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Volatility spillover effects of oil, gold and bulk shipping prices on financial markets

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Abstract. *The volatility spillover effect plays an increasingly important role in the transmission of shocks mainly in recent periods, with the further advance of globalization and the rapid development in international linkages. This analysis of the interconnections between economic and financial markets has particular importance for investors in risk hedging strategies and portfolio diversification. Moreover, current turbulent periods, characterized by a volatile oil price, instability of gold price and supply bottlenecks caused by the outbreak of the COVID-19 pandemic impose the necessity to study this effect. The novelty brought by this paper is related to the analysis of the spillover effect coming from oil, commodity and bulk shipping markets to financial markets of Eastern-Europe emerging markets, namely Czech Republic, Hungary, Poland and Romania. To assess this effect, in this study it was implemented a widely used model in research papers model, more exactly the bivariate GARCH-BEKK (1,1) from the period July 2012 – February 2022. The results suggest the long-term memory of volatility in these markets, while direct interconnection and unidirectional spillovers effects are expected to be underlined by the volatility of gold returns on the stock markets returns.*

Keywords: volatility spillover, financial markets, contagion.

Introduction

The spillover effect, also known as financial contagion, began to prevail on financial markets with the currency crisis of July 1997 in Thailand, which produced global repercussions, initially in East Asia and then expanded to Russia and Brazil. Moreover, developed markets in North America and Europe were affected by price changes of financial instruments, which caused the collapse of the American Long-Term Capital Management (LTCM) investment fund. Therefore, the financial spillover effect is related to a significant increase in the correlation between markets, especially in times marked by economic turmoil (Forbes & Rigobon, 2002; Diebold & Yilmaz, 2009). When two markets are moderately correlated in a stable period, the occurrence of a shock on one of them implicitly manifests a ripple effect, leading to simultaneous spread on the second market.

This research study attempts to address two principal aspects. First, given the importance of crude oil, gold price and bulk shipping, their price fluctuations could exert a strong influence on financial markets. In recent periods, the further advance of globalization and the rapid development in international linkages play an important role in the transmission of shocks. Crude oil is a major source of energy in the entire world and there is no question that its volatility has increased in the period 2012-2022. Crude oil prices react to many factors, including supply and demand prospects and also the perceived risk of market disruptions. After the COVID-19 pandemic price crash that was unlike anything seen before, oil prices escalated as a result of production constraints and geopolitical tensions at a level that almost reached 100$ per barrel in February 2022. Besides this, in times of market volatility, gold tends to be a safe investment being desirable for investors, as a strategic inflation hedge. But, during the pandemic, the gold price was quite volatile, experiencing corrections from its peak. Last but not the least, the freight rates in the shipping industry are important for the price of a shipping company, affecting maritime markets. A surge in freight rates

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could threaten to push up import prices, having a profound impact on trade, especially in developing countries.

The analysis of spillover effects at economic and financial markets has a particular importance mainly in risk hedging strategies and portfolio diversification. One of the principles of investment strategies states that economic disruptions have specific, internal causes, so capital markets in different countries should have relatively low correlations. International economic diversification would therefore reduce portfolio risk and increase expected returns. Emerging markets are more vulnerable and susceptible to be affected by contagion effects as a result of significant corrections in asset markets.

To address the features aforementioned, we implement a bivariate generalized autoregressive conditional heteroskedasticity model using the BEKK method, namely GARCH – BEKK (1,1). This multivariate time series is widely used in the literature, commonly in economics, finance and capital markets to assess different levels of spillover or contagion effects (see among others Fedorova & Salem, 2009). This model, which was first proposed by Baba, Engle, Kraft and Kroner (1990) and then further developed by Engle and Kroner (1995) has the convenient specification to ensure positive definite covariance matrices under mild regularity and initial conditions. Therefore, we study the case of a bivariate system, where the volatility of Brent oil price, gold price, or bulk shipping costs represented by Baltic Dry index changes produce spillover effects, in turn, on the central-eastern European financial markets. The latter is represented by the stock market indices, as follows: PX index (Czech Republic), BUX index (Hungary), BET index (Romania) and WIG (Poland). The analysis covers almost ten years of daily data from 2012 to 2022. The results are in line with previous studies that validate the presence of this process.

