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Volatility Spillover Effect from Energy Markets to Foreign Exchange Markets: The Case of Central and Eastern European and Eurasian Countries

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Abstract:
This paper investigates the nonlinear risk transmission from the oil and natural gas markets to the foreign exchange markets of five energy importers and one major energy exporter. We separate conditional volatility into the transitory (short-term) and permanent (long-term) parts, and then these volatilities are embedded in an elaborate robust linear quantile regression model. We find that the risk spillover effect is relatively low in Central and Eastern European countries (CEECs) probably because they pursue a managed float exchange rate regime. On the other hand, this effect is higher for Turkey and Russia, which is especially true for the effect from oil to the rouble at the highest quantile. This happens because Russia receives the largest amount of foreign currency from oil exports. The results indicate that the short-term risk spillover effect is notably stronger than the long-term one, which means that the exchange rate volatility is mainly determined by market sentiment. The rolling regression results coincide very well with the estimated quantile parameters.

Keywords: risk spillover, energy markets, exchange rate, CGARCH, quantile regression

JEL Classification: C21, C51, F31, O13

1. Introduction

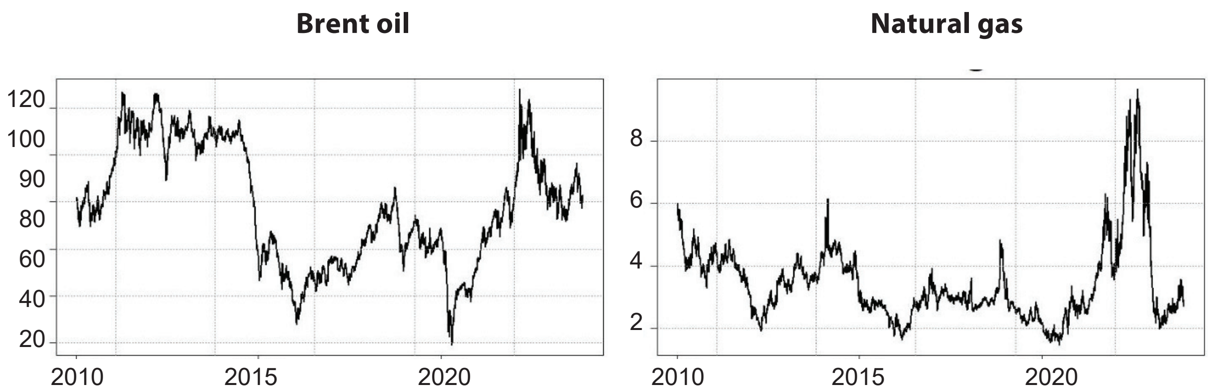
Energy commodities are indispensable resources for development of global economies, and they are becoming more and more relevant for developing countries, which are already accounting for more than a half of world total energy consumption (Pershin et al., 2016;

Durusu-Ciftci et al., 2020). However, unstable energy price movements have a profound effect on various macroeconomic aggregates, while the impact on the exchange rate is well known in the literature (see, e.g., Sahbaz et al., 2014; Huang et al., 2021; Sekmen and Topuz, 2021; Verma and Bansal, 2021). According to Wen et al. (2020), energy assets can affect the exchange rate via two channels. The first links energy commodities to exchange rate trough the traditional trade conduit. In other words, the trade balance of energy-importing countries declines when energy prices rise, which leads to higher outflow of foreign currency and exchange rate depreciation. On the other hand, energy exporters in this situation might record higher exchange rate inflows if the volume of exports does not change, which can lead to currency appreciation. The second channel refers to macroeconomic determinants, such as inflation and production. In other words, an increase in energy prices raises production costs in oil-importing countries and worsens the competitiveness of domestic goods, which eventually depreciates domestic currency. This channel affects energy importers more than energy exporters because energy exporters are not directly exposed through the production channel as energy importers, since they do not depend on energy imports.

According to the above, it can be argued that energy markets and changes in exchange rates are intrinsically linked to a greater or lesser extent because all countries in the world are either net oil importers or net oil exporters. In this regard, it is logical to assume that there is also a volatility spillover nexus between these markets. However, relatively few papers have examined this topic, particularly from the aspect of emerging markets (see, e.g., Zhu et al., 2022; Sun et al., 2023; Mo et al., 2024). This leaves a lot of room for our research to contribute to the international literature, and this is where our motivation comes from. In particular, this study investigates the unidirectional volatility-to-volatility transmission effect from two key energy markets to the exchange rates of five emerging oil importers and one major oil exporter. More specifically, we consider volatility transmission from Brent oil and natural gas to the exchange rate volatilities of energy importers (Poland, Czechia, Hungary, Romania and Turkey) and an energy exporter (Russia). All these countries are large emerging markets. We use futures rather than spot prices of the energy commodities because futures process new information faster, making these prices more relevant. In other words, futures markets typically have higher trading volumes and liquidity compared to spot markets. This means that futures prices may be more reliable indicators of market trends and are less prone to manipulation or distortion by a few large traders.

Looking at Figure 1, it can be seen that the prices of these two energy assets experienced huge roller-coaster ride in the past decade, which inevitably implies existence of high volatilities on these two energy markets. The task of this paper is to find out to what extent volatility from the energy markets is transmitted to the volatility of national currencies of selected Central and Eastern European and Eurasian countries.

Figure 1: Empirical dynamics of Brent oil and natural gas futures



Note: prices of Brent oil futures are expressed in USD per barrel, while prices of natural gas futures are in USD per million metric British thermal units (mmBtu).

In the research process, we use several elaborate methods, helping us conduct an in-depth analysis. In other words, we try to answer two questions: (1) how the volatility spillover effect transmits in different time periods, i.e., short and long term, and (2) how this phenomenon changes when different market conditions are at stake – i.e., low, moderate and high volatility regimes. To this end, we first decompose the time-varying conditional volatility into a permanent (long-run) and transitory (short-run) component, using the component GARCH (CGARCH) model. Dividing the entire volatility process into short-term and long-term parts, we can highlight heterogeneous information flows, which are connected with various factors shaping dynamic conditional volatility (Cheng et al., 2023). In other words, the transitory component is associated with market sentiment and the prevailing behaviour of market participants that come to the fore in the short-term horizons, while the permanent component is affected by long-term fundamental factors. In this way, we can see which factor coming from the energy markets has a stronger effect on the exchange rate volatility. To the best of our knowledge, only three papers have investigated the short-term and long-term volatility spillover effect using the CGARCH model (Morales-Zumaquero and Sosvilla-Rivero, 2018; Wong, 2019; Živkov et al., 2020), but none of them investigated the link between oil (gas) and the exchange rate volatilities. Besides, in order to be as accurate as possible in the process of conditional volatility estimation, we combine the CGARCH model with three different distribution functions: normal, Student's t and normal inverse Gaussian (NIG) distribution of Barndorff-Nielsen (1997). Applying different distribution functions in the CGARCH model, we can better recognize the stylized facts of selected time series, which produces more accurate conditional volatilities.

After the construction of the transitory and permanent parts of the volatility, the second phase of the research involves measuring the volatility spillover effect in different market conditions. For this type of investigation, researchers usually use the quantile regression (QR) of Koenker and Bassett (1978) because the QR method can estimate the impact of all covariates on a specific part of the distribution of the dependent variable (see, e.g., Viola et al., 2019; Azimli, 2020; Monjazeb et al., 2024). However, the classical QR method can produce relatively wide confidence intervals of the estimated quantile parameters, jeopardizing the reliability of these results. To avoid possible bias of the classical QR, we use a relatively new QR approach of Galarza et al. (2017), which is called the robust linear quantile regression (RLQR). The RLQR technique uses a likelihood-based approach for the quantile parameter estimation, considering several new skewed distributions – normal, Student's t, Laplace, slash and contaminated normal distribution. The use of several different distributions in the QR estimation process can produce robust quantile estimates. This means that RLQR parameters have narrower confidence intervals, making them more trustworthy compared to the classical QR approach.

