6	5	5	5

Source: Authors' calculation.

In order to estimate the transitory and permanent part of volatility of the selected assets in the most accurate way, besides adding structural breaks in the CGARCH model, we also combine the model with the six different distribution functions. Table 4 indicates which density function is optimal, taking into account all the selected assets. AIC values show that in the six out of seven cases, unconventional distributions better explains the empirical time-series. JSU is the most prevalent one.

Table 4

AIC Values of the CGARCH Models with Different Distributions

	Brent	PX	WIG	BUX	OMXV	OMXR	OMXT
Normal	2.5398	1.1798	1.3427	1.6476	0.5487	1.1855	0.6717
Student-t	2.4864	1.1309	1.2986	1.6230	0.2886	0.9820	0.5352
GED	2.4926	1.1403	1.3031	1.6285	0.3243	1.0002	0.5444
NIG	2.4836	1.1248	1.2971	1.6238	0.2996	0.9855	0.5354
GHYP	2.4830	1.1244	1.2968	1.6229	0.2894	0.9813	0.5351
JSU	2.4829	1.1241	1.2970	1.6231	0.2915	0.9811	0.5343

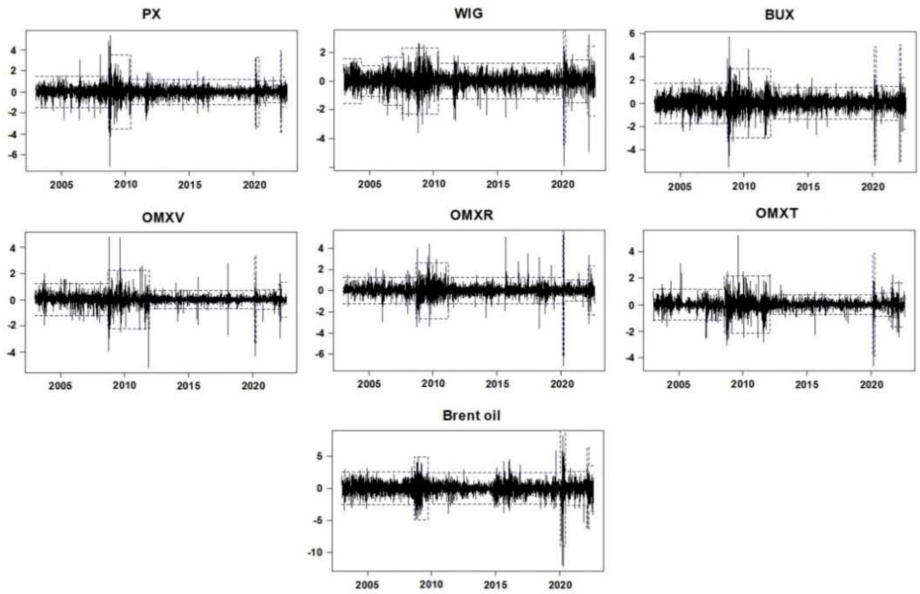
Note: Greyed values indicate the lowest AIC.

Source: Authors' calculation.

Table 5 contains estimated parameters with the best-fitting CGARCH model, where all parameters are evaluated as highly statistically significant. The ϕ_2 coefficient is very high for all the assets, which is a clear sign of long-run volatility persistence. In particular, all ϕ_2 coefficients are very close to one, which indicates that permanent volatility converges to its mean very slowly. The ϕ_4 parameter of transitory component gauges the initial impact of a shock to the CGARCH transitory component, and it is most expressed in the Baltic stock markets. The parameter ϕ_5 indicates the degree of memory in the transitory component, and the highest value have Brent and WIG markets. It is important to say that coefficient of the permanent component (ϕ_2) is greater than the sum of the transitory components ($\phi_4 + \phi_5$) in all the cases, which suggests that mean reversion is slower in long run, and these findings make the models stable. Diagnostic tests confirm an absence of autocorrelation and heteroscedasticity in all the residuals. Due to brevity, parameters in front of dummy variables are not presented in Table 5.

F i g u r e 2

Detected Structural Breaks



Note: Doted lines indicate bands of ±3 standard deviations.

Source: Authors' calculation.

