Multiscale non-linear tale risk spillover effect from oil to stocks – The case of East European emerging markets

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Abstract: *This paper investigates the multiscale non-linear risk transmission effect from Brent oil to eleven European emerging stock markets. Dynamic extreme risk time series are created using the FIAPARCH-CVaR approach. The MODWT transformation is applied to make three wavelet details that represent different time horizons. In the final step, the MODWT time series are fitted into the Markov switching model to examine the spillover phenomenon. The results indicate that the Czech and Hungarian stock markets endure the spillover effect in crisis regime in the short term, probably because these markets are among the most efficient emerging European markets. On the other hand, a relatively high spillover effect is found in a peaceful rather than a crisis regime in the case of Poland. This is probably because the Polish index lists almost 300 stocks, which means that oil shocks disperse to a large number of different industry sectors. In small and less developed markets, such as Estonia, Slovenia, Bulgaria, and Croatia, a high spillover effect exists in a tranquil regime because these countries have high oil consumption per capita. Lithuania and Latvia do not report the spillover effect in the short run, while this is true for all time horizons in the case of Slovakia.*

Keywords*: Extreme risk spillover effect, conditional value-at-risk (CVaR), wavelet methodology, Brent oil, stock markets.*

JEL classification*: C58, G12, G32.*

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Introduction

Oil is the key strategic energy source that runs corporate businesses around the world. This means that the oil market and stock markets are inevitably interconnected, where a plethora of literature confirmed this relationship (Abakah et al., 2023; Aydin et al., 2022; Mensi et al., 2022a). Tian et al. (2022) list several economic conduits that connect oil and stock markets. One of the most important and most detrimental channels is the supply-side shock effect passed on to the effect of inflation. In other words, an increase in the price of crude oil directly affects production by increasing the marginal costs of new products. As a result, inflation increases due to rising oil prices. This lowers spending power of consumers and reduces the profits of companies, which causes stock prices to fall. On the other hand, the so-called aggregate-demand effect also occurs, where purchasing power can be transferred from oil-importing countries to oil-exporting countries. This results in a rise of stock prices in oil-exporting countries and a fall of stock prices in oil-importing countries.

The recent crises, such as the COVID-19 pandemic and the ongoing war in Ukraine, have inflicted unprecedented shocks to oil and stocks (Gemra et al., 2022). These developments intensified the efforts of academics, investors, and commodity traders to better understand the interlinks between oil and stock markets because they have important repercussions for the stability and successful operation of companies. The left plot in Fig. 1 clearly shows that the two crises had a very deep impact on the Brent oil market. Travel restrictions and lockdowns caused a steep drop in global oil demand, provoking oil prices to fall to 20 USD per barrel in April 2020. On the other hand, the war in Ukraine pushed the price of oil to over 120 USD per barrel in May 2022. These happenings induced huge risk in the oil market, as can be seen in the right plot (Fig. 1), part of which has certainly been transferred to stock markets.

The paper tries to estimate univariate risk transmission from Brent oil to eleven stock indices of East European economies, which are members of the EU (Poland, Czechia, Hungary, Slovakia, Lithuania, Latvia, Estonia, Slovenia, Romania, Bulgaria and Croatia). Risk transmission between the markets is important to study because the oil-stock risk interdependence is growing stronger, whereas the risk transmission mechanism is becoming more complex due to the deepening of commodity financialization and global financial integration (Wen et al., 2022).

In order to measure extreme risk, researchers usually consider value-at-risk (VAR) to be the most famous measure of downside risk. However, one of the major issues of the VaR model is its inability to measure the losses beyond the threshold amount of VaR. Rockafellar and Uryasev (2002) tried to resolve this drawback by proposing the parametric conditional VaR (CVaR), which can address losses beyond VaR. In other words, the parametric CVaR calculates the average loss of the worst returns taking into account a certain level of probability (Živkov et al., 2021). In order to properly calculate dynamic CVaR, empirical time series need to be independently and identically distributed, which is usually not the case because daily time series are prone to autocorrelation, heteroscedasticity, volatility clustering, leverage effects, fat tails, and long memory. With the aim to better recognize the idiosyncratic features of the time series, we use the FIAPARCH model because this model produces the most accurate VaR and expected shortfall, according to Alkathery et al. (2022). Student *t* distribution is utilized to fit

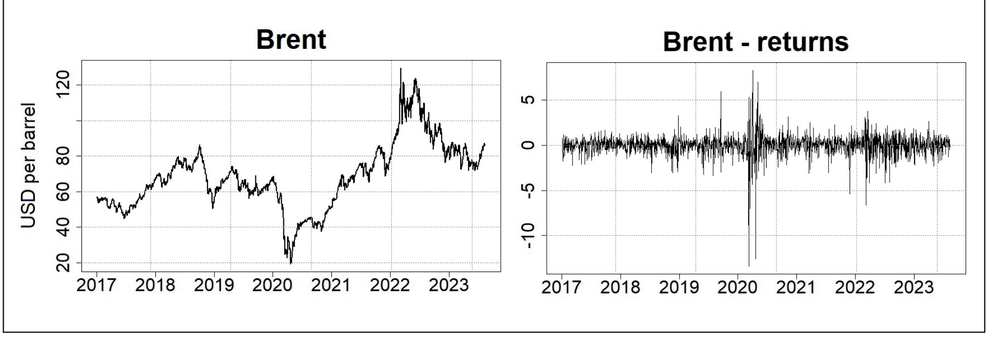

Fig. 1: **Empirical dynamics of Brent oil**

Source: own

the fat tails of the empirical time series. Accordingly, the white noise residuals of this model are used to create the dynamic CVaR time series of Brent oil and stock indices.