To be more thorough, we additionally use the rolling regression approach as a complementary analysis. This method can produce time-varying parameters, indicating in which time period the volatility spillover effect is higher (lower). Also, this method can serve as a robustness check for the results of our primary method, the RLQR model.

Our contribution to the international literature is threefold. Firstly, this is the first paper that investigates the volatility spillover effect from oil and gas markets on the exchange rate volatility of four Central and Eastern European and two Eurasian countries. Secondly, this phenomenon is studied by taking into account the decomposed segments of conditional volatilities, which has never been done before. Thirdly, we use the elaborate RLQR method to estimate reliable quantile parameters.

The rest of the paper is structured as follows. Section 2 provides an overview of the existent literature. Section 3 explains the methods – the CGARCH model and robust linear quantile regression. Section 4 introduces the dataset and preliminary findings. Section 5 presents the results of the estimated RLQR parameters, while Section 6 reveals the rolling regression findings. The last section concludes.

2. Literature Review

Research papers that have investigated the nexus of energy commodities versus exchange rate are not rare in the literature, but most of them focus on oil and returns, while a relatively small number of papers has studied the transmission of volatility from energy to the exchange rate. This section brings a review of the existing studies. For instance, Gomez-Gonzalez et al. (2020) studied the dynamic connectedness and predictive causality between oil prices and exchange rates in a sample of six oil-producing and six net oil-importing countries. They used a generalized VAR model and reported that oil prices are net spillover receivers from exchange rate markets in oil-producing countries. On the other hand, oil prices are net spillover transmitters in oil-importing countries and the causality is stronger from oil prices to exchange rates, mainly in the aftermath of the Global Financial Crisis. Hashmi et al. (2022) examined the interaction between oil prices, exchange rate and stock returns in Pakistan. They used the quantile ARDL model on quarterly data. They found that the impact of oil prices and exchange rate on stock prices varied across bullish, bearish and normal states of the stock market. On the other hand, the impact of oil prices and stock prices on exchange rate did not vary across different states of the currency market. Saidu et al. (2021) investigated the oil price fluctuation on exchange rates for main African net oil-importing countries (South Africa, Morocco, Côte d'Ivoire, Kenya, Ghana, and Senegal). They used the symmetric ARDL model and asymmetric NARDL model. Evidence suggests that rising oil prices had a positive effect on the exchange rate in South Africa, Morocco, Côte d'Ivoire and Senegal, leading to a depreciation of the exchange rate. On the other hand, the drop in the price of oil led to an appreciation of the exchange rate in South Africa, Ghana and Senegal, but a depreciation of the exchange rate in Morocco and Côte d'Ivoire. Brahmasrene et al. (2014) studied the short-run and long-run dynamic relationship between the US imported crude oil prices and eight exchange rates. They used the Granger causality test, variance decomposition and impulse response function analysis. Their empirical results indicated that the exchange rates Granger-caused crude oil prices in the short run while the crude oil prices Granger-caused the exchange rates in the long run. They contended that oil prices were affected by the exchange rate changes at a minimal level. On the other hand, in the medium run and the long run, oil price shocks had a significant impact on exchange rate changes.

A relatively small number of papers has examined the risk transmission from oil to exchange rate. For example, Zhang et al. (2008) used the VAR model, ARCH type models and Granger causality test to investigate the mean and volatility spillover effects between WTI oil and the USD. For the mean spillover effect, they concluded that the US dollar depreciation is the key factor in driving up the international crude oil price. On the other hand, they asserted that the price volatility of oil and the USD take relatively independent paths, and the instant fluctuation of the USD exchange rate did not cause a significant change on the oil market. Hameed et al. (2021) examined the volatility spillover effect of oil prices on the exchange rate, focusing on the five major oil importers (Pakistan, India, China, Japan, and Germany) and five major oil exporters (UAE, Canada, Iraq, Russia, and Saudi Arabia). Using the generalized VAR method, they found that oil prices have a greater volatility spillover effect in oil-exporting countries compared to oil-importing countries. Wen et al. (2020) examined the extreme risk spillover effect between crude oil prices and exchange rates in seven major oil-exporting and oil-importing countries. They reported the existence of upside and downside risk spillover effects, where risk spillovers are stronger from exchange rates to crude oil than from oil to exchange rates. In addition, they asserted that risk spillovers were much stronger for oil exporters than for oil importers. Zolfaghari et al. (2020) examined the relationship between return and volatility for energy, foreign currency and stock markets using the diagonal BEKK model. They used daily crude oil, natural gas and coal prices as proxies for energy prices, the S&P500 index as a proxy for the US stock market and the EUR/USD exchange rate as a proxy for the exchange rate. They found robust evidence for the volatility spillover effects among the three markets.

3. Methods

3.1. Component GARCH model

We decompose the conditional volatilities of the assets into the permanent and transitory parts using the component GARCH[1] model. We try to overcome possible autocorrelation bias by applying the AR(1) process in the conditional mean of all the examined assets. Also, in order to recognise stylized facts of the selected assets as well as possible, such as asymmetry and heavy tails in distribution, we combine the CGARCH model with three different distributions. These distributions are normal $\varepsilon \sim N\left(0, h_t\right)$, Student's t $\varepsilon \sim St\left(0,\, h_t,\, \nu\right)$ and normal inverse Gaussian (NIG) distribution $\varepsilon \sim NIG\left(0,\, h_t,\, \nu,\, \kappa\right)$. Student's t distribution has one shape parameter for heavy tails, while NIG distribution has two parameters for both asymmetry and heavy tails. The normal distribution serves as a benchmark. We estimate each asset with all three distributions and the lowest Akaike information criterion (AIC) value determines the best model. Subsequently, the best CGARCH model is used for creation of the permanent and transitory volatilities. The mean and GARCH specifications can be seen in Equations (1)–(3).

1 The component GARCH model with different distributions was estimated using the 'rugarch' package in 'R' software.

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

$$q_t = \omega + \eta_1 \left(q_{t-1} - \phi_1\right) + \eta_2 \left(\varepsilon_t^2 - \sigma_t^2\right) \tag{2}$$

$$\sigma_t^2 = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta\left(\sigma_{t-1}^2 - q_{t-1}\right) \tag{3}$$

where r_t denotes log returns of the energy futures and selected exchange rates, while r_{t-1} is an autoregressive term. α_0 and α_1 are parameters of the mean equation. The symbol ε_t is the independently and identically distributed error term, which can take the form of three distribution functions. The symbol σ_t^2 is the conditional variance, while q_t is the long-run component of the conditional variance. q_t describes the long-run persistent behaviour of the variance, and it converges to the long-run time-invariable volatility level ω with a magnitude of η_1. The CGARCH model is stable if the coefficient η_1 of permanent volatility exceeds the sum of the coefficients α and β in the transitory component. This means that the short-run volatility converges faster than the long-run counterpart. The term β suggests the degree of memory in the transitory component, while α measures the initial impact of a shock to the transitory component. As for Equation (2), if η_1 is closer to one, then q_t approaches ω more slowly. On the other hand, if η_1 is closer to zero, then q_t approaches ω faster. In other words, the parameter η_1 measures the long-run persistence, while η_2 indicates how shocks affect the permanent component of volatility.