Figure 3 indicates that Brent permanent component of volatility is higher than the temporary counterpart in all the plots, which suggests that fundamental factors tend to be more important determinant of volatility. This is expected because oil is the key energy commodity in the world, and as such, subject to various global events. On the other hand, transitory volatility is higher in the stock markets, which means that short-term market sentiment has stronger effect in the stock markets, and that is a characteristic of stock markets. Two periods are particularly obvious in Figure 3, i.e. the global financial crisis (GFC) and the ongoing COVID-19 pandemic. During these periods, both volatilities are increased. It can be seen that for the most indices, GFC has stronger effect than the pandemic, while Brent reports very high permanent volatility during the pandemic. The existence of high volatility spikes, gives us a confidence that robust QR is appropriate methodology for this research, because it can estimate volatility spillover effect during calm and very turbulent periods, also giving quantile parameters strong reliability.

T a b l e 5

Estimated CGARCH Parameters

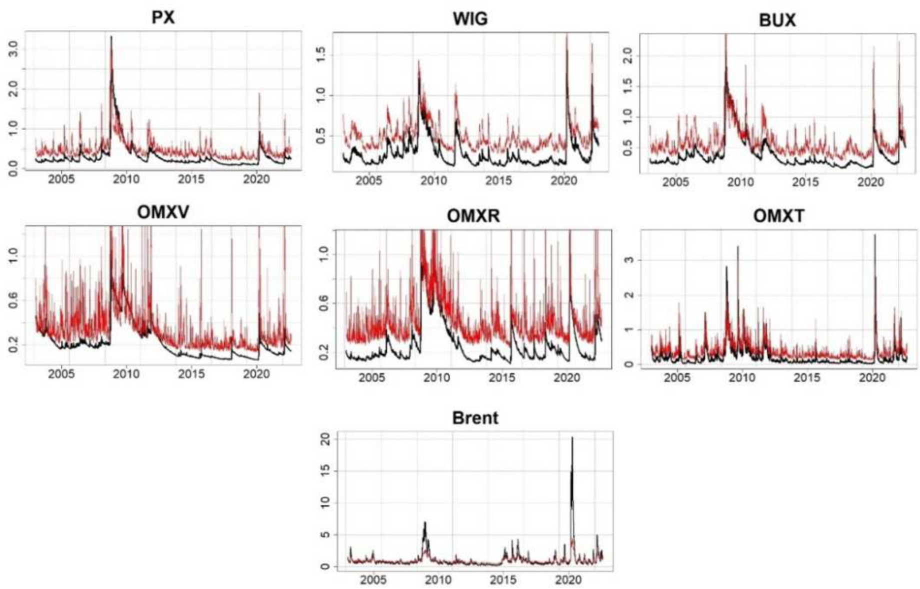
	Brent	PX	WIG	BUX	OMXV	OMXR	OMXT
ϕ_1	0.011***	0.001***	0.002***	0.001***	0.001***	0.001***	0.002***
ϕ_2	0.995***	0.997***	0.994***	0.996***	0.999***	0.996***	0.996***
ϕ_3	0.055***	0.028***	0.028***	0.017***	0.020***	0.017***	0.111***
ϕ_4	0.045***	0.112***	0.041***	0.083***	0.252***	0.192***	0.201***
ϕ_5	0.917***	0.819***	0.917***	0.859***	0.670***	0.625***	0.375***
Diagnostic tests							
LB(Q)_20	0.559	0.135	0.537	0.590	0.215	0.178	0.335
LB(Q^2)_20	0.692	0.679	0.198	0.582	0.960	0.742	0.814

Source: Authors' calculation.

Using the well specified CGARCH models, we create permanent and transitory parts of the conditional volatilities, without worrying that the models are biased. These dynamic time-series are presented in Figure 3.

F i g u r e 3

Estimated Dynamic Permanent and Transitory Volatilities of the Selected Assets



Note: Red and black lines denote transitory and permanent volatilities, respectively.

Source: Authors' calculation.

The final task involves finding the best SKD of the particular CEECs indices in the robust QR framework, taking into account both transitory and permanent segments of volatilities. We rely on the estimated AIC values, and Table 6 contains these numbers. In other words, we estimate robust QR with different distribution functions, performing a median regression ($\tau^{0.5}$). Table 6 indicates that in the nine out of twelve cases, the best robust QR model is with Slash distribution, while only in the three cases the advantage goes to Student-t distribution.