Jin et al. (2023) assert that oil price shocks can impact stock prices in different time horizons, which means that risk spillovers can be observed at multiple time scales. This concept is also important from the aspect of different market participants. In other words, short-term agents, such as arbitrageurs and speculators primarily look at temporary happenings, such as unusual events and socio-economic news (Rösch et al., 2022). Fund managers, as mid-term investors, are concerned to medium-term market developments (Barunik & Krehlik, 2018). On the other hand, policymakers and large financial institutions, such as insurance companies and pension funds, are keen to know how the macroeconomic environment and fundamental factors function (Fong et al., 2022). To address the issue of the multi-frequency spillover effect, we use the maximum overlap discrete wavelet transformation (MODWT) methodology in order to generate the wavelet signals of different frequencies that personify short-, medium- and long-term horizons.

In the final stage of the research process, we embed eleven wavelet-based oil-stock pairs into the Markov switching (MS) model in a pairwise manner in order to investigate the unidirectional oil-stock causality. This model is used to capture shifts in economic or financial data when they cannot be fully explained by a single set of parameters and assumptions. Since we cover a relatively long time span, which includes the two crises, it is logical to hypothesize that the relationship is non-linear. In particular, assuming the presence of a non-constant relationship, we allow stock indices to rely on the two independent state regimes that shape the conditional mean process. Basher et al. (2016) explain that the Markov switching model uses the information from the varying regime-switching probabilities of being in a particular regime to allow time-varying causality across regimes. From this aspect, we can get information in which time the horizon extreme risks from the oil market have the greatest impact on the stock market and in which regime this happens.

The existing literature found mixed results regarding the oil-stock risk spillover relationship without reaching a consensus, which indicates the complexity of this phenomenon. Ahmed and Huo (2021) utilized the tri-variate VAR-BEKK-GARCH model to examine the dynamic nexus among commodity markets, the Chinese stock market and global oil price. They found bidirectional shocks spillovers between oil and stock markets but unidirectional volatility spillovers from the oil market to the Chinese stock market. Jiang et al. (2022) used the long-memory Copula-CoVaR-MODWT method to document the risk spillovers from oil to BRICS stock markets, addressing both time and frequency domains. They showed that significant risk spillovers exist with time-varying and heterogeneous characteristics. The paper of Okorie and Lin (2022) researched the information spillovers in return and volatility, considering the two crude oil markets (Brent and WTI) and the Nigerian stock index (NSE) using the asymmetric VAR-MGARCH-GJR-BEKK model. They found a bidirectional volatility spillover effect between the crude oil markets and the NSE index, and significant asymmetric shocks. Chan and Qiao (2023) investigated the volatility interdependencies between oil and stock markets, taking into account the WTI oil price and ten S&P500 sub-indices. According to their results, demand shocks to stock markets and oil cause much stronger spillover effects than supply shocks.

The main research question of the paper and its contribution to the existing literature pertains to whether and how extreme risk from the Brent market spills over to the stock markets of Central and Eastern European countries. This type of research has never been done before for this group of countries, to the best of our knowledge, and this is our motive to do this study. Contribution is also reflected in the fact that the spillover effect is observed from the aspect of various time horizons, which deepens the understanding of this phenomenon. The use of elaborate methodologies contributes to the reliability of the results, which is also a relevant characteristic of this paper.

Besides the introduction, the rest of the paper is structured as follows. The first section explains the used methodologies – the FIAPARCH model, wavelet transformation, and Markov switching model. The second section introduces the research data and preliminary findings. The results and discussion are presented in the third section. The last section is reserved for conclusions.

1. Used methodologies

1.1 Long memory GARCH and dynamic CVaR

If a time series has a slow declining autocorrelation function (ACF), then it has the long memory property, as Ding and Granger (1996) explained. It is said that time series is a stationary long-memory process if the autocorrelation function (ACF), ρ(*k*) behaves as $\rho(k) \approx c|k|^{2d-1}$ as $|k| \rightarrow \infty$, where $0 < d < 0.5$, and *c* is a positive constant. The ACF has a very slow rate of decline to zero as *k* strives to infinity and $\sum_{k=-\infty}^{\infty}|\rho(k)| = \infty$. Long memory property can be modelled by the fractionally integrated GARCH (FIGARCH) model, which is an extension of the classical GARCH model. It is used to capture long-memory persistence in volatility, which means it accounts for the fact that volatility tends to persist over time. In the traditional GARCH model, volatility is modeled using lagged squared errors and lagged conditional variances. However, these models assume that volatility persistence is finite. In contrast, the FIGARCH model allows for the possibility of infinite persistence, meaning that shocks to volatility can have a lasting impact on future volatility.

Some papers found the long memory process in energy commodities and stocks (Chkili et al., 2021; Youssef et al., 2015), so we apply the fractional integrated asymmetric power ARCH model – FIAPARCH of Tse (1998) in order to address this issue. The mean equation includes the first-order autoregressive term, which is enough to deal with autocorrelation. Student *t* distribution tackles fat tails in the empirical distributions. The mean and FIAPARCH(*p*, *d*, *q*) specifications look as follows:

$$y_t = C + \Theta y_{t-1} + \varepsilon_t;\ \varepsilon_t \sim St(0, \sigma_t, \nu) \tag{1}$$

$$\sigma_t^\delta = \omega[1 - \beta(L)]^{-1} + \\ + \{[1 - \beta(L)]^{-1}\, \alpha(L)(1-L)^d\}\, (|\varepsilon_t| - \gamma\varepsilon_t)^\delta \tag{2}$$

where: ω is constant; *L* denotes the lag-operator; γ, δ and *d* are the model parameters. Parameter γ is the leverage coefficient, where $\gamma < 0$ means that positive shocks affect volatility more than negative shocks and vice-versa. Symbol δ stands for the power term parameter, and it has finite positive values. When $\gamma = 0$ and $\delta = 2$, the FIAPARCH process becomes FIGARCH(*p*, *d*, *q*) model. *d* represents the fractionally differencing parameter measuring the persistence of shocks to the conditional variance. FIGARCH(*p*, *d*, *q*) model permits an intermediate range of persistence, where *d* parameter can be found in the scope: $0 < d < 1$. When $d = 0$, FIGARCH model reduces to ordinary GARCH, whereas when $d = 1$, FIGARCH is equivalent to integrated GARCH or IGARCH.