3.2 Robust linear quantile regression

After construction of the transitory and permanent parts of volatilities, we utilize the RLQR[2] method of Galarza (2017) to measure the short-term and long-term volatility spillover effect from energy markets to the selected exchange rates. The RLQR method uses a generalized class of skew densities (SKD) for the analysis of QR, which was originally developed by Wichitaksorn et al. (2014). In particular, the robust skew density class distribution construction involves mixing the skew-normal distribution of Fernandez and Steel (1998) and the symmetric class of scale mixture of normal distributions of Andrews and Mallows (1974). Morales et al. (2017) asserted that y has a skewed distribution (SKD) with the location parameter μ, scale parameter σ, skewness parameter $p \in (0.1)$ and weight function $\kappa(\cdot)$, if y can be presented stochastically as $y = \mu + \sigma\kappa(U)^{1/2}Z$, where Z follows the skewed normal distribution (SKN), $Z \sim SKN\ (0.1, p)$. Also, the following expressions applies: $P\left(y \le \mu\right) = p$ and $P\left(y > \mu\right) = 1 - p$, which means that

2 The estimation of robust quantile regression was done using the 'lqr' package in 'R' software.

application to the quantile regression is straightforward, according to Morales et al. (2017). If U is integrated out, then the marginal probability density function (*pdf*), of y is given as in Equation (4):

$$f\left(y|\mu,\sigma,p\right)=\int_{0}^{\infty}\frac{4p\left(1-p\right)}{\sqrt{2\pi k\left(u\right)\sigma^{2}}}exp\left\{-2p_{p}^{2}\left(\frac{y-\mu}{k^{\frac{1}{2}}\left(u\right)\sigma}\right)\right\}dH(u\,|\,\nu) \tag{4}$$

where v is a scalar parameter indexing the distribution of U and $Z \sim N\,(0.1)$, with U independent of Z. Equation (4) can be used to derive four more skewed and thick-tailed distributions, regarding different specifications of the weight function $\kappa(\cdot)$ and probability density functions: $pdf\ h(u\,|\,\nu)$ According to Morales et al. (2017), Equations (5)–(8) present mathematical formulations respectively of Student's t, Laplace, slash and contaminated normal distribution.

$$\frac{4p\left(1-p\right)\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{2\pi\sigma^{2}}}\left\{\frac{4}{\nu}p_{p}^{2}\left(\frac{y-\mu}{\sigma}\right)+1\right\}^{-\frac{\nu+1}{2}} \tag{5}$$

$$\frac{2p\left(1-p\right)}{\sigma}\,exp\left\{-2\rho_{p}\left(\frac{y-\mu}{\sigma}\right)\right\} \tag{6}$$

$$\nu\int_{0}^{1}u^{\nu-1}\phi_{skd}\left(y\,|\,\mu,u^{-\frac{1}{2}}\sigma,\ p\right)du \tag{7}$$

$$\nu\phi_{skd}\left(y\,|\,\mu,\gamma^{-\frac{1}{2}}\sigma,p\right)+\left(1-\nu\right)\phi_{skd}(y\,|\,\mu.\sigma,p) \tag{8}$$

Before the RLQR parameter estimation, we determine which skewed distribution is the best for the dependent exchange rate variables, taking into account both permanent and transitory parts of conditional volatilities. The lowest AIC determines the best SKD. In the RLQR framework, we insert created volatilities of the energy assets and exchange rates, where the conditional quantile function of y at the quantile τ has a form as in Equation (9). The symbol x is the regressor, while F_u stands for some form of SKD. In our case, y stands for the permanent or transitory component of a particular exchange rate, while x denotes the permanent and transitory component of Brent oil or gas volatility.

$$Q_{y}\left(\tau|x\right)=\beta_{0}+\beta_{1}x+F_{u}^{-1}\left(\tau\right) \tag{9}$$

β_0 and β_1 are the parameters to be estimated. Morales et al. (2017) contended that the quantile regression estimation of a particular quantile parameter $\beta\tau$ can be achieved by minimizing Equation (10):

$$\hat{\beta}(\tau) = \arg\min \sum_{i=1}^{n} \rho_\tau (y_i - x_i^{'}\beta); \quad \beta \in \Re \tag{10}$$

where $\tau \in (0.1)$ is any quantile of interest, while $\rho_\tau(z) = z(\tau - I(z<0))$ and $I(\cdot)$ represents the indicator function.

4. Dataset and Preliminary Findings

The paper uses daily near-to-maturity futures prices of Brent oil and natural gas, and six exchange rates *vis-à-vis* the USD – Polish zloty, Czech koruna, Hungarian forint, Romanian lev, Turkish lira and Russian rouble. All assets are collected from the website investing.com. The time span ranges from January 2010 to February 2022. We intentionally limit the sample to February 2022 because this is when Russia invaded Ukraine. As a consequence, the West introduced unprecedented sanctions against Russia, which created immense turbulences to the rouble. In order to evade possible spurious effects caused by the Western sanctions and to make all the currencies comparable, our sample is up to February 2022. All the selected variables are transformed into log returns according to the expression: $r_{i,t} = 100 \times log(P_{i,t} / P_{i,t-1})$. Also, all the exchange rates are jointly synchronized with the energy commodities according to the existing observations.

Table 1 contains the descriptive statistics of the empirical log return time series. The basic statistics encompass the first four moments, the LB(Q) tests of level and squared empirical log returns as well as the DF-GLS unit root test. It can be seen that energy assets have a relatively high risk compared to exchange rates, whereas only the Turkish lira has a relatively high standard deviation. Most variables are skewed to the right, while Brent oil and the lira are skewed to the left. Besides, all the assets have high kurtosis values, while Brent oil, the lira and the rouble report a significant presence of outliers. This justifies using the two heavy-tailed distributions. The lev, the lira and the rouble report the presence of autocorrelation, while all the time series have an issue with the time-varying variance. Applying the AR-CGARCH model, we can resolve these issues. The Dickey-Fuller generalized least square (DF-GLS) test indicates that all the time series are stationary, which is a necessary precondition for unbiased GARCH estimation.

Table 1: Descriptive statistics of two energy assets and six exchange rates

	Mean	St. dev.	Skew.	Kurt.	JB	LB(Q)	LB(Q^2)	DF-GLS
Brent oil	0.001	0.946	−0.454	18.514	30,268.9	0.410	0.000	−5.131
Natural gas	−0.009	1.282	0.250	6.819	1846.1	0.420	0.000	−5.301
Zloty	0.005	0.325	0.268	6.131	1284.2	0.735	0.000	−5.404
Koruna	0.002	0.289	0.284	6.288	1417.0	0.186	0.000	−7.143
Forint	0.006	0.342	0.160	5.197	627.3	0.104	0.000	−4.751
Lev	0.006	0.258	0.300	5.248	689.0	0.021	0.000	−53.266
Lira	0.071	1.060	−0.969	70.527	580,729.3	0.000	0.000	−38.971
Rouble	0.017	0.445	0.983	44.236	216,867.1	0.000	0.000	−1.136

Source: author's calculations

Notes: JB stands for the value of Jarque-Bera coefficients of normality, the LB(Q) and LB(Q^2) tests refer to the p-values of Ljung-Box Q-statistics of level and squared residuals of 10 lags. Assuming only constant, 1% and 5% critical values for the DF-GLS test with 10 lags are −2.566 and −1.941, respectively.

Table 2 shows the calculated AIC values when different distribution functions are combined with the CGARCH model. It can be seen that heavy-tailed distributions dominate, which is expected, since all the time series have relatively high kurtosis.

Table 2: AIC values of estimated CGARCH models

	Brent	N. gas	Zloty	Koruna	Forint	Lev	Lira	Rouble
Normal	2.374	3.166	−0.746	−1.757	−0.627	−2.359	0.642	0.503
Student's t	2.294	3.125	−0.779	−2.011	−0.637	−2.474	0.537	0.464
NIG	2.288	3.126	−0.784	−2.004	−0.636	−2.471	0.535	0.463

Source: author's calculations

Note: greyed numbers indicate the lowest AIC.

Table 3 presents the estimated parameters with the best-fitting CGARCH model. Almost all the estimated parameters are highly statistically significant. It is important to note that all the η_1 parameters are very high and highly significant, which suggests the presence of long-run volatility persistence. In other words, the long-run component converges to the long-run time-invariable volatility level ω with a magnitude of η_1. Since all the η_1 parameters are very close to one, this means that q_t approaches ω very slow. All the η_2 parameters are relatively small, which means that shocks have a relatively small effect on the permanent component of volatility. All the CGARCH models are stable because the η_1 parameters exceed the sum of the α and β parameters. In addition, the LB diagnostic tests indicate the absence of autocorrelation and heteroscedasticity in all the models, which means that the estimated parameters are reliable.