Table 6

RQR Estimated AIC Values under Different SKD

CEEC indices	Type of volatility	Types of different SKD				
		Normal	*Student-t*	*Laplace*	*Slash*	*Cont. Normal*
PX	Transitory	6801.8	–2858.6	–2234.9	–2896.5	–1140.8
	Permanent	8755.1	–4.788.9	–2787.0	–5110.4	584.7
WIG	Transitory	2343.8	–5066.8	–4868.6	–5054.0	–4715.6
	Permanent	1139.5	–6306.3	–6167.5	–6274.3	–5773.2
BUX	Transitory	5793.8	–2731.1	–2433.1	–2715.3	–1728.1
	Permanent	6025.8	–3826.0	–3026.1	–3996.6	–1326.7
OMXV	Transitory	6631.7	–3339.4	–2648.3	–3403.4	–1483.0
	Permanent	2301.8	–5888.6	–5589.0	–5925.1	–4676.7
OMXR	Transitory	5326.7	–4287.0	–3690.4	–4315.7	–2470.2
	Permanent	1790.3	–7732.9	–7107.3	–7972.5	–5380.9
OMXT	Transitory	6092.6	–2619.3	–2256.8	–2621.3	–1451.9
	Permanent	7310.1	–4673.1	–3128.8	–5280.6	–715.9

Source: Authors' calculation.

4. Research Results

This section presents the RQR results of the transitory and permanent spillover effect from Brent oil futures towards the selected CEEC stock indices. Table 7 contains the results, while Figure 4 graphically illustrates quantile plots. Dividing conditional volatilities into their transitory and permanent parts, we can estimate the levels of short- and long-run volatility transmission. As have been said, the short-run transmissions are explained by market sentiments, i.e. investor behaviour, whereas the strength of the long-run connection is caused by fundamental factors. Table 7 shows that all the estimated RQR parameters are highly statistically significant, while Figure 4 additionally confirms these findings because confidence levels of all the estimated quantiles are very narrow. This suggests that the selected SKDs are appropriate.

According to Table 7, the size of the parameters gradually increases with the rise of quantiles. This is a clear sign that volatility transmission from oil to CEEC stocks is more intense in the periods of increased market turbulence, which is not surprising, because the papers of Arouri, Lahiani and Nguyen

(2011) also found significant volatility spillover effect between oil and GCC stocks, especially in the crisis sub-period. The results are also in line with the papers of Khalfaoui et al. (2019) and Wang and Wu (2018), which found significant volatility spillover effect from oil to stock markets. In particular, it can be seen that the short-run (transitory) transmission effect is higher two or three times more than the long-run (permanent) effect in the quantiles from 0.05 to 0.80. This undoubtedly indicates that short-term information flow, which comes from oil market, has stronger and more immediate volatility transmission effect on the stock markets than fundamental factors.

Table 7

Estimated Daily Transitory and Permanent Volatility Quantile Parameters

	Type of volatility	**Estimated robust quantiles**						
		0.05	0.20	0.35	0.50	0.65	0.80	0.95
Panel A. Dependent variable – PX index								
β_2	Transitory	0.095***	0.125***	0.124***	0.126***	0.148***	0.253***	0.386***
	Permanent	0.023***	0.031***	0.031***	0.032***	0.034***	0.038***	0.339***
Panel B. Dependent variable – WIG index								
β_2	Transitory	0.038***	0.113***	0.167***	0.208***	0.256***	0.321***	0.378***
	Permanent	0.006***	0.033***	0.044***	0.072***	0.112***	0.125***	0.160***
Panel C. Dependent variable – BUX index								
β_2	Transitory	0.076***	0.098***	0.113***	0.134***	0.175***	0.333***	0.474***
	Permanent	0.029***	0.028***	0.031***	0.035***	0.052***	0.065***	0.274***
Panel E. Dependent variable – OMXV index								
β_2	Transitory	0.011***	0.024***	0.032***	0.041***	0.091***	0.144***	0.261***
	Permanent	0.007***	0.006**	0.007**	0.006**	0.005	0.006*	0.111***
Panel F. Dependent variable – OMXR index								
β_2	Transitory	0.018***	0.049***	0.075***	0.092***	0.124***	0.207***	0.319***
	Permanent	0.004***	0.013***	0.034***	0.048***	0.054***	0.126***	0.137***
Panel G. Dependent variable – OMXT index								
β_2	Transitory	0.030***	0.061***	0.091***	0.119***	0.176***	0.241***	0.319***
	Permanent	0.009***	0.017***	0.028***	0.034***	0.039***	0.110***	0.144***

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

Source: Authors' calculation.

Ross (1989) claimed that synonym for information transfer is volatility spillover effect, whereas the variance of price changes is directly linked with the rate of information flow to the markets. In that regard, our findings fit well with the argumentation of Behmiri et al. (2019), who contended that higher speculative activity in the energy markets is linked with the stronger dynamic conditional correlations between energy and other non-energy markets. Speculative activities are connected with the short-term volatility transmissions, and our results are in line with this assertion because transitory effect has an upper hand in all the countries.