After the estimation of the FIAPARCH models, we use the fitted residuals to calculate the dynamic CVaR time series at 5% probability level. CVaR measures the average amount of loss that investor could have in one day with a certain probability. CVaR is the integral of VaR, where VaR can be expressed as $VaR_\alpha = \hat{\mu} + Z_\alpha\hat{\sigma}$. $\hat{\mu}$ and $\hat{\sigma}$ denote the estimated mean and standard deviation of a particular asset, respectively, while Z_α is the left quantile of the normal standard distribution. CVaR is calculated as in Equation (3):

$$CVaR_\alpha = -\frac{1}{\alpha}\int_0^\alpha VaR(x)dx \tag{3}$$

1.2 MODWT transformation

After constructing the dynamic CVaR time series of all assets, we use wavelet methodology to build three wavelet details representing short-, medium- and long-term horizons. On the theoretical basis, the wavelet operates with the two elementary wavelet functions: mother wavelet (ψ) and father wavelet (ϕ). Father wavelets depict the low frequency or smooth parts of a signal, having an integral of 1. On the other hand, mother wavelets explain high-frequency components with an integral equal to 0. The father ($\phi_{J,k}(t)$) and mother ($\psi_{J,k}(t)$) wavelet functions can be presented in the following way:

$$\phi_{J,k}(t) = 2^{-\frac{J}{2}}\phi\left(\frac{t-2_k^J}{2^J}\right),\quad \psi_{J,k}(t) = 2^{-J/2}\psi\left(\frac{t-2_k^J}{2^J}\right) \tag{4}$$

where: symbol 2^J stands for the scale factor, while 2_k^J is the translation or location parameter.

For the wavelet computation process, the study uses the non-orthogonal wavelets, known as the maximum overlap discrete wavelet transformation (MODWT), which has highly redundant and non-orthogonal transformation characteristics. Decomposed signals in the MODWT framework are presented as follows:

$$S_{J,k} \approx \int f(t)\phi_{J,k}(t)dt \tag{5}$$

$$D_{J,k} \approx \int f(t)\psi_{J,k}(t)dt,\ j = 1, 2, ..., J \quad (6)$$

where: symbols $S_{J,k}$ and $D_{J,k}$ denote the fluctuation and scaling coefficients, respectively, at particular j^{th} level, which decomposes empirical signal or time series in terms of a specific frequency (trending and fluctuation components).

According to Equations (5–6), an empirical time series $y(t)$ can be expressed in terms of those signals as:

$$f(t) = \sum_k S_{J,k}\,\phi_{J,k}(t) + \sum_k D_{j,k}\,\psi_{j,k}(t) + \\ + \sum_k D_{j-1,k}\,\psi_{j-1,k}(t) + ... + \sum_k D_{1,k}\,\psi_{1,k}(t) \quad (7)$$

1.3 Markov switching model

The scale-dependent Markov switching model was originally developed by Goldfeld and Quandt (1973), and we are using it to research the non-linear extreme risk spillover effect between Brent oil and stock markets in different time horizons. The Markov chain governs the Markov switching model, where the future state depends only on the current state and the probability of a particular value (Rosen et al., 2023). In this paper, two states are assumed (S_t = 1, 2), where S_t is an unobserved state variable. S_t = 1 depicts increased volatility in the stock markets, while state S_t = 2 refers to calm market conditions. Besides the switching process in the mean, we also permit the variance of the error term to switch between the states. The unidirectional wavelet-based Markov switching estimation equation looks like as follows:

$$SI^j_{i,t} = c^j_{st} + \phi^j_{st} OIL^j_t + \varepsilon^j_t;\ \varepsilon_t \sim N(0, \sigma^2_{st}) \quad (8)$$

where: *SI* denotes the dynamic CVaR of a particular stock index *i*, and OIL is the dynamic CVaR of Brent time series. Both constant *c* and the spillover parameter ϕ are scale-dependent, where the wavelet scale is labelled by the symbol *j*. The Markov chain is unobservable by definition, which means that probabilities need to be included in order to estimate an output. In other words, changing regimes is not governed deterministically but with a certain probability (Qian et al., 2022). Therefore, the unobserved state variable S_t follows a two-state Markov process with transition probabilities as in Equation (9):

$$\left.\begin{array}{l} P(S_t = 1 \mid S_{t-1} = 1) = p_{11} \\ P(S_t = 1 \mid S_{t-1} = 2) = p_{12} \\ P(S_t = 2 \mid S_{t-1} = 1) = p_{21} \\ P(S_t = 2 \mid S_{t-1} = 2) = p_{22} \end{array}\right\} \begin{array}{l} \text{where} \\ p_{11} + p_{12} = \\ = p_{21} + p_{22} = 1 \end{array} \quad (9)$$

The Markov switching model is estimated by the maximum likelihood function, where the filtering procedure of Hamilton (1990) and the smoothing algorithm of Kim (1994) are used.