Table 3: Estimated CGARCH parameters

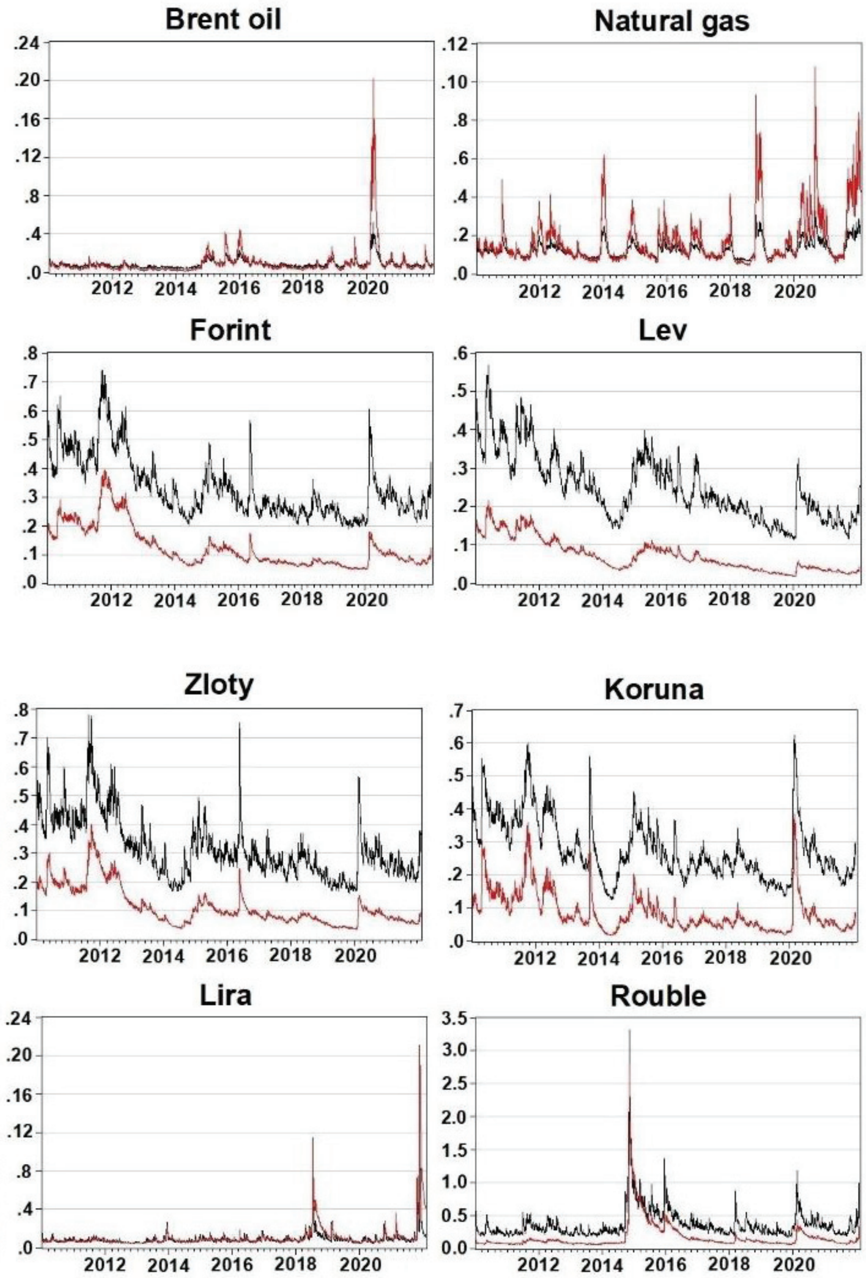
	Brent	N. gas	Zloty	Koruna	Forint	Lev	Lira	Rouble
ω	0.008**	0.027***	0.000	0.001*	0.001***	0.000	0.008***	0.001***
α	0.043*	0.000	0.052***	0.003	0.034***	0.027***	0.150***	0.097***
β	0.343*	0.072	0.875***	0.996***	0.926***	0.953***	0.763***	0.828***
η_1	0.993***	0.984***	0.999***	0.998***	0.999***	0.999***	0.991***	0.995***
η_2	0.082***	0.072***	0.024***	0.182***	0.020***	0.018***	0.038**	0.028***
Shape	1.479***	7.396***	3.304***	3.813***	10.576***	7.577***	1.345***	2.232***
Skewness	–0.183***	–	0.159***	–	–	–	0.127***	0.094**
Diagnostic tests								
LB(Q)_20	0.338	0.932	0.229	0.646	0.183	0.219	0.106	0.153
LB(Q²)_20	0.989	0.920	0.901	0.971	0.632	0.916	0.488	0.530

Source: author's calculations

Notes: LB(Q) and LB(Q^2) tests denote p-values of Ljung-Box Q-statistics of level and squared residuals for 10 lags. ***, **, * represent statistical significance at the 1%, 5% and 10% level, respectively.

After estimation of the CGARCH models, we construct the permanent and transitory parts of the conditional volatilities for all the selected assets. The dynamic changes of these volatilities are presented in Figure 2. As can be seen, the temporary component of volatility is lower in the case of energy commodities, which means that market sentiment is a less important determinant of volatility on energy markets than the shocks of the fundamentals. This is expected because Brent oil and natural gas are globally demanded commodities susceptible to various global events and crises. On the other hand, in the case of currencies, the black line is above the red line and for the Central and Eastern European countries this is quite obvious, which means that volatility of exchange rates is dominantly determined by transitory shifts or market sentiment, and much less by long-term fundamental factors. This is also in line with economic logic because exchange rate markets react promptly to all information, which means that the overall attitude of market participants towards domestic and global events plays a dominant role in shaping the exchange rate volatility.

Figure 2: Estimated permanent and transitory volatilities of selected assets



Source: author's calculations

Notes: the black (red) line is the transitory (permanent) volatility. The X axis represents the values of conditional volatility, while the Y axis denotes years.

In addition, the Russian rouble and the Turkish lira suffered huge exchange rate depreciations around 2015 and at the end of 2021, respectively, which caused massive exchange rate volatilities. These happenings are clearly visible in Figure 2. In the Russian case, the enormous volatility of the rouble can undoubtedly be linked to the severe oil price drop around 2015 (see Figure 1). As for the Turkish case, there are a number of factors that contributed to a significant lira depreciation in a relatively short amount of time. High inflation is one of the primary factors, as is the excessive current account deficit of the Turkish economy and unorthodox ideas about interest rate policy, which decreased the interest rate from 19% to 14% in 2021. All these factors jointly contributed to a 44% depreciation of the lira against the USD in 2021.

To determine which SKD best fits the dependent variables, we calculate the AIC values taking into account all five SKDs. In other words, we estimate median regression ($\tau^{0.5}$) in the RLQR models with different distribution functions, where the transitory and permanent volatilities are the dependent variable. Table 4 presents these results. It can be seen that the slash distribution is the best in most cases. Only in three cases, some other distribution is better. To be parsimonious, we present Figure 3, which shows the residuals of zloty transitory volatility with the five probability distribution functions. Visual inspection confirms that the slash distribution is the best for the transitory volatility of the zloty. The fitted distributions of all the other currencies can be obtained on request.