As for the Visegrad stock markets, we find that the Czech and Polish stock markets endure relatively higher transitory volatility spillover effect in low volatility regime, compared to the Hungarian market. For instance, in calm market conditions that is represented by 0.20 quantile, the magnitude of transitory parameters is 0.125 and 0.113 for the Czech and Polish stock exchange, respectively. This means that 100% rise in the oil volatility transmits to the Czech and Polish stock markets in 12.5% and 11.3%, respectively. On the other hand, Hungarian market endures 9.8% transitory effect in tranquil period. In moderate market conditions, i.e. from the 0.35 to 0.65 quantiles, the Polish market takes the lading position with the highest transitory spillover effect compared to the Czech and Hungarian counterparts.

However, in the high volatility regime, 0.80 and 0.95 quantiles, Hungary catch up the Czech and Polish markets, reporting the highest transitory spillover effect from the oil market, 0.333 and 0.474, respectively. This means that the Hungarian stock exchange is the most sensitive on the short-term volatility shocks from the oil market in very turbulent times.

On the other hand, all the Visegrad stock markets report relatively low permanent volatility effect up to the highest 0.95 quantile. This means that the long-term volatility shocks from the oil market have weak effect on the permanent volatility of the stock markets. In the most cases, this effect is well below 10%, while only in the case of Poland at 0.65 and 0.80 quantiles, the spillover effect is somewhat above 10%.

However, in the conditions of very high volatility (0.95 quantile), the permanent volatility spillover effect increases considerably, particularly in the Czech and Hungarian markets.

T a b l e 8

Sectoral Composition of GDP in Percent

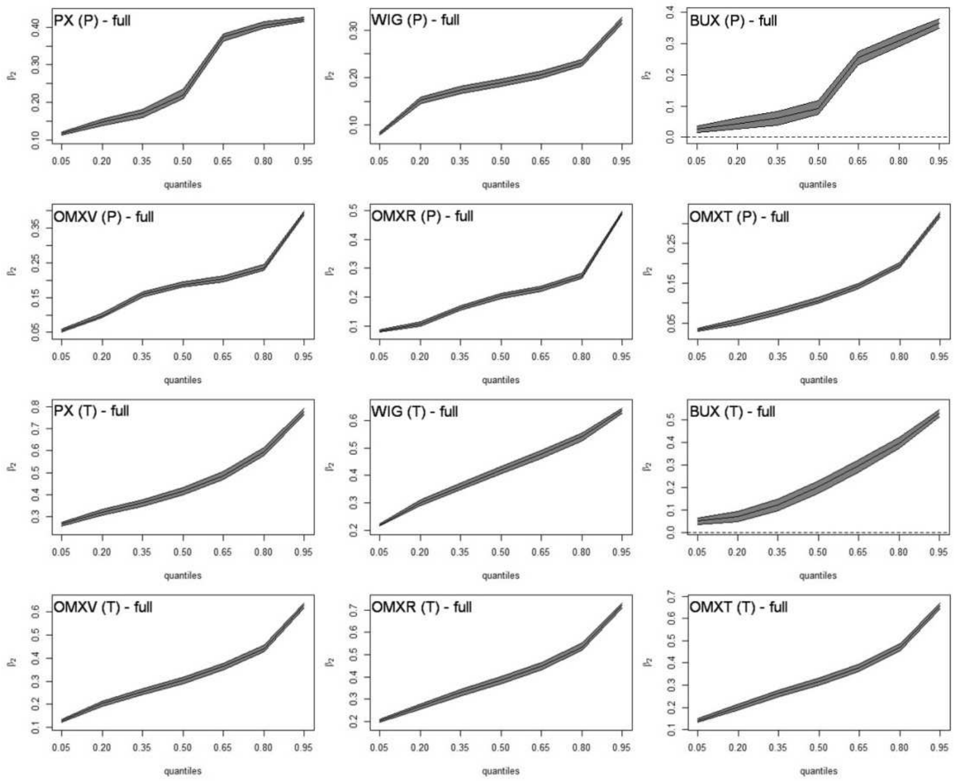
	CZE	POL	HUN	LIT	LAT	EST
Industry	36.9	40.2	31.3	29.4	22.4	29.2
Service	60.8	57.4	64.8	67.2	73.7	68.1
Agriculture	2.3	2.4	3.9	3.5	3.9	2.8

Source: The World Factbook – GDP composition by sector of origin for 2017. <https://www.cia.gov/the-world-factbook/field/gdp-composition-by-sector-of-origin/>.