The rest of the paper is structured as follows: the next section presents a survey of the literature related to financial contagion, then, in the third section we present the methodology of the univariate classical GARCH model and the extension to BEKK, that was implemented in this study. Section 4 describes the dataset introduced in this paper and presents results from this method. The last section concludes.

Literature review

As previously mentioned, the financial contagion or financial spillover is mainly related to the hypothesis that in an economically unstable period, such as a crisis, market evolutions tend to show similar patterns. But, there is disagreement in the literature (see among others Forbes & Rigobon, 2002) concerning a precise definition of this phenomenon and a delimitation between contagion and interdependence which is defined as a strong correlation between markets. Contagion occurs when an excessive transmission of shocks from one market, affected by a shock or a crisis, to another one arises beyond any idiosyncratic disturbances and fundamental linkages between them. Bekaert et al. (2005) define it as excessive correlation beyond and above what would be expected from economic fundamentals.

Rigobon (2001) assesses the transmission mechanisms of shocks using three econometric models: linear regression, logit/probit models and correlation coefficients. Starting from this approach, Serwa and Bohl (2005) analyze the contagion effect in financial markets from Europe. Specifically, they propose a comparison between developed markets in Western Europe and emerging markets in Eastern Europe to distinguish between contagion, interdependence and breaks in financial markets. According to them, a positive significant change in the correlation coefficients between a stable periodic and a turbulent one is seen as a change in the structure of these relationships and therefore provides evidence in the favor of contagion. Moreover, the diminishing

correlations between the returns of the capital markets can be interpreted as a break of the links between them. The authors note some patterns in the behavior of markets in terms of contagion and market fragmentation. Therefore, the conclusion reached by them was that the capital markets in Central and Eastern Europe are more vulnerable to the effect of contagion as opposed to those in Western Europe.

To explain the phenomenon of volatility transmission on financial markets, the literature distinguishes between pure contagion and fundamental contagion. On the one hand, Dornbush et al. (2000) argue that the effect can be explained by macroeconomic fundamentals such as interest rates, the balance of payments and inflation. It demonstrates that macroeconomic shocks have repercussions on an international scale and the local shocks transmitted through trade links, competitive devaluation and financial linkages are possible channels for the spread of crisis in different markets. On the other hand, the second meaning discussed in the study by Lin et al. (1994) attributes this effect to liquidity problems, information asymmetries and irrational investors behavior which can lead to herd effect, loss of confidence and increased risk aversion of investors.

The study of volatility models was materialized by estimating different analysis models. Using the impulse response approach to study the persistence of volatility shocks in market yields, Jin and An (2016) analyze the interdependence between the BRICS countries and the USA. Although the shocks are absorbed by the market almost simultaneously, their size and dynamics are specific to each country, for example, Brazil is the most volatile, while China seems to be more stable and isolated. In a chaotic financial environment specific to an unstable period, investors may overreact not only to local news but also to those from other markets, especially if they were adverse (Lim et al., 2008). A financial crisis like the one that started in 2007 can disrupt normal activity causing uncertainty, as it significantly influences the confidence of investors, who will have to sell their risky assets and turn them into cash.

Fedorova and Saleem (2010) show that at the level of four Central European Eastern European states: the Czech Republic, Poland, Hungary and Russia, the spread of volatility is present following the establishment of unidirectional and bidirectional links. Starting from three directions of analysis, namely, the effects produced by the interconnections between the money markets, the foreign exchange markets, respectively the connection between them at the level of each country, the authors study the transmission of shocks and volatility between 1995 and 2008 using an unrestricted bivariate model GARCH-BEKK (1,1). Based on a model widely used for this purpose, the authors find evidence of a clear link between countries in terms of both shocks and money market volatility.