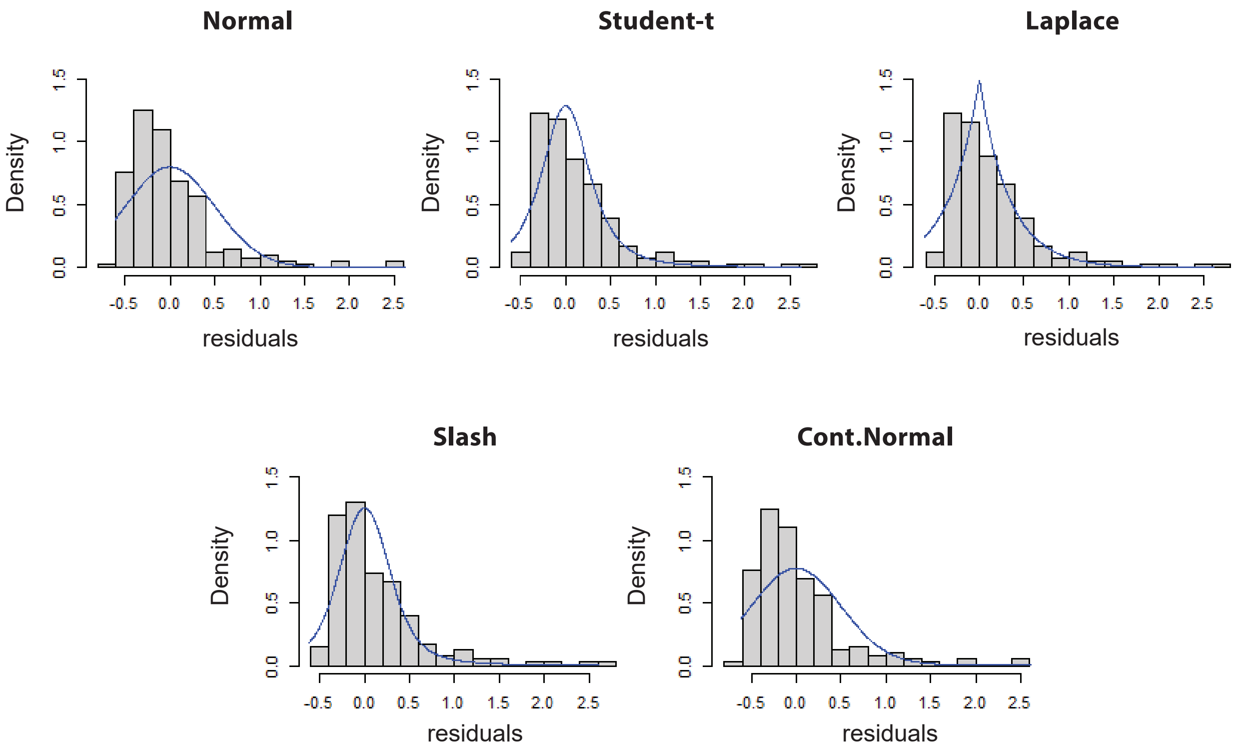
Table 4: AIC values of the estimated RLQR models

Currencies	Type of volatility	Types of different SKD				
		Normal	Student's t	Laplace	Slash	Cont. normal
Zloty	Transitory	585.0	235.2	249.3	231.7	275.4
	Permanent	929.0	646.8	695.1	646.5	646.2
Koruna	Transitory	399.1	116.1	132.8	116.2	116.3
	Permanent	575.6	249.3	257.9	248.0	279.4
Forint	Transitory	275.7	−88.3	−72.4	−88.9	−32.8
	Permanent	491.9	189.5	194.6	187.3	202.6
Lev	Transitory	414.3	132.3	189.9	131.9	131.5
	Permanent	525.8	227.9	254.5	224.2	233.9
Rouble	Transitory	778.8	414.6	430.1	414.0	474.3
	Permanent	1310.5	857.7	904.6	843.1	996.8
Lira	Transitory	597.5	192.2	219.9	185.7	256.7
	Permanent	989.1	672.0	692.4	667.9	688.1

Source: author's calculations

Note: greyed numbers indicate the lowest AIC.

Figure 3: Fitted distributions of estimated residuals of zloty transitory volatility



Source: author's calculations

5. Empirical Results

This section presents the results of the volatility spillover effect in the short and long term from two energy markets to six exchange rates. Tables 5 and 6 contain the estimated quantile parameters with the best-fitting RLQR models. Figure 4 shows plots of the estimated quantile parameters of the volatility transmission in the short and long term. In order to preserve space, the gas spillover effect figure is not presented, but can be obtained on request. All the RLQR parameters are estimated at the 95% confidence interval, which guarantees high reliability of the results. It can be seen in Figure 4 that all the confidence intervals are relatively narrow, which means that all the quantile parameters are highly trustworthy. This is the main advantage of the RLQR approach compared to the classical quantile regression of Koenker and Bassett (1978). It should be said that all the estimated RLQR parameters are positive, which is expected since the paper examines volatilities. The estimated RLQR parameters can distinguish between periods of low volatility (lower quantiles), moderate volatility (median quantile) and high volatility (upper quantiles). Panels A and B in Tables 5 and 6 contain the estimated parameters of the short-term and long-term volatility transmission, respectively.

It can be seen in both tables that most of the estimated RLQR parameters are statistically significant, which is especially true for the volatility transmission from Brent oil. Also, the estimated quantile parameters are not particularly high, except for the case of Russia. This means that the exchange rates of the Central and Eastern European Countries (CEECs) and Turkey endure a volatility transmission effect from energy markets, but this effect is relatively low, i.e., far below 10% in most cases. This finding is in line with the paper of Zhang et al. (2008), who studied the volatility nexus between WTI oil and the USD, claiming that the interaction between the oil price and the US dollar does not seem to be strong. Besides, low parameters are primarily detected in the oil-importing countries, i.e., the CEECs and Turkey. On the other hand, Russia, as a major oil exporter, suffers a much stronger effect from energy markets, where a particularly strong effect is recorded from oil at the 95th quantile in the short term. These results coincide very well with the paper of Hameed et al. (2021), who investigated the volatility spillover effect from oil to exchange rate, focusing on the five major oil importers and oil exporters. They concluded that oil prices have a greater volatility spillover effect in oil-exporting countries compared to oil-importing countries. In addition, they contended that Russia is the only country which is more affected by external shocks compared to other countries. This is not surprising, since Russia obtains the largest amounts of foreign currency from energy exports. According to the report of Russian Ministry of Finance[3] in 2021, Russian oil and gas revenues exceeded initial plans by 51.3% in 2021, totalling 9.1 trillion roubles ($119 billion). In other words, if any turbulence occurs in the volume of energy exports or in the prices of energy commodities, this directly transfers to the stability of the rouble, and this is the reason why we observe higher RLQR parameters in the case of Russia.

It is interesting to note that Turkey, as an oil importer, has higher quantile parameters than any of the CEECs. The rationale behind these findings probably lies in the exchange rate policy of the selected countries. In particular, Central and Eastern European countries pursue managed float policy, while Turkey and Russia follow the free float regime. In the case of the CEECs, this means that central banks maintain stable exchange rates, not allowing too big oscillations. On the other hand, in the cases of Turkey and Russia, their exchange rates are determined by market forces, that is, by the demand and supply of foreign currency on the foreign exchange market. The difference in the two exchange rate policies is easily visible on the descriptive statistics of the data. In other words, Table 1 indicates that the lira and the rouble report very high kurtosis values, which signals the presence of outliers. This means that these exchange rates experienced large swings in value in the observed period, instigated by market forces. On the other hand, the kurtosis values of the CEECs are very low compared to the Turkish and

3 Source: https://www.reuters.com/markets/europe/russias-oil-gas-revenue-windfall-2022-01-21/

Russian counterparts, which reflects the managed float exchange rate policy of these countries. The findings of descriptive statistics can be transferred straightforwardly to the estimated quantile parameters, in a sense that free floaters suffer notably stronger volatility shocks from oil markets, compared to managed floaters. On the other hand, Russia, as a free floater, endures even more spillover effect from oil markets than Turkey because Russia is the second largest oil exporter in the world (after Saudi Arabia), and the oil revenues are crucial for the stability of the rouble.