As for the Baltic States, both short-term and long-term volatility spillover effects are significantly lower than the Visegrad counterparts. In other words, the transitory spillover effect is mostly below 10% up to the 0.50 quantile, while the permanent effect is very low, going slightly above zero. On the other hand, in the high volatility states, the 0.80 and 0.95 quantiles, both spillover effects increases notably, and this is particularly true for the Latvian and Estonian stock markets.

Figure 4

Plots for Permanent and Transitory Spillover Effect for the Selected Indices



Note: Letters 'P' and 'T' in brackets indicate permanent and transitory transmission effect.

Source: Authors' calculation.

Table 9

Fuel Import and Export in Percent of GDP in 2018 of the Selected CEEC

	CZE	POL	HUN	LIT	LAT	EST
Fuel import♦	4.61	5.95	6.21	14.65	14.96	10.42
Fuel export♦	0.63	0.96	1.91	13.00	3.13	6.49
Net import of fuel	3.98	4.99	4.30	1.65	11.83	3.93

Note: ♦ Fuel involves crude petroleum, petroleum gas and refined petroleum.

Source: <https://oec.world/en/profile/country/>.

In order to offer a rational explanation for the findings in Table 7, we present Table 8 and 9. In particular, Table 8 presents weights in GDP of the three key sectors – industry, service and agriculture. This is important to have in mind because higher weight of industry in GDP could imply higher consumption of oil. On the other hand, Table 9 contains actual percent of fuel import and export *vis-à-vis* GDP, as well as the net oil position of every country. Empirical values in Tables 8 and 9 are well in line with the results in Table 7. In other words, the Czech Republic and Poland have higher transitory and permanent spillover effects than Hungary, and these countries also have higher share of industry in GDP. This means that higher percent of companies depend on oil prices in the Czech Republic and Poland than in Hungary, and this might explain why the first two countries suffer higher volatility spillover effects from the oil markets. Besides, Poland has the highest net import of oil, which coincides with the highest estimated transitory and permanent RQR parameters in the quantiles from 0.35 to 0.65.

As for the Baltic States, we find that Estonia and Latvia record the highest volatility spillover effects, while Lithuania lags behind. Estonia and Lithuania have the highest industry percent in GDP, according to Table 9, but Estonia has higher net oil import, and this might explain why Estonia has higher volatility spillover effects from the oil market than Lithuania. On the other hand, Latvia has the lowest industry percentage *vis-à-vis* GDP, but Latvia has the highest net fuel import comparing to all the CEECs. This might be a rationale why we find relatively high RQR parameters in the case of Latvia, although Latvia has relatively low weight of industry in GDP. The assertion of Žiković and Vlahinić-Dizdarević (2011) speaks in favour of our findings. They claimed that causality between real GDP and oil consumption in transitional countries is more related to transportation, cooling and heating needs rather than the industry.

5. Robustness Check *via* Weekly Data

This section presents the results of the volatility spillover effects in the weekly data, and they serve as a robustness check for the daily data results. We take this approach because daily time-series are subject to the nonsynchronous trading effects (see e.g. Chou et. al., 2006; Resnick and Shoesmith, 2017). In other words, different time-series usually have unequal numbers of observations because trading days in different countries are subject to different national and religious holidays, unexpected events, and so forth. In this respect, some of data could be lost in the process of data-synchronization, which might disrupt final results. Weekly data overcomes this problem, but produces higher returns because it observes average weekly prices. We repeat the procedure of entering dummy variables in the CGARCH model. Table 10 shows the number of breaks found in the weekly data. It can be seen that the ICSS algorithm failed to finish computation for the WIG and OMXR indices, while all the other indices report 4 breaks. Table 11 contains estimated RQR parameters of the transitory and permanent volatility spillover effects.

T a b l e 10

Number of Breaks in the Weekly Time-series

	Brent	PX	WIG	BUX	OMXV	OMXR	OMXT
Weekly data	4	4	N/A	4	4	N/A	4

Source: Authors' calculation.

At the first glance on Table 11, it can be seen that the estimated weekly permanent parameters are higher than the daily counterparts, which may be a consequence of using the lower frequency data. However, the relative relationship of the evaluated parameters between the countries remained largely unchanged, which adds to the robustness of the overall results. In other words, regarding the Visegrad group, Poland retains the highest transitory parameters from the 0.35 to 0.80 quantiles, while Hungary takes over the leading position at the 0.80 and 0.95 quantiles, which perfectly coincides with the daily results.