2. Dataset and preliminary findings

The paper uses daily data of Brent spot oil and eleven stock market indices from the countries of Central and Eastern Europe: WIG (Poland), PX (Czechia), BUX (Hungary), SAX (Slovakia), OMXV (Lithuania), OMXR (Latvia), OMXT (Estonia), SOBITOP (Slovenia), BET (Romania), SOFIX (Bulgaria) and CROBEX (Croatia). All assets are collected from the stooq.com and investing.com websites. The sample covers the period between January 2017 and August 2023, which includes relatively calm and turbulent periods before and during the pandemic and the war in Ukraine. All indices are separately combined and synchronized with Brent oil. Also, all time series are transformed into log returns (r_i) according to the expression: r_i = 100 × log($P_{i,t}$ /$P_{i,t-1}$), where P_i is the price of a particular asset. It should be said that SAX is the least liquid index, while Bratislava SE is the least developed stock exchange (Baele et al., 2015), which means that there was no trading at all on a significant number of days. This is reflected in the modeling and construction of extreme downside and upside risks. In other words, the created dynamic downside risk time series of SAX are not smooth as in the case of other indices (Fig. 2).

Descriptive statistics in Tab. 1 include the first four moments, the Jarque-Bera test of normality, the Ljung-Box test of level and squared residuals and the DF-GLS unit root test. Brent has high kurtosis, which implies the presence of extreme risk, but all other indices also have high kurtosis, which means that high risk is a common phenomenon in the observed period, particularly due to the pandemic. Autocorrelation is present in all assets except Brent and WIG, whereas all the time series report time-varying variance. These features of the time series can be resolved by some form of the AR-GARCH model. Besides, all the time series are stationary, as the DF-GLS test indicates, which is necessary for the GARCH modelling.

Tab. 1: Descriptive statistics of the selected assets

	Mean	Std. dev.	Skewness	Kurtosis	JB	LB(Q)	LB(Q^2)	DF-GLS
Brent	0.011	1.177	−1.562	26.170	38,310.0	0.241	0.000	−8.758
WIG	0.008	0.546	−1.248	17.372	14,654.9	0.155	0.000	−6.374
PX	0.010	0.419	−1.064	15.414	10,946.7	0.000	0.000	−7.403
BUX	0.015	0.574	−1.383	15.700	11,621.9	0.000	0.000	−20.909
SAX	0.000	0.418	−0.403	14.509	8,923.4	0.001	0.000	−44.632
OMXV	0.014	0.292	−3.096	56.475	198,993.5	0.000	0.000	−16.888
OMXR	0.017	0.504	−0.777	41.551	102,095.1	0.000	0.000	−15.721
OMXT	0.014	0.363	−2.460	34.828	71,785.7	0.000	0.000	−35.429
SOBITOP	0.014	0.372	−1.785	22.859	27,887.3	0.000	0.000	−5.765
BET	0.016	0.458	−1.709	24.696	33,185.9	0.000	0.000	−10.056
SOFIX	0.005	0.346	−2.451	35.449	73,144.7	0.000	0.000	−11.661
CROBEX	0.005	0.345	−3.468	48.391	144,426.2	0.000	0.000	−2.772

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

Source: own

Tab. 2: Long memory tests

	Absolute returns			Squared returns		
	Lo's R/S	**GPH**	**GSP**	**Lo's R/S**	**GPH**	**GSP**
Brent	3.864***	0.246***	0.257***	2.737***	0.178***	0.161***
WIG	4.400***	0.234***	0.235***	2.601***	0.161***	0.165***
PX	4.911***	0.305***	0.273***	3.248***	0.344***	0.290***
BUX	4.074***	0.295***	0.268***	2.766***	0.222***	0.209***
SAX	2.591***	0.105***	0.153***	1.660***	0.071***	0.070***
OMXV	3.301***	0.285***	0.271***	1.812*	0.210***	0.200***
OMXR	1.653	0.335***	0.302***	1.246	0.246***	0.240***
OMXT	4.864***	0.370***	0.314***	2.847***	0.381***	0.289***
SOBITOP	3.383***	0.359***	0.312***	2.481***	0.230***	0.215***
BET	2.531***	0.257***	0.241***	2.262***	0.195***	0.162***
SOFIX	3.274***	0.261***	0.249***	1.911**	0.148***	0.138***
CROBEX	2.601***	0.384***	0.322***	2.076***	0.285***	0.231***

Note: *** significance at 1% level, ** significance at 5% level; the critical values Lo's R/S statistics test are 90%: [0.861, 1.747], 95%: [0.809, 1.862] and 99%: [0.721, 2.098].

Source: own

Besides standard descriptive statistics, Tab. 2 tests the long memory property of the unconditional returns and unconditional volatility. Following Youssef (2015) and Alkathery et al. (2022), three tests are performed on absolute and squared returns. These tests are modified R/S statistics of Lo (1991), and two semiparametric estimates of Hurst coefficient, which are the long periodogram (GPH) estimate of Geweke and Poter-Hudak (1983) and Gaussian semiparametric (GSP) estimate of Robinson (1995). Tab. 2 clearly indicates that both GPH and GSP tests verify the presence of long memory for all assets in absolute and squared returns at very high probability. The same applies for the Lo's R/S test, except for the case of OMXR. This means that the use of the FIAPARCH model is justified.

Tab. 3 shows the estimated parameters of the FIAPARCH model of all assets, and also the Ljung-Box Q-statistics of level and squared residuals. The FIAPARCH model fits well for all time series, except for the Slovakian SAX index, where symmetric FIGARCH is used instead. In all cases, δ parameter is highly statistically significant, which means that all assets display strong evidence of volatility asymmetry.

In the seven out of twelve cases, γ parameter is positive and significant, suggesting that negative shocks affect volatility more than positive shocks, which is strong evidence that the leverage effect exists in the stock markets. In addition, all *d* parameters are highly statistically significant, which means that the long memory GARCH model can capture the long-range memory phenomenon. All *v* parameters are significant at 99% probability, indicating that Student *t* distribution recognizes fat-tail properties of the time series very well. The Ljung-Box test results suggest that the residuals are free of autocorrelation and heteroscedasticity issues and are therefore suitable for the dynamic CVaR calculation.