The evolution of financial markets and the changing macroeconomic context as a result of the occurrence of events with a significant global impact may affect the interconnections that exist between two ore more states. Regarding the Central Eastern European countries, Reboredo et al. (2015) conducted an analysis concentrated on the Czech Republic, Poland, Hungary and Romania with implications for risk management, financial and economic policies. Although all countries are considered by the investor to be a homogenous group of investors, they have different grades of integration. Therefore, less developed markets have investment opportunities that could be exploited from the perspective of diversification of the portfolio of financial assets.

But the financial contagion is not the only one important when it comes to major events that are not related directly to the financial system. There are other crucial events such as pandemic crisis that triggered supply chain bottlenecks or an oil crisis that can become the one generated by the aggressive conflict between Russia and Ukraine in February 2022, as analysts appreciate. Numerous studies have analyzed the volatility spillover and linkages mechanism among the oil

market, commodity, shipping and financial markets. A shock in the price of oil, commodity, or shipping cost may differ depending on whether it is due to supply-side (e.g. disruptions in oil production) or the demand side. For example, Boldanov et al. (2016) prove that it is a dynamic correlation between the volatility of the oil market and the stock market which depend on the events. Therefore, studying the contagion of volatility could become determinant to understand developments in these markets. Also, the link between crude oil and financial markets is studied into a standard vector autoregressive with time-varying parameters (i.e TVP-VAR) by Chatziantoniou et al. (2021). Their findings suggest that the crude oil market is an important net transmitter of volatility shocks. Following a multivariate GARCH-BEKK methodology, Malik and Ewing (2009) provide evidence of significant spillover of both shocks and volatility between oil prices and some of the equity sectors.

Expanding this issue to the context of commodity markets, more particularly in the gold market, the research has been relatively less explored in the literature. Uncertainty usually drives investors to seek safer assets, such as gold which is described as a "safe-haven asset". Precious metals are likely to rise in the medium term, amid inflation and uncertainty. But, the pandemic COVID-19 outbreak demonstrated that the price of gold has been quite volatile and registered a decline due to increased panic that made investors liquidate their assets. Both crude oil and gold are used for hedging strategies and diversification. Pandey and Vipul (2017) suggest evidence of asymmetric volatility spillover from crude oil and gold to the BRICS market through widely used econometric models DCC (i.e. Dynamic Conditional Correlation), CCC (i.e. Constant Conditional Correlation) and Baba, Engle, Kraft and Kroner (BEKK) model. According to a sub-sample analysis of the authors, the volatility spillover from the gold market was not significant before the global financial crisis of 2008 but became significant after that.

Other limited studies are concentrated on the asymmetric and nonlinear linkages between cost shipping and the stock market and also on the contagion risk when an extreme event occurs. Gong et al. (2020) employ a tri-variate Markov-switching (MS) copula model finding stronger contemporaneous bidirectional lead-lag relationships between shipping freight market (using Baltic Dry Index index as a proxy) and US and Chinese stock markets. Moreover, contagion risk increases as a result of a decrease in the volume of US-China trade.

However, even if the literature paid smaller attention to emerging markets than developed countries, the different co-movements and volatility spillovers among these markets (e.g. CEE countries) are determinants in finding the best investment opportunities and protecting financial exposures.

Methodology

Univariate GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model

To measure markets volatility, there have been developed different econometric methods. Conventional methods such as standard variance or deviation are unconditional and cannot capture some key features of time series including volatility clustering, asymmetry, leverage, or long-term memory. One of the most representative models that capture the behavior of volatility turned out to be the GARCH (p,q) (Generalized Autoregressive Conditional Heteroskedasticity) model.