T a b l e 11

Estimated Weekly Transitory and Permanent Volatility Quantile Parameters

	Type of volatility	Estimated robust quantiles						
		0.05	0.20	0.35	0.50	0.65	0.80	0.95
Panel A. Dependent variable – PX index								
β_2	Transitory	0.186^{***}	0.184^{***}	0.175^{***}	0.174^{***}	0.182^{***}	0.186^{***}	0.593^{***}
	Permanent	0.046^{***}	0.030^{***}	0.024^{***}	0.057^{***}	0.125^{***}	0.186^{***}	0.233^{***}
Panel B. Dependent variable – WIG index								
β_2	Transitory	0.030^{***}	0.076^{***}	0.210^{***}	0.262^{***}	0.284^{***}	0.288^{***}	0.345^{***}
	Permanent	0.037^{**}	0.112^{***}	0.152^{***}	0.203^{***}	0.256^{***}	0.291^{***}	0.302^{***}
Panel C. Dependent variable – BUX index								
β_2	Transitory	0.067^{***}	0.098^{***}	0.136^{***}	0.167^{***}	0.202^{***}	0.333^{***}	0.423^{***}
	Permanent	0.104^{***}	0.139^{***}	0.147^{***}	0.150^{***}	0.150^{***}	0.537^{***}	0.569^{***}
Panel E. Dependent variable – OMXV index								
β_2	Transitory	0.024^{***}	0.023^{***}	0.027^{*}	0.043^{***}	0.067^{***}	0.098^{***}	0.133^{***}
	Permanent	0.044^{***}	0.038^{***}	0.029	0.072^{*}	0.172^{***}	0.231^{***}	0.370^{***}
Panel F. Dependent variable – OMXR index								
β_2	Transitory	0.031^{*}	0.041^{*}	0.073^{***}	0.106^{***}	0.167^{***}	0.227^{***}	0.410^{***}
	Permanent	0.021^{***}	0.017	0.019	0.022	0.275^{***}	0.290^{***}	0.446^{***}
Panel G. Dependent variable – OMXT index								
β_2	Transitory	0.109^{***}	0.175^{***}	0.197^{***}	0.233^{***}	0.312^{***}	0.380^{***}	0.390^{***}
	Permanent	0.085^{***}	0.125^{***}	0.120^{***}	0.116^{***}	0.113^{***}	0.450^{***}	0.628^{***}

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

Source: Authors' calculation.

On the other hand, in the permanent volatility spillover effect, Hungary reports the highest permanent RQR parameters which is somewhat different from daily data because in daily data the Czech Republic has the highest permanent volatility parameter, while Hungary follows.

As for the Baltic States, Estonia reports the highest transitory and permanent parameters, which is in line with daily data findings. Latvia has the second highest transitory and permanent parameters, which coincides with the findings in Tables 8 and 9, and also with the explanation why Latvia endures relatively high volatility spillover effect from oil.

Conclusion

This paper investigates the magnitude of the risk transmission from Brent futures market to the six stock markets of CEECs, making a distinction between short-term (transitory) and long-term (permanent) effect. This research highlights the accurateness and reliability of the results, which means that we use several novel and sophisticated methodological approaches in this regard. In other words, first we create the transitory and permanent parts of volatilities for every stock index and Brent futures by using the component GARCH model with an optimal density function and inserted dummy variables. In the second step, created volatilities are embedded in the robust quantile regression framework, which estimates RQR parameters under the assumption of the best SKD.

We have several noteworthy findings to report. Regarding the Visegrad countries, the estimated quantile parameters clearly show that in more volatile conditions, the spillover effect from oil market is stronger. The results undoubtedly indicate that the short-term (transitory) shocks are higher than the long-term (permanent) counterparts. This particularly applies for investors in the Polish and Czech stock markets, because these markets endure the strongest volatility impact from oil, regarding all the three Visegrad countries. On the other hand, the Hungarian stock market suffers the lowest volatility effect from oil, in both short and long terms in calm and moderate market conditions. All the findings can be explained very well with the weight of industry sector in GDP and the net-import of oil.

As for the Baltic States, the quantile parameters indicate that Estonia records the highest volatility spillover effect, while Latvia follows. Estonia has relatively high weight of industry and net-import of oil, which indicates why Estonia has the largest RQR parameters. On the other hand, Latvia has the lowest industry percentage *vis-à-vis* GDP of all three Baltic states, but Latvia has the highest net fuel import, which puts Latvia at the second place.

Weekly data results concur very well with the daily data findings, which adds to the robustness of the overall results. The results of this paper could be useful for investors who combine Brent oil and CEEC indices in a single portfolio taking into account the basic principle that says if volatility from one financial (commodity) market transmits to another in high intense, then assets from such market should not be included in the same portfolio with the asset that receives these shocks. In addition, these results are interesting for investors who operate in different time-horizons. Based on the results, Hungarian BUX and Lithuanian OMXV indices could be good instruments to combine with oil, because increasing oil volatility affects the least these indices in both short- and long-terms.