Tab. 3: Estimated FIAPARCH models of the selected assets

	Brent	POL	CZE	HUN	SLK	LIT	LAT	EST	SLO	ROM	BUL	CRO
Panel A: Variance equation												
α	0.248**	0.186	−0.152	0.152**	0.618***	−0.467	−0.216	0.315	0.137	0.138	−0.109	−0.001
β	0.476***	0.316***	−0.034	0.360***	0.189	−0.409	−0.181	0.281	0.165	0.311***	−0.046	0.086
γ	0.472*	0.997***	0.518***	0.437***	NA	−0.018	0.244**	−0.026	0.192***	0.390***	0.080	0.075
δ	1.532***	1.443***	1.692***	1.669***	NA	1.637***	1.767***	1.955***	1.689***	1.554***	1.572***	1.651***
d	0.309***	0.188***	0.214***	0.296***	0.371***	0.320***	0.252***	0.326***	0.264***	0.297***	0.234***	0.303***
v	4.509***	8.034***	5.931***	9.991***	2.139***	4.089***	3.243***	4.150***	4.792***	4.836***	4.357***	3.881***
Panel B: Diagnostic tests												
LB(Q)	0.272	0.247	0.529	0.783	0.369	0.329	0.212	0.402	0.377	0.171	0.535	0.222
LB(Q^2)	0.220	0.293	0.652	0.316	0.428	0.476	0.994	0.511	0.118	0.960	0.579	0.998

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

Source: own

Fig. 2 presents the log returns of the selected assets and the two dynamic VaR and CVaR risks, calculated at 95% probability. Fig. 2 clearly shows that extreme risk is present in the observed sample, which is especially evident in early 2020 when the pandemic erupted and in early 2022 when the war in Ukraine started.

The paper tries to estimate the multiscale spillover effect in different time horizons. In this regard, every dynamic downside CVaR time series is transformed into three wavelet scales: scale 1 (2–4 days), scale 5 (32–64 days), and scale 6 (64–128 days). We considered only these three scales in order to avoid results overload.

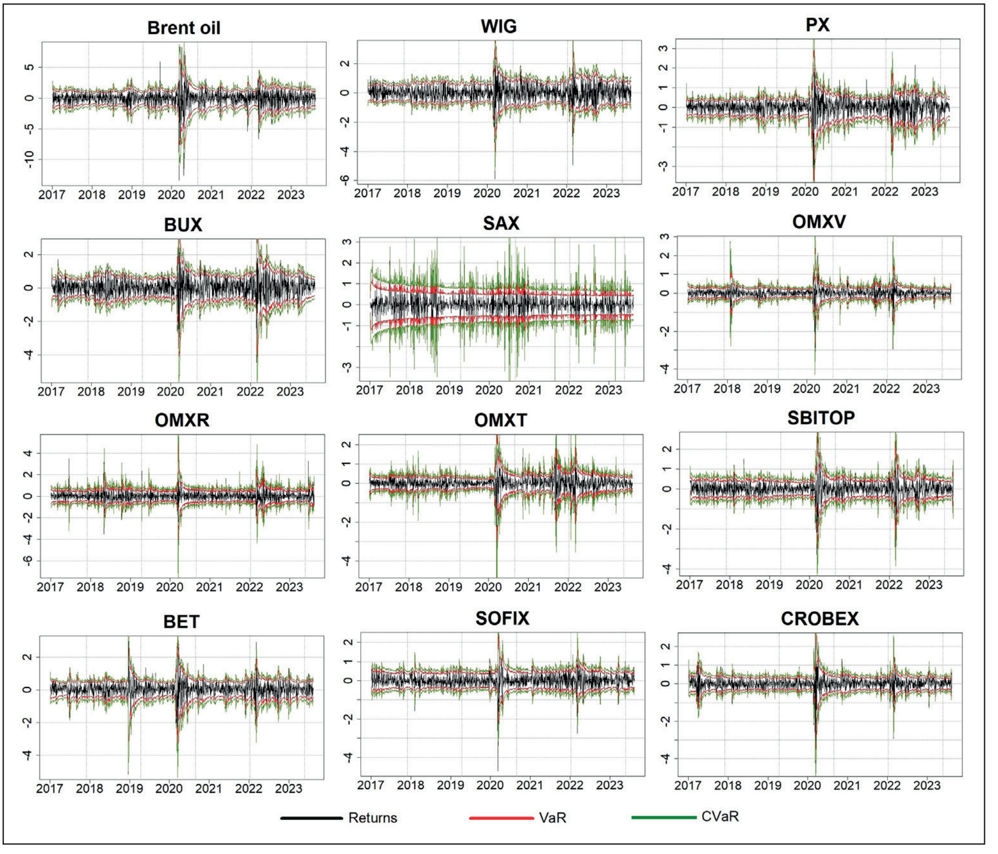

Fig. 2: **Calculated extreme downside and upside risk time series of the stock indices and Brent**

Source: own

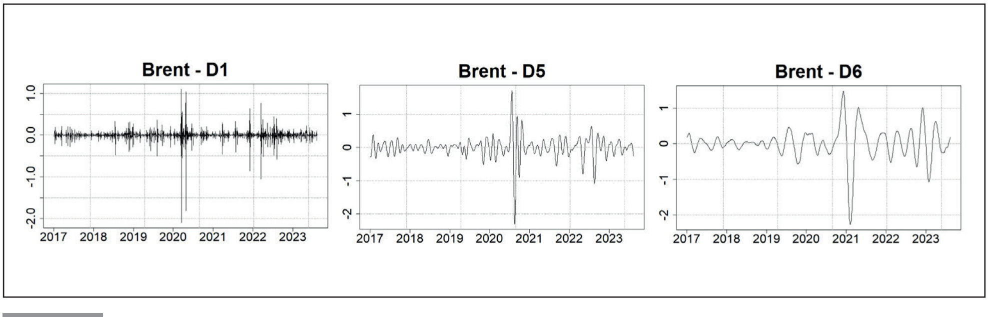

Fig. 3: **Three wavelet details of Brent oil**

Source: own

The first scale corresponds to the short-term horizon, whereas the fifth and sixth scales are regarded as mid-term and long-term, respectively. Fig. 3 shows three transformed wavelet time series of Brent oil using the MODWT methodology.