Table 5: Short and long-term volatility spillover from Brent oil to exchange rate volatilities

Estimated quantiles					Estimated quantiles				
0.05	0.25	0.5	0.75	0.95	0.05	0.25	0.5	0.75	0.95
Panel A: Brent short-term volatility spillover to short-term exchange rate volatility									
Poland					**Czechia**				
0.022***	0.028***	0.021*	0.011	0.024***	0.041***	0.059***	0.064***	0.067***	0.080***
Hungary					**Romania**				
0.007	0.026**	0.027***	0.017***	0.021***	0.022***	0.019*	0.014	0.009	0.068***
Turkey					**Russia**				
0.035***	0.075***	0.077***	0.070***	0.061**	0.091***	0.121***	0.167***	0.297***	0.532***
Panel B: Brent long-term volatility spillover to long-term exchange rate volatility									
Poland					**Czechia**				
0.002*	0.003*	0.003**	−0.004*	−0.006***	0.011***	0.012***	0.012***	0.012***	0.017***
Hungary					**Romania**				
0.002*	0.005***	0.006***	−0.003*	−0.006***	0.001	0.000	−0.002	−0.005***	−0.006***
Turkey					**Russia**				
0.012***	0.007***	0.005***	0.000	−0.014***	0.016***	0.017***	0.034***	0.112***	0.153***

Source: author's calculations

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

Table 6: Short and long-term volatility spillover from natural gas to exchange rate volatilities

Estimated quantiles					Estimated quantiles				
0.05	0.25	0.5	0.75	0.95	0.05	0.25	0.5	0.75	0.95
Panel A: Natural gas short-term volatility spillover to short-term exchange rate volatility									
Poland					**Czechia**				
0.024***	0.014*	0.005	0.012	0.053***	0.032***	0.019**	0.012	0.027***	0.038***
Hungary					**Romania**				
0.023***	0.020**	0.015	0.030**	0.077***	−0.002	−0.003	−0.019	−0.044***	−0.070***
Turkey					**Russia**				
0.064***	0.072***	0.094***	0.094***	0.145***	0.026***	0.043***	0.064***	0.076***	0.111***
Panel B: Natural gas long-term volatility spillover to long-term exchange rate volatility									
Poland					**Czechia**				
0.003***	0.000	−0.003	−0.004	−0.010***	0.003***	0.002	0.000	0.001	0.004**
Hungary					**Romania**				
0.003***	0.001	0.000	−0.006*	0.007***	0.000	−0.002	−0.006**	−0.010***	−0.007***
Turkey					**Russia**				
0.025***	0.008*	0.008	0.004	0.142***	0.001***	0.005***	0.007***	0.009***	0.012***

Source: author's calculations

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

The results in Table 6 refer to the volatility spillover effect from natural gas to exchange rate. Table 6 shows that the volatility spillover effect is significantly smaller from natural gas than from the oil market, while some RLQR parameters are even statistically insignificant. Two reasons might explain the findings. Firstly, Table 7 shows that energy importers consume more energy per capita from oil than from gas. Secondly, gas-importing countries in Central and Eastern Europe, as well as Turkey, make long-term deals with Gazprom, i.e., the biggest gas supplier on the European market before the war in Ukraine. These gas contracts usually involve agreed gas quantities and gas prices. This means that changes in gas prices on the free market should not affect the national exchange rate because every country that imports gas ensures funds for this purpose. This prevents surprises regarding the potential lack of stable currencies (USD and EUR), which might affect the exchange rate. The problem might occur only if a country consumes more gas than predicted by a contract, which coerces the country to buy missing gas quantities on the free market at higher prices. However, these situations are relatively rare. Therefore, all these aforementioned factors explain a very small volatility effect from the gas market.

Table 7: Oil and natural gas consumption per capita in kWh in 2021

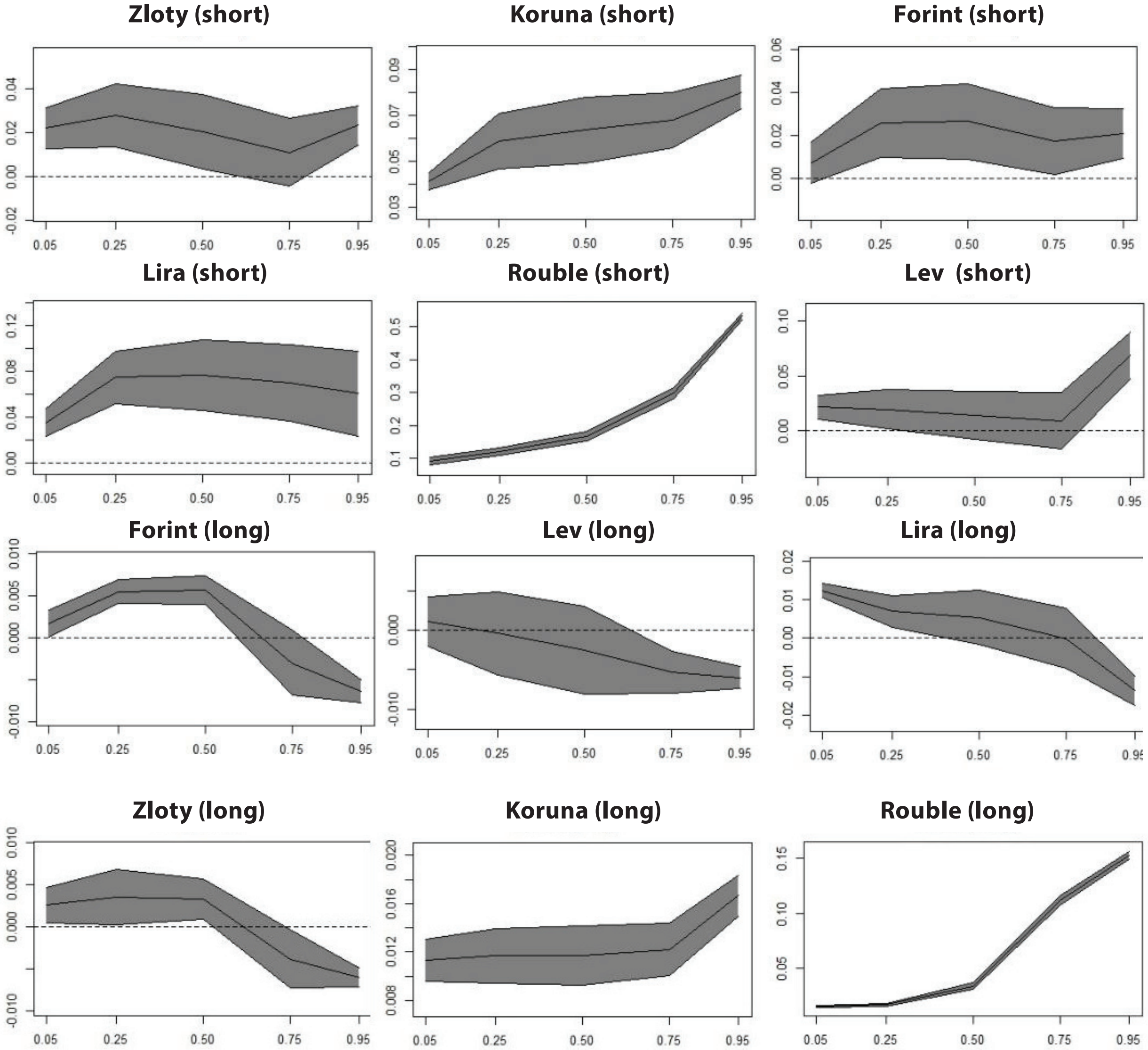
	Poland	Czechia	Hungary	Romania	Turkey	Russia
Oil per capita (kWh)	9,858	11,149	10,580	6,503	6,767	12,509
Gas per capita (kWh)	5,378	7,788	10,130	5,621	5,180	30,459

Source: Our World in Data (2023)

Using the RLQR method, we can see how strong the volatility transmission effect is when the exchange rate market is in a different mode, i.e., low, moderate and high volatility. It can be seen in Table 5 that the spillover effect gradually increases when higher quantiles are observed. This is in line with expectations because in the regime of higher volatility, the exchange rate market is more susceptible to a higher volatility transmission effect from all external markets, including the very important oil market. As for the volatility shock from the gas market, this is not so obvious, particularly for the CEECs, while the increased volatility transmission is visible only at the 95th quantiles for the free floaters, i.e., when exchange rate markets are in a very high volatility regime.