The first model, ARCH (p) was introduced by Engle (1982) and it has the following general form

$$\sigma_t^2 = \alpha + \sum_{i=1}^{q} \beta_i \, \varepsilon_{t-i}^2, \quad (1)$$

where σ_t^2 is the conditional variance and ε_t is the error terms. To obtain a positive conditional variance, are imposed: $\alpha > 0$, $\beta > 0$ și $\beta < 1$, also the process is stationary(Angabini & Wasiuzzaman, 2011). In the ARCH (p) model, the expected current volatility depends on the square of the estimated errors in the previous periods. In many applications, the ARCH model requires the length of the lag, and q can be very large. To overcome these limitations of ARCH models, Bollerslev et al. (1992) extended this model to have a much more flexible lag structure with long-term memory, by adding a variance conditioned by their lags. The proposed model, GARCH (p, q) (en. Generalized Autoregressive Conditional Heteroskedasticity) allows persistent volatility, specific to most financial series, having the representation in equation (3)

$$R_t = \mu + \varepsilon_t \tag{2}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2, \tag{3}$$

where p and q represent the orders of the GARCH and ARCH terms. R_t are the returns of the price series at time t, μ is an average value of yields, ε_t are error terms assumed to be normally distributed by zero mean and conditional variance given by σ_t^2, while μ, ω, α_i and β_j are the parameters of the model, which in the equation of the variance must be positive. As for ω, the expectations are that its value to be very small. Parameter α_i measures the volatility response to market developments and β_j express the persistence degree of the shocks caused by the extreme values of the conditional variances. It is expected that $\alpha + \beta < 1$. The GARCH (1,1) model is sufficient to capture all moments of volatility clustering in the data series.

$$\sigma_t^2 = \omega + \alpha_1 \, \varepsilon_{t-1}^2 + \beta_1 \, \sigma_{t-1}^2, \tag{4}$$

The GARCH model described above starts from the premise that both positive and negative error terms have symmetrical effects on volatility, namely positive and negative shocks have the same impact. A general finding of several studies is that negative returns tend to be followed more by periods of high volatility than those with positive returns. In other words, bad news will increase volatility more than good news.

Bivariate GARCH – BEKK model

The extension from the univariate to the bivariate model requires that the two-dimensional conditional variance-covariance matrix of zero-mean random terms depend on the information contained in the data set. The BEKK parameterization of the GARCH model proposed by Engle and Kroner (1995) provides an appropriate framework to assess the transmission of volatility between two markets. The BEKK model encompasses the hypothesis of a constant correlation and allows the dispersion of volatility in the markets. The empirical specification begins with a bivariate GARCH (1,1) for modeling the returns of each market to the previous period

$$R_t = \alpha + \beta R_{t-1} + u_t \tag{5}$$

$$u_t | \Omega_{t-1} \sim N(0, H_t) \, ,$$

where R_t is an $nx1$ vector of daily returns at time t for each market. The random error vector μ_t $(nx1)$ represents the innovations at time t corresponding to a conditional variance-covariance matrix H_t. The information available at time t-1 are captured by the matrix Ω_{t-1}. The spread of volatility on one's market and cross-markets is quantified by the estimated elements of the β matrix representing the parameters of the autoregressive term. This multivariate structure facilitates the assessment of the transmission of innovations from one market in own stock returns or delayed returns to other markets.

Given the above equation and following the parametrization of Engle and Kroner (1995) the variance-covariance matrix can be represented as follows

$$H_t = C_0'C_0 + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + G_{11}'H_{t-1}G_{11}\,, \tag{6}$$

where the matrix of parameters for the variance equation is defined as C_0, which is lower triangular restricted to ensure a positively defined variance-covariance H_t. The matrices A_{11} and G_{11} are unrestricted. In the matrix representation, equation (6) is equivalent to

$$\begin{aligned} H_t &= C_0'C_0 + [a_{11}\ a_{12}\ a_{21}\ a_{22}\ ]'\left[\varepsilon_{1,t-1}^2\ \varepsilon_{1,t-1}\varepsilon_{2,t-1}\ \varepsilon_{1,t-1}\varepsilon_{2,t-1}\ \varepsilon_{1,t-1}^2\ \right][a_{11}\ a_{12}\ a_{21}\ a_{22}\ ] \\ &+ [g_{11}\ g_{12}\ g_{21}\ g_{22}\ ]'H_{t-1}[g_{11}\ g_{12}\ g_{21}\ g_{22}\ ]\,, \end{aligned} \tag{7}$$