3. Results and discussion

3.1 Results

This section presents the results of the estimated wavelet-based two-state Markov switching model. State 1 (2) refers to the crisis (tranquil) period, respectively. Tab. 4 shows the results of regime-dependent ϕ parameters, transition probabilities, average expected duration of each regime and regime-specific error variances. All these values are calculated in respect to the three wavelet details. It can be seen that the regime parameters are different across the regimes, wavelet scales and countries, which justifies the use of the wavelet-based MS model.

Most of the regime-dependent parameters are highly statistically significant, which means that the extreme risk spillover phenomenon exists from Brent oil to stock markets in CEECs. On the other hand, the statistically significant parameters are positive and in line with logic in most cases, which suggests that when extreme risk rises in the oil market, the rise of risk in stock markets follows. Only in a few cases, we find statistically significant negative parameters, which means that rising risk in the oil market actually decreases extreme risk in the stock market. However, these parameters are very low, indicating that this counterintuitive phenomenon is very weak and almost non-existent.

Observing Panel A in Tab. 4, which portrays the short-term horizon, it can be seen that relatively strong spillover effect exists in both crisis and tranquil regimes. It is interesting to note that almost always, one regime parameter is significantly higher than the other, suggesting that the spillover effect happens dominantly in one regime. In particular, relatively high statistically significant parameters are found in Czechia, Hungary and Romania in the crisis regime,

Tab. 4: Estimated wavelet-based Markov switching models – Part 1

	POL	CZE	HUN	SLK	LIT	LAT	EST	SLO	ROM	BUL	CRO
Panel A: D1 wavelet scale											
ϕ_1	0.003	0.114***	0.195***	−0.009	0.091	−0.037	−0.010	0.018***	0.309***	0.008	0.042***
ϕ_2	0.170***	−0.002	0.000	−0.280	−0.004	0.024***	0.324***	0.436***	−0.004	0.273***	0.484***
P_{11}	0.920	0.840	0.710	0.900	0.750	0.760	0.930	0.930	0.850	0.930	0.960
P_{22}	0.750	0.920	0.920	0.790	0.970	0.950	0.770	0.700	0.800	0.730	0.720
ED_1	12.300	6.300	3.500	9.700	4.000	4.100	15.000	14.100	1.200	15.100	23.800
ED_2	4.000	12.200	11.900	4.800	32.000	18.50	4.400	3.300	5.000	3.700	3.600
σ_1^2	−3.980***	−2.410***	−2.110***	−3.030***	−1.530***	−1.280***	−3.360***	−3.570***	−1.790***	−3.980***	−3.840***
σ_2^2	−2.410***	−4.220***	−3.800***	−0.980***	−3.860***	−3.150***	−1.480***	−1.740***	−3.780***	−2.350***	−1.840***
Panel B: D5 wavelet scale											
ϕ_1	0.163***	0.370***	−0.002	−0.076***	0.256***	0.296***	0.323***	0.313***	0.114***	0.250***	0.330***
ϕ_2	0.351***	0.091***	0.500***	0.018	−0.005	0.059***	0.094***	0.012**	0.449***	−0.027***	0.014***
P_{11}	0.980	0.940	0.980	0.970	0.950	0.950	0.940	0.950	0.760	0.950	0.950
P_{22}	0.930	0.980	0.950	0.960	0.980	0.990	0.980	0.980	0.240	0.970	0.980
ED_1	48.400	17.700	41.100	36.300	20.300	21.800	16.300	20.600	4.200	20.100	20.800
ED_2	15.100	41.000	19.600	26.800	50.800	74.100	41.400	62.800	1.300	31.000	66.200
σ_1^2	−2.960***	−1.520***	−3.070***	−3.510***	−1.920***	−1.120***	−1.600***	−1.750	−2.720***	−2.380***	−1.600***
σ_2^2	−1.530***	−3.180***	−1.340***	−2.060***	−3.890***	−2.970***	−3.290***	−3.570	−1.370***	−4.100***	−3.510***

Tab. 4: Estimated wavelet-based Markov switching models – Part 2

	POL	CZE	HUN	SLK	LIT	LAT	EST	SLO	ROM	BUL	CRO
Panel C: D6 wavelet scale											
ϕ_1	0.064***	0.037***	0.438***	−0.003**	0.201***	−0.065***	0.263***	0.259***	0.371***	0.196***	0.013***
ϕ_2	0.301***	0.379***	0.045***	−0.016	0.003	0.315***	0.051***	0.027	0.107***	−0.020***	0.307***
P_{11}	0.970	0.980	0.970	0.970	0.970	0.980	0.980	0.980	0.390	0.980	0.980
P_{22}	0.970	0.970	0.980	0.960	0.990	0.970	0.990	0.990	0.600	0.980	0.970
ED_1	35.500	72.600	29.800	37.600	38.200	55.400	42.100	40.600	1.700	44.300	64.200
ED_2	31.000	34.500	44.400	25.900	66.800	36.900	78.600	73.700	2.500	49.400	37.500
σ_1^2	−3.520***	−3.250***	−1.730***	−3.750***	−1.970***	−3.160***	−1.520***	−1.810***	−1.600***	−2.770***	−3.750***
σ_2^2	−1.850***	−1.840***	−3.290***	−2.310***	−3.730***	−1.910***	−3.710***	−3.630***	−2.750***	−4.180***	−1.900***

Note: ***, **, * indicate significance at 1, 5 and 10% level, respectively; the regime-specific error-variances are shown in quadratic form, so they should be observed in absolute values.