In addition, by splitting the conditional volatilities into the transitory and permanent parts, we can see how the short-term and long-term spillover effects differ. It is apparent that the long-term effect is significantly smaller than the short-term one, and this applies to all exchange rates. As a matter of fact, the long-term effect is almost negligible, and this is the case for the spillover effects from both energy markets. This is in line with the findings in Figure 2, where we can see that the volatility of exchange rates is primarily determined by the short-term component. Due to this fact, this means that the short-term volatility is the primary receiver of the volatility shocks from the energy markets, which is determined by the market sentiment and the overall behaviour of market participants. The detection of a higher transitory volatility spillover effect indicates information transfer between markets, according to Ross (1989). This means that highly liquid exchange rate markets process more short-term than long-term information. This is expected because all participants on the exchange rate markets respond very quickly to all relevant external information, which means that the short-term information enters and embeds much faster on the exchange rate market.

Figure 4: Estimated RLQR parameters of short-term and long-term spillover effect from oil



Source: author's calculations

Note: the confidence intervals are at 95% probability. The X axis represents the values of the robust quantile parameters, while the Y axis denotes quantiles.

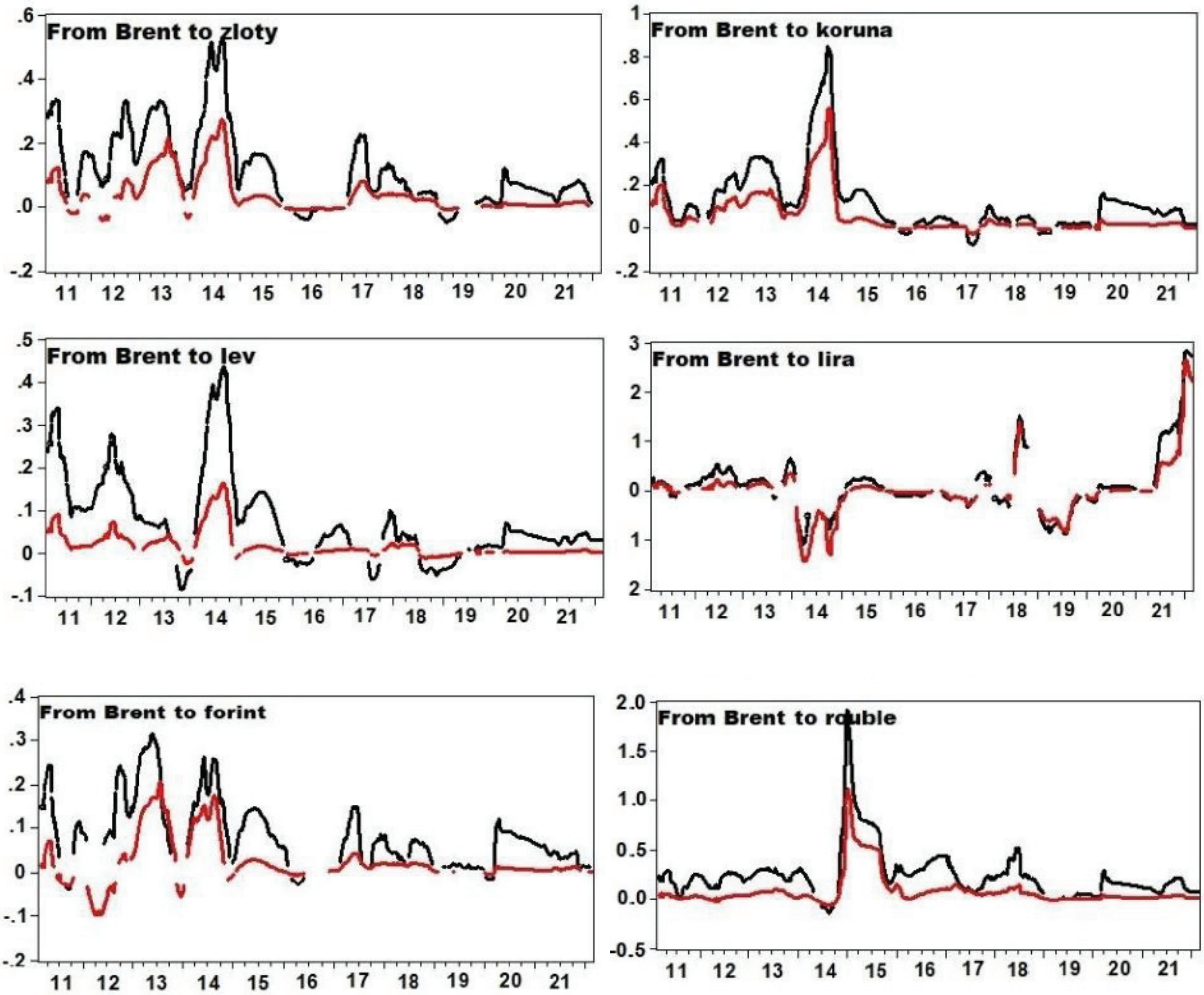
6. Complementary Analysis via Rolling Regression

The quantile regression can estimate the size of volatility impacts from energy markets in different market conditions. However, we cannot see how this effect varies over time when the level of energy volatility changes. In that regard, we complement the quantile regression results with the rolling regression[4]. At the same time, this approach can serve as a robustness check for the estimated RLQR parameters, which lends more credibility to the overall findings. The idea to use the rolling regression is borrowed from Bartosik and Mycielski (2020) and Poghosyan and Poghosyan (2021). The size of the rolling window is set to be one year, which is approximately 250 working days. This means that the number of consecutively calculated rolling volatility spillover parameters is 2,778 for every exchange rate volatility. We apply the generalized least square (GLS) method to the rolling regression estimation in order to correct standard errors for autocorrelation and avoid possible spurious regression. Besides, we use the White method for heteroscedasticity, introduced by MacKinnon and White (1985). Figures 5 and 6 present the estimated rolling parameters, and they are significant only if the probability is 90% or higher. This is the reason why some lines in the figures are broken, i.e., the statistically insignificant parameters are not taken into account. The black lines denote the statistically significant rolling parameters of the transitory part, while the red lines are the rolling parameters of the permanent part. For the rolling regression estimation, we use Equation (5), as it is used for the RLQR computation.

Figures 5 and 6 show that the rolling parameters are time-varying, which justifies the use of this method. Also, the black lines are above the red lines, indicating that the transitory effect is stronger than the permanent counterpart most of the time. As for Figure 5, we find a higher volatility spillover effect around 2014 in the CEECs' plots and in the Russian plot. At this particular time, oil recorded a severe price drop and the increased volatility on the oil market was transferred to the volatility of the national exchange rates of the CEECs and Russia. Regarding the CEECs, we find that the Czech koruna suffered the most from the oil volatility in 2014, which is in line with the fact that the Czech oil consumption per capita is the highest (see Table 7). The volatility spillover effect was particularly strong at that time in the case of Russia because Brent oil plummeted from over 110 USD per barrel to below 50 USD per barrel in the period 2014-2015, while at the same time the rouble depreciated by 100%, from 35 roubles/USD to 70 roubles/USD. This severe volatility spillover effect, particularly on the transitory part, happened because the oil export revenues are the major source of stable currencies (USD or EUR) for Russia, and decreasing oil prices significantly reduce their inflow on the Russian exchange rate market. Also, it should be noted that the volatility of oil market was higher during the COVID-19 crisis (see Figure 2). However, this higher volatility did not spill over to the exchange rate markets of the selected countries intensively, probably because this effect at its peak lasted relatively shortly.