References

AN, P. – LI, H. – ZHOU, J. – LI, Y. – SUN, B. – GUO, S. – Qi, Y. (2020): Volatility Spillover of Energy Stocks in Different Periods and Clusters Based on Structural Break Recognition and Network Method. Energy, *191*, 116585. DOI: 10.1016/j.energy.2019.116585.

AROURI, M. E. H. – RAULT, C. (2011): Oil Prices and Stock Markets in GCC Countries: Empirical Evidence from Panel Analysis. International Journal of Finance and Economics, *17*, No. 3, pp. 242 – 253. DOI: 10.1002/ijfe.443.

AROURI, M. E. H. – LAHIANI, A. – NGUYEN, D. K. (2011): Return and Volatility Transmission between World Oil Prices and Stock Markets of the GCC Countries. Economic Modelling, *28*, No. 4, pp. 1815 – 1825. DOI: 10.1016/j.econmod.2011.03.012.

AROURI, M. E. H. – JOUINI, J. – NGUYEN, D. K. (2012): On the Impacts of Oil Price Fluctuations on European Equity Markets: Volatility Spillover and Hedging Effectiveness. Energy Economics, *34*, No. 2, pp. 611 – 617. DOI: 10.1016/j.eneco.2011.08.009.

BARNDORFF-NIELSEN, O. E. (1997): Normal Inverse Gaussian Distributions and Stochastic Volatility Modelling. Scandinavian Journal of Statistics, *24*, pp. 1 – 13.

BARNDORFF-NIELSEN, O. (1977): Exponentially Decreasing Distributions for the Logarithm Of Particle Size. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, *353*, No. 1674, pp. 409 – 419.

BARUNÍK, J. – KOČENDA, E. (2019): Total, Asymmetric and Frequency Connectedness between Oil and Forex Markets. Energy Journal, *40*, No. SI2, pp. 157 – 174.

CHEN, S-W. – SHEN, C-H. – XIE, Z. (2008): Evidence of a Nonlinear Relationship between Inflation and Inflation Uncertainty: The Case of the Four Little Dragons. Journal of Policy Modeling, *30*, No. 2, pp. 363 – 376.

CHEN, J. (2015): Factor Instrumental Variable Quantile Regression. Studies in Nonlinear Dynamics and Econometrics, *19*, No. 1, pp. 71 – 92.

CHOU, P-H. – LI, W-S. – LIN, J-B. – WANG, J-S. (2006): Estimating the VaR of a Portfolio Subject to Price Limits and Nonsynchronous Trading. International Review of Financial Analysis, *15*, No. 4 – 5, pp. 363 – 376.

DAS, D. – KANNADHASAN, M. – BHATTACHARYYA, M. (2022): Oil Price Shocks and Emerging Stock Markets Revisited. International Journal of Emerging Markets, *17*, No. 6, pp. 1583 – 1614.

DIEBOLD, F. X. – YILMAZ, K. (2009): Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. Economic Journal, *119*, No. 534, pp. 158 – 171. DOI: 10.1111/j.1468-0297.2008.02208.x.

FERNANDEZ, C. – STEEL, M. F. (1998): On Bayesian Modeling of Fat Tails and Skewness. Journal of the American Statistical Association, *93*, No. 441, pp. 359 – 371.

JOHNSON, N. L. (1949): Systems of Frequency Curves Generated By Methods of Translation. Biometrika, *36*, No. 1 – 2, pp. 149 – 176.

KHALFAOUI, R. – SARWAR, S. – AVIRAL KUMAR TIWARI, A. K. (2019): Analysing Volatility Spillover between the Oil Market and the Stock Market in Oil-importing and Oil-exporting Countries: Implications on Portfolio Management. Resources Policy, *62*, pp. 22 – 32.

KIRKULAK-ULUDAG, B. – SAFARZADEH, O. (2018): The Interactions between OPEC Oil Price and Sectoral Stock Returns: Evidence from China. Physica A: Statistical Mechanics and Its Applications, *508*, pp. 631 – 641. DOI: 10.1016/j.physa.2018.02.185.

KOENKER, R. – BASSETT, G. (1978): Regression Quantiles. Econometrica, *46*, No. 1, pp. 33 – 50.

KRAMER, W. – AZAMO, B. T. (2007): Structural Change and Estimated Persistence in the GARCH(1,1)-Model. Economics Letters, *97*, No. 1, pp. 17 – 23.