Source: own

while five countries endure stronger extreme risk spillover effects when stock markets are in the calm regime (Poland, Estonia, Slovenia, Bulgaria and Croatia). In three countries (Slovakia, Lithuania and Latvia), the parameters are either insignificant or very low. In order to find a rational explanation for the results in Tab. 4, some peculiarities of the countries and stock markets need to be addressed. In other words, it is important to know the level of oil consumption per country, and also the number of stocks in the selected indices. The latter factor is relevant because not all companies listed in some indexes react equally to oil shocks, meaning that the greater the number of shares in the index, the greater the effect of dispersion, that is, the lower the impact of oil shocks on the index. In this regard, Tab. 5 contains oil consumption per capita and the number of stocks in the indices.

Czechia, Hungary and Romania endure the strongest spillover effect from oil in the crisis regime in the short term, 0.114, 0.195 and 0.309, respectively. At first glance, these results seem perplexing because Romania has the lowest oil consumption per capita (Tab. 5), but suffers the greatest impact from oil shocks. However, Romania is the largest oil producer in Central and Eastern Europe, according to CIA World Factbook data from 2020, with a production of 70.000 bbl per day. This means that the Romanian energy industry is an important contributor to the Romanian economy in terms of manufacturing, tax revenues, and export. Besides, several Romanian energy companies are listed in the BET index, which could be the reason why BET suffers the highest impact from the oil market in the crisis regime in the short term. On the other hand, for the Czech and Hungarian cases, the reasons are different. These stock exchanges, and particularly Hungarian, are among the most developed stock exchanges in Central and Eastern Europe, according to Baele et al. (2015), which means that these markets process new information the most effectively. This is especially true in turbulent times, which explains why statistically significant ϕ parameters are found in the first regime. In addition, it should be noted that expected duration of the crisis regime is significantly shorter compared to the calm regime in these countries, which is particularly true for the more developed Hungarian market. This signals that investors in these markets react promptly at any sign of negative information shocks in order to avoid further losses. These results coincide with Marek and Benada (2020), who investigated the Prague Stock Exchange. The Polish stock exchange is also in the group of the developed markets in CEECs, according to Baele et al. (2015), but ϕ parameter in the first regime is insignificant, which means that extreme oil shocks do not affect WIG in crisis, but rather in tranquil period. The rationale

Tab. 5: Oil consumption per capita and number of stocks in the indices

	POL	CZE	HUN	SLK	LIT	LAT	EST	SLO	ROM	BUL	CRO
Bbl/day per 1,000 people[a]	14.69	19.23	14.72	15.29	19.00	13.63	24.32	15.29	8.97	12.93	15.29
Number of stocks in index[b]	296	10	17	1	10	9	9	8	17	15	11

Note: Bbl – barrel of crude oil.

Source: own (based on [a] CIA World Factbook – information is accurate as of January 1, 2020 (Central Intelligence Agency, 2020); [b] https://www.investing.com, accessed on August 2023; www.nasdaqomxnordic.com is used for OMXV, OMXR and OMXT indices)

could lie in the fact that the Polish stock market is the biggest, with significantly more quoted companies than in any other country from Central and Eastern Europe (Tab. 5). This suggests that the effect of dispersion is more present in the Polish stock market than in any other CEEC.

In the cases of smaller and less developed markets, such as Estonia, Slovenia, Bulgaria and Croatia, we find relatively high parameters in the second regime. Estonia has the highest oil consumption per capita, while all other countries have relatively high oil consumption (Tab. 5). However, all these markets are relatively underdeveloped and illiquid, which means that the fast reaction of market participants to external shocks is not happening. This is probably the reason why extreme risk spillover is detected in the second regime. Slovakia, Lithuania and Latvia also belong to the group of less-developed markets, while the Slovakian stock market is particularly illiquid. In these cases, statistically significant ϕ parameters are not detected. In the Slovakian case, SAX lists only one company, Biotika, which is a pharmaceutical company that is by default less susceptible to oil shocks. This fact explains a lot of why statistically insignificant parameters are found in the Slovakian case.

Our results are generally in line with Salisu and Gupta (2021) and Gupta et al. (2021). The former paper researched the response of stock market volatility of the BRICS countries to oil shocks and found heterogeneous results. They asserted that differences in the economic size, financial system, oil production (consumption) profile of the countries and regulation efficiency can explain these divergences. The latter paper analysed the impact of different factors such as: global economic activity, oil supply, oil-specific consumption demand, and oil-inventory demand shocks on the tail risk of equity markets in the panel of 48 emerging and developed economies. They asserted that oil-specific consumption-demand shocks are associated with an increase in tail risks.

Looking at additional findings, Tab. 4 shows that all regime-dependent probabilities are relatively high, which refers to the likelihood of being in a particular state at a given point in time. This indicates the probability that the observed data at a specific time period were generated by a particular regime. Besides, all sigma parameters are highly significant, which means that a certain magnitude of volatility is present in each regime.

On the other hand, Panels B and C show results in midterm and long term, revealing different findings compared to the short-term horizon. In the first place, some countries, such as Lithuania and Latvia, report spillover effect in the longer time horizons, whereas this is not the case in the short term. Besides, the spillover effect intensity is generally higher in longer terms, which is especially the case for countries which have high spillover effect in the crisis regime, such as Czechia, Hungary and Romania. In particular, Czechia has significant ϕ parameters in midterm and long term in amounts of 0.370 and 0.379, respectively. Hungarian parameters are 0.500 and 0.438, while for the case of Romania, they are 0.449 and 0.371, respectively. Our findings of higher risk spillover effect in the longer time horizons is similar to Mensi et al. (2022b), who researched the extreme risk spillover effect from oil to ASEAN stock markets, using the CVaR measure of risk. They claimed that these results suggest that long-term spillovers persist more than short-term spillovers. The paper of Li and Wei (2018), also finds a higher oil spillover effect in the long term, researching the case of China. They explained that this may indicate that market participants are paying more attention to long-term volatility in the crude oil market when creating their trading strategies. It is interesting to note that Slovakia is the only country where the spillover effect is not found in the mid-term and long-term horizons, whatsoever, which strongly indicates that Slovakian stock market is highly inefficient and illiquid. This means that the Slovakian stock market is not capable to record shocks from the oil market in any time horizon.