4 The rolling regression was calculated using the 'rollRegres' package in 'R'.

Figure 5: Estimated rolling parameters of spillover effect from Brent oil to exchange rate

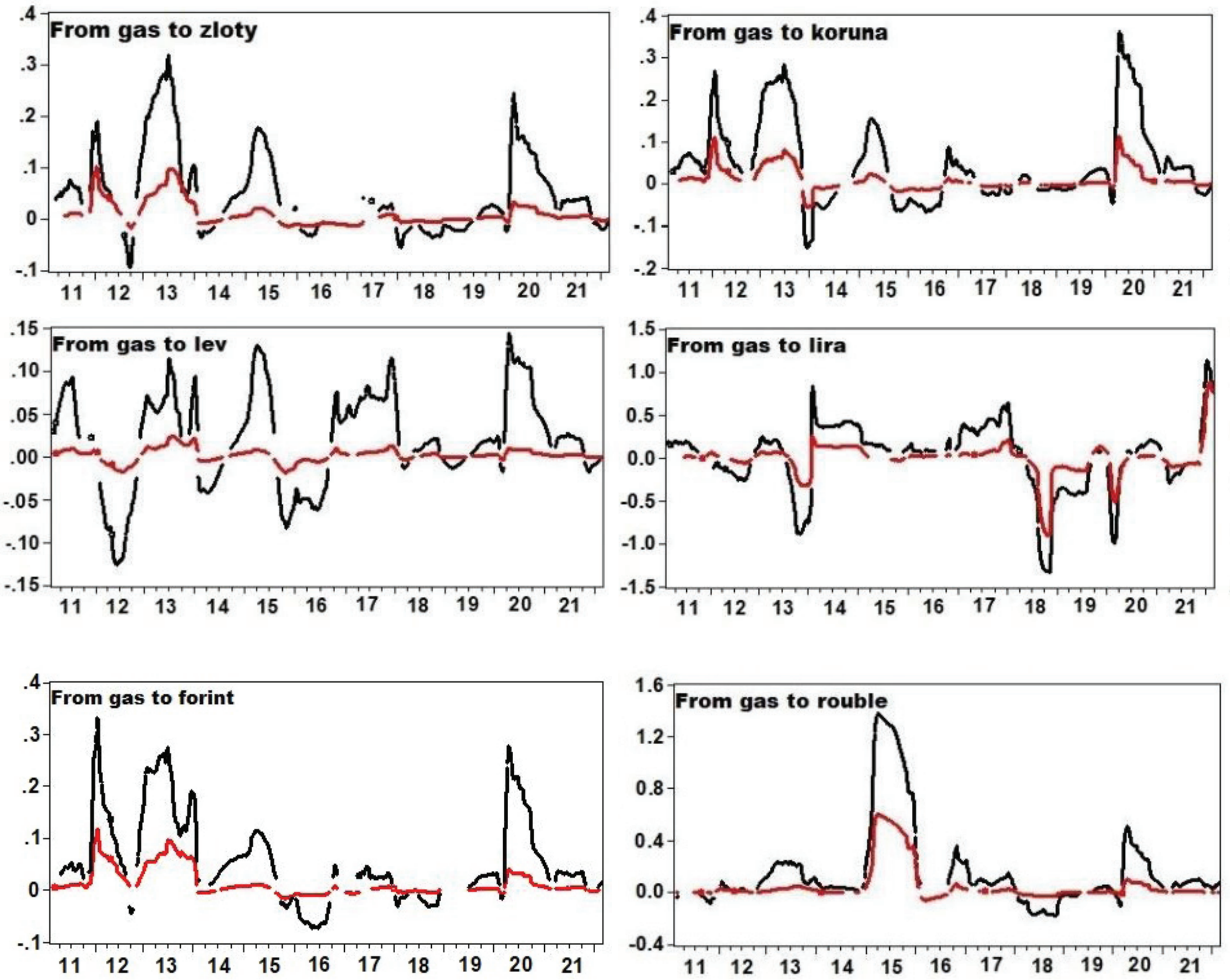


Source: author's calculations

Notes: the black (red) line denotes estimated rolling parameters of transitory (permanent) volatility spillover effect. The X axis represents the values of rolling parameters, while the Y axis denotes years.

It seems that the Turkish lira did not experience a volatility spillover effect in the period 2014–2015. On the other hand, we find a higher spillover effect in the periods when the lira depreciated significantly, which was in the period 2018-2019 and even more notably at the end of 2021 (see Figure 2). This indicates that oil volatility only added to the increased volatility of the lira at that time, while the total volatility of the lira was caused primarily by other reasons – high inflation, excessive current account deficit and inadequate interest rate policy.

Figure 6: Estimated rolling parameters of spillover effect from natural gas to exchange rate



Source: author's calculations

Notes: the black (red) line denotes estimated rolling parameters of transitory (permanent) volatility spillover effect. The X axis represents the values of rolling parameters, while the Y axis denotes years.

Figure 6 shows the estimated rolling parameters of the gas volatility spillover effect. The level of these parameters is lower compared to the oil counterparts, which coincides with the RLQR findings. Only in the cases of the Russian rouble and the Turkish lira we find relatively high transitory spillover parameters. For Russia, it is the period 2014–2015, while it is the year 2021 for Turkey. In these particular periods, the rouble and the lira recorded significant depreciations caused by the reasons explained above, and any volatility from whatever external markets was only added to the current volatility of these exchange rates at that time.

7. Conclusion

This paper investigated the volatility transmission from two energy markets to six Central and Eastern European and Eurasian foreign exchange markets. Five of them are energy importers and one is a major energy exporter. In this process, we first split the conditional volatilities into the transitory and permanent parts, using the best-fitting CGARCH model. The created volatilities were embedded into a novel robust linear quantile regression model, which chose an optimal distribution function in order to estimate highly reliable quantile parameters. As a complementary analysis, we used the rolling regression, which showed how the estimated parameters vary over time.

We report several noteworthy findings. Firstly, the spillover effect is relatively low (below 10%), for all the CEECs, taking into account the highest quantile. All these countries pursue managed float exchange rate regimes, which probably contributes to the relatively modest risk spillover effect from the energy markets. A somewhat higher oil to exchange rate parameter at the 95th quantile was found for the Czech koruna compared to all the other CEECs, probably because this country has the highest oil consumption per capita. On the other hand, for Turkey and Russia, we found higher RLQR parameters, where the 95th quantile parameter from oil to the rouble amounts to 0.532. The rouble endures the highest risk spillover effect from oil because Russia obtains significant volumes of foreign currency from oil exports, and any changes in the price of oil directly transfer to the volatility of the rouble. In addition, Turkey and Russia are free floaters, which means that their currencies are not protected from large oscillations, which increases their exchange rate volatilities.

As for the difference between the short-term and long-term spillover effects, the results undoubtedly indicate that the transitory spillover effect is much stronger than the long-term one. This suggests that the primary determinant of the exchange rate volatility is market sentiment mirrored in the prevailing behaviour of market participants, while long-term fundamental factors play a secondary role.

The rolling parameters are in line with the RLQR estimates, which boosts credibility of the overall findings. Also, the rolling parameters reveal that oil price drops are a major source of the rouble volatility, while the oil volatility factor only adds to the increased volatility of the lira, which depreciates due to other fundamental factors.

The results of this paper can be interesting for participants on the exchange rate markets of the selected countries. The results indicate how energy volatility is transmitted to exchange rate volatility and in which periods. Investors can use this knowledge to make proper decisions whether and when to apply some hedging actions in order to protect themselves from energy volatility shocks. A limitation of this research is the relatively narrow sample of countries, and future papers may overcome this by considering other emerging markets.

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