The above system can be estimated under the maximum log-likelihood method and can be optimized by the algorithm developed by Berndt, Hall, Hall and Hausman (BHHH). From the equation (7) it can obtain the log-likelihood $L(\theta)$ and the maximum likelihood function for T observations

$$L(\theta) = \sum_{t=1}^{T} l_t(\theta)$$

$$l_t(\theta) = -\,log\ log\ 2\pi\ - \frac{1}{2}log\ log\ |H_t(\theta)|\ - \frac{1}{2}\,\varepsilon_t'(\theta)\ log\ log\ H_t^{-1}(\theta)\varepsilon_t(\theta)\,, \tag{8}$$

where θ is the vector of all unknown parameters. This model was implemented using Eviews Software but it can be adapted to different restricted variants depending on the research questions.

To investigate the volatility spillover effects among oil, commodities, bulk shipping and stock markets, we use relevant proxies for all these markets. Thus, we use daily data from July 2012 to February 2022 for Brent spot crude oil that is the leading global price for this market, the price of gold, the cost of shipping bulk dry goods tracked by the Baltic Dry Index and reported daily by the Baltic Exchange in London. From the other side of the bi-directional linkages, we compute daily returns of stock market indices as following BET – the reference index developed by Bucharest Stock Exchange, BUX – the representative index for the capital market of Hungary, PX – the index of Prague Stock exchange and WIG – the Warsaw Stock Exchange index which include all listed companies. Data series are available on Investing.com financial platform.