3.2 Discussion

The results can have significant implications for investors in the CEE stock markets, portfolio managers and policymakers. The investors in stock markets should take into account the magnitude of the spillover effect during a crisis and tranquil conditions regarding different time horizons, in order to properly manage external oil shocks, which coincides with the paper of Jiang et al. (2022). In other words, knowing the size of the risk spillover effect, market participants could formulate workable hedging strategies that will mitigate the impact of oil markets. Also, in every stock exchange, different market participants operate in different time horizons. Therefore, having information about the size of the spillover effect in different time periods can indicate what type of hedging instruments market agents should apply in order to reduce extreme risk shocks from the oil market. In some instances, such as the Slovakian case, no hedging strategies are needed in any time horizon because the Slovakian stock market does not absorb oil shocks due to high illiquidity. Based on the results, investors in stock markets can decide whether and when to take short- or long-term positions in particular indices. The aforementioned is in line with the conclusions reached by Gupta et al. (2021), who asserted that investors must be aware that the nature of oil-market shocks matters in driving tail risks, and, hence, the corresponding impact on the equity premium is shock-dependent. They researched the effect of tail risk as we did, but with a different methodology and on a different sample. Our improvement compared to the paper of Gupta et al. (2021) is reflected in the fact that we add the wavelet methodology to distinguish between different time horizons.

Besides, the results have implications for portfolio managers or investors who want to pair oil with CEEC stock indices in the same portfolio. In other words, if a particular index endures a heavy risk spillover effect from the oil market, this is a strong indication that these two assets should not be combined in the same portfolio. For instance, it is not a good decision to combine the Romanian BET index with oil, when the stock market is in turbulent mode in the short time horizon. The same applies to the Estonian, Slovenian and Croatian index in tranquil times in the short term. On the other hand, when a less sensitive index to spillovers dominates the portfolio, diversification may be more effective. Being aware of the presence of risk spillovers requires thoughtful placement and careful rebalancing of the oil stock portfolio. This takes careful thinking about the perspective of different investment horizons because it is obvious that long-term stock investments are more exposed to extreme oil risk shocks than short-term investments. This is in line with the assertion of Tian et al. (2022), who state that fund managers and global investors should evaluate comprehensively the risk measurement of risk contagions and accordingly adjust their positions to optimize their portfolio strategies.

At the end, the results also have important message for policymakers and their macroprudential regulation measures. In other words, in those countries that are very susceptible to extreme risk shocks from the oil market, policymakers may need to implement and enforce stricter regulations to limit the risk transmission between oil and stock markets. These regulations could include requirements directed at financial institutions exposed to oil shocks or placing limits on their holdings of oil-related assets. In addition, regular stress testing of financial institutions to assess their vulnerability to oil price shocks can help identify potential weaknesses in the financial system and guide appropriate policy responses. Based on the different time horizons in which shock spillovers occur, it would be very useful if policymakers could implement targeted reforms that reduce the vulnerability of stock markets in different time horizons. Such reforms could help regulators to control systemic spillover effects while at the same time minimizing the fear effect arising from investor behavior during downturn market scenarios.

Conclusions

This paper investigates the extreme risk transmission from oil to eleven emerging stock markets of Central and Eastern Europe. In this process, the scale-dependent non-linear relationship is analysed. First, the dynamic CVaR time series are estimated by the long memory FIAPARCH model. Then, three decomposed wavelet details are created by the MODWT methodology, which reflects different time horizons. In the final step, the wavelet time series are embedded in the two-state Markov switching model that reveals non-linear dependence between the markets.

According to the results, most of the regime-dependent parameters are highly statistically significant, confirming that extreme risk spillover effect exists in the CEECs. The regime-dependent parameters are always significantly higher in one regime, which means that the spillover effect dominantly happens in one regime. Results are heterogeneous among the countries, which indicates that certain idiosyncratic characteristics of the countries are responsible for such findings. Relatively high statistically significant parameters are found in the cases of relatively developed Polish, Czech and Hungarian stock markets. On the other hand, the Romanian market does not belong to developed stock markets, but it is the largest oil producer in Central and Eastern Europe, whereas several Romanian energy companies are quoted on the Romanian stock exchange. This could be the reason why BET suffers the highest impact from the oil market in the crisis regime in the short term.

In the case of relatively small and inefficient stock markets, such as Estonia, Slovenia, Bulgaria and Croatia, the results indicate a relatively high spillover effect in the tranquil regime. All these countries have high oil consumption per capita, which might explain high spillover effect in the second regime. Slovakia, Lithuania and Latvia do not report the spillover effect whatsoever in the short term, probably because they are inefficient and illiquid. An interesting finding is that the spillover effect is stronger in longer time horizons, which suggests that the long-term spillover effect is more persistent than the short-term counterpart, and also, this could mean that market participants are more cautious about the long-term volatility in the crude oil market when making their trading strategies.

Based on the results, stock investors could formulate viable hedging strategies that will reduce the impact of oil markets. Portfolio managers could also benefit from the results, particularly those that combine oil and stocks in a portfolio. The policymakers could use the results to decide whether particular measures have to be implemented in order to reduce the vulnerability of stock markets in different time horizons.

This paper researches emerging East European countries, but future studies can use the same methodological approach, focusing on other emerging markets around the globe, e.g., the region of South East Asia, Central Asia, North Africa, Pacific-basin countries and countries of Latin America.

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