LEE, B. – LIU, J-Y. – HUNG-HAO CHANG, H-H. (2020): The Choice of Marketing Channel and Farm Profitability: Empirical Evidence from Small Farmers. Agribusiness, *36*, No. 3, pp. 402 – 421.

MALIK, F. – HAMMOUDEH, S. (2007): Shock and Volatility Transmission in the Oil, US and Gulf Equity Markets. International Review of Economics and Finance, *16*, pp. 357 – 368.

MORALES-ZUMAQUERO, A. – SOSVILLA-RIVERO, S. (2018): Volatility Spillovers between Foreign Exchange and Stock Markets in Industrialized Countries. The Quarterly Review of Economics and Finance, *70*, pp. 121 – 136.

MORALES, G. C. – DAVILA, L. V. – CABRAL, B. C. – CEPERO, C. L. (2017): Robust Quantile Regression Using a Generalized Class of Skewed Distributions. Stat – The ISI’s Journal for the Rapid Dissemination of Statistics Research, *6*, No. 1, pp. 113 – 130.

MUN, K. C. (2007): Volatility and Correlation in International Stock Markets and the Role of Exchange Rate Fluctuations. Journal of International Financial Markets, Institutions and Money, *17*, No. 1, pp. 25 – 41. DOI: 10.1016/j.intfin.2005.08.006.

OZCELEBI, O. (2021): Assessing the Impacts of Global Economic Policy Uncertainty and the Long-term Bond Yields on Oil Prices. Applied Economic Analysis, *29*, No. 87, pp. 226 – 244.

RESNICK, B. G. – SHOESMITH, G. L. (2017): A Note on Modeling World Equity Markets with Nonsynchronous Data. Journal of International Financial Markets, Institutions and Money, *51*, pp. 125 – 132.

ROSS, S. A. (1989): Information and Volatility. The No Arbitrage and Martingale Approach to Timing and Resolution Irrelevancy. Journal of Finance, *44*, No. 1, pp. 1 – 17.

SANSÓ, A. – ARAGÓ, V. – CARRION-I-SILVESTRE, J. (2004): Testing for Changes in the Unconditional Variance of Financial Time Series. Revista de Economia Financiera, *4*, pp. 32 – 53.

SARWAR, S. – KHALFAOUI, R. – WAHEED, R. – DASTGERDI, H. G. (2019): Volatility Spillovers and Hedging: Evidence from Asian Oil-importing Countries. Resources Policy, *61*, pp. 479 – 488.

WANG, X. – WU, C. (2018): Asymmetric Volatility Spillovers between Crude Oil and International Financial Markets. Energy Economics, *74*, pp. 592 – 604.

WEN, F. – MIN, F. – ZHANG, Y-J. – YANG, C. (2019): Crude Oil Price Shocks, Monetary Policy, and China’s Economy. International Journal of Finance and Economics, *24*, No. 2, pp. 812 – 827. DOI: 10.1002/ijfe.1692.

WICHITAKSORN, N. – CHOY, S. – GERLACH, R. (2014): A Generalized Class of Skew Distributions and Associated Robust Quantile Regression Models. Canadian Journal of Statistics, *42*, No. 4, pp. 579 – 596.

WONG, H. T. (2019): Volatility Spillovers between Real Exchange Rate Returns and Real Stock Price Returns in Malaysia. International Journal of Finance and Economics, *24*, No. 1, pp. 131 – 149.

XU, W. – MA, F. – CHEN, ZHANG, B. (2019): Asymmetric Volatility Spillovers between Oil and Stock Markets: Evidence from China and the United States. Energy Economics, *80*, pp. 310 – 320.

ŽIKOVIĆ, S. – VLAHINIĆ-DIZDAREVIĆ, N. (2011): Oil Consumption and Economic Growth Interdependence in Small European Countries. Ekonomska istraživanja – Economic Research, *24*, No. 3, pp. 15 – 32.

ŽIVKOV, D. – MANIĆ, S. – ĐURAŠKOVIĆ, J. (2020a): Short and Long-term Volatility Transmission from Oil to Agricultural Commodities – The Robust Quantile Regression Approach. Borsa Istanbul Review, *20*, No. S1, pp. S11 – S25.

ŽIVKOV, D. – DAMNJANOVIĆ, J. – ĐURAŠKOVIĆ, J. (2020b): The Effect of Oil Uncertainty on Industrial Production in the Major European Economies – Methodologies Based on the Bayesian Approach. Finance a úvěr – Czech Journal of Economics and Finance, *70*, No. 6, pp. 566 – 588.