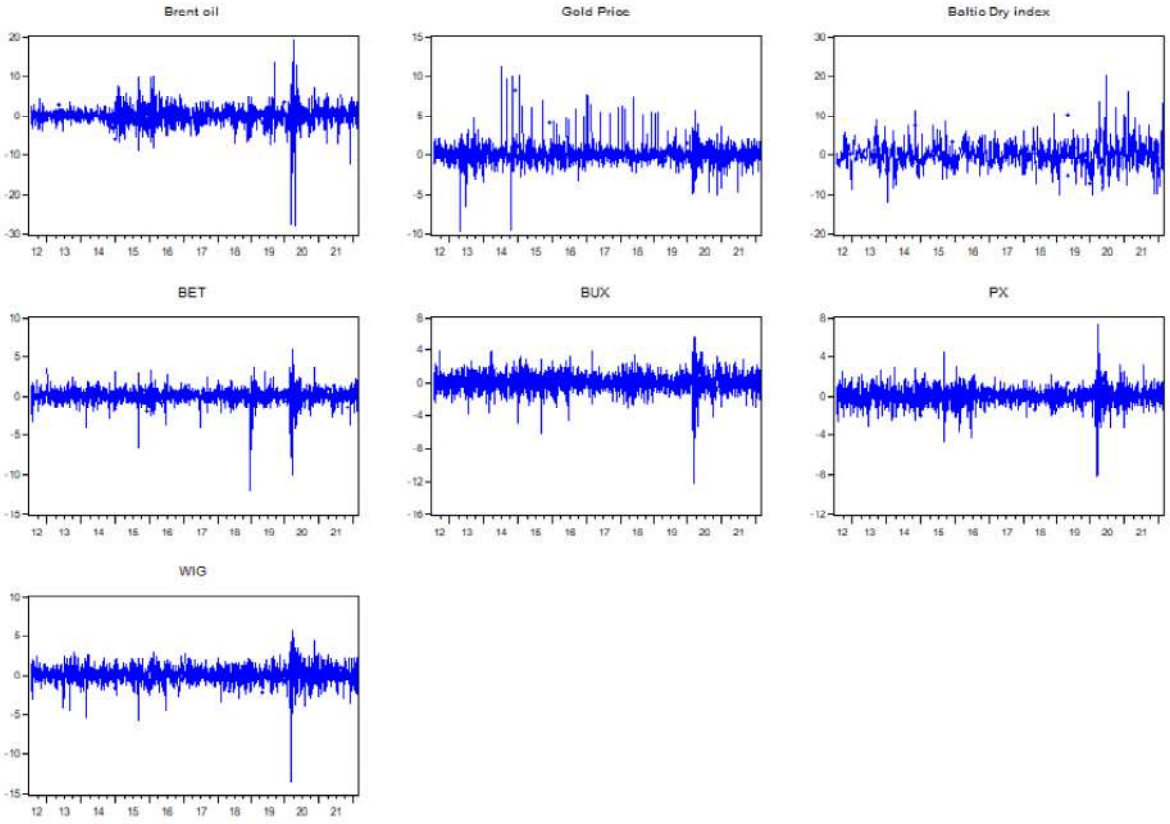


Figure 1. The evolution of the data series from July 2012 to February 2022
Source: Authors' own calculations, based on data available on www.investing.com.

Table 1. The correlation coefficients between variables

	Brent oil	Gold Price	Baltic Dry Index	BET	BUX	PX	WIG
Brent oil	1.0000						
Gold Price	0.2765	1.0000					
Baltic Dry index	-0.0755	-0.0226	1.0000				
BET	0.1417	0.0974	-0.0287	1.0000			
BUX	0.2035	0.0761	0.0220	0.2549	1.0000		
PX	0.2096	0.1125	-0.0120	0.3583	0.4259	1.0000	
WIG	0.1692	0.1776	-0.0340	0.2406	0.3412	0.4775	1.0000

Source: Authors' own research.

In Figure 1, we plot the evolution of daily data returns between the period July 2012 to February 2022. We can see that these indicators are quite volatile, especially in turbulent periods such as the COVID-19 pandemic. The outbreak of the pandemic led to a significant decline in market returns, then bounced back with positive returns in a short period. As regards the degree of correlation between these indicators, the coefficients prove that financial markets are more mutually correlated and are moving in the same way. But there is also a little correlation degree between the oil market and financial markets that should be taken into account.

Results and discussions

The GARCH (1,1) is the most commonly used specification to model volatility assuming that the variance in the next period is a weighted average of the long-term average variation of that period and the information captured by the squared residuals from the current period. It also supposes that the response of a shock is independent of its sign, being only a function that depends on size.

As it can be seen in Table 1, all estimated parameters of the GARCH (1,1) model are statistically significant at 1% level and present a notable GARCH effect (i.e. exhibit the persistence or long-memory in volatility) given by the β_1 coefficient, except for Baltic Bry Index returns. This latter aspect could be explained by the definition of this indicator as a benchmark for the price paid for the transport of dry bulk materials. Also, the most pronounced volatility persistence is revealed by the stock market returns and Brent oil price. The sum of the two coefficients is very close to one which suggests the specifications GARCH process described by Bollerslev (1986).

Table 1. The parameters of GARCH (1,1) for modeling volatility

	Brent Oil	*Gold Price*	*Baltic Dry index*	*BET*	*BUX*	*PX*	*WIG*
α 1	0.1219***	0.0427***	0.7522***	0.2416***	0.0914***	0.0987***	0.0691***
	(0.006)	(0.0043)	(0.0535)	(0.0129)	(0.0097)	(0.0101)	(0.0063)
β 1	0.8743***	0.6657***	0.0942***	0.6809***	0.8547***	0.8626***	0.8944***
	(0.0061)	(0.0290)	(0.02675)	(0.0162)	(0.0165)	(0.0146)	(0.0123)

*** significant at 1%, ** significant at 5%, * significant at 10%.

Source: Authors' own research.

The multivariate model following the BEKK methodology used in this paper assesses the transmission of long-term volatility of oil, gold and bulk shipping markets on central-eastern European countries' capital markets: Czech Republic, Hungary, Poland and Romania (see below Table 2 – Table 5).

The elements of the diagonal of the matrix A, a_{ii}measure the ARCH effect given by the own shock in the conditional variance of respective series. This is validated for all models and indicates the major role played by the previous shocks on volatility in emerging markets. The value estimated on the diagonal of matrix G, g_{ii}, quantify the effect of the previous volatility in the present conditional volatility. All parameters are significant at 1% level of significance and the values close to one indicate a long-term memory of volatility discussed above.

The study objective of this paper, the volatility spillover, can be measured by the elements outside the main diagonal of the matrices A and G. Therefore, the elements below of the matrix A, a_{ij}, captures the effect of previous shocks to measure the interconnection between the two markets. For all countries, there is a stronger transmission of innovation from the gold market to capital markets.

Regarding the interconnection of stock market volatility according to the GARCH-BEKK (1,1) model, the term outside the main diagonal corresponding to the lower triangular matrix G, g_{ij}, explain to what extent the conditional variance of market j is influenced by the effect of the volatility in the immediately previous period of the other market i. Thus, for each of these countries, the conditional volatility of index return is negatively influenced by the volatility of the gold market, while for the other two markets the estimated coefficients are not statistically significant.

This means that there are no spillover effects or contagion effects from the oil market or bulk shipping market on stock markets.

Table 2. The bi-variate GARCH – BEKK (1,1) for volatility spillover to Czech stock market

Coefficient	Brent Oil - PX	Gold price - PX	Baltic Dry index - PX
c11	0.2724***	0.7087***	1.600***
	(0.0223)	(0.0324)	(0.0387)
c12	0.0343	0.0015	-0.0202
	(0.0238)	(0.0124)	(0.0322)
c22	0.1521***	0.1691***	0.1344***
	(0.0144)	(0.0158)	(0.0154)
a11	0.3112***	0.1800***	0.8575***
	(0.0122)	(0.0099)	(0.0297)
a21	0.0597*	0.1648***	0.1609***
	(0.0330)	(0.0213)	(0.0395)
a22	0.2629***	0.3008***	0.2576***
	(0.0114)	(0.0149)	(0.0110)
g11	0.9453***	0.7911***	0.1802***
	(0.0040)	(0.0198)	(0.0527)
g21	-0.0230	-0.0680***	0.0443
	(0.0149)	(0.0133)	(0.0740)
g22	0.9488***	0.9347***	0.9544***
	(0.0055)	(0.0071)	(0.0044)

*** significant at 1%, ** significant at 5%, * significant at 10%.

Source: Authors' own research

Table 3. The bi-variate GARCH – BEKK (1,1) for volatility spillover to Hungarian stock market

Coefficient	Brent Oil - BUX	Gold price - BUX	Baltic Dry index - BUX
c11	0.2655***	0.7330***	1.5268***
	(0.0219)	(0.0315)	(0.0444)
c12	0.10544**	0.0649***	-0.0312
	(0.0419)	(0.0187)	(0.0452)
c22	0.2178***	0.2933***	0.2113***
	(0.0289)	(0.0271)	(0.0227)
a11	0.3177***	0.1937***	0.8495***
	(0.0123)	(0.0103)	(0.03117)
a21	0.0483*	0.1693***	0.1143***
	(0.0256)	(0.0210)	(0.0410)
a22	0.2593***	0.3215***	0.2371***
	(0.0126)	(0.0187)	(0.01126)
g11	0.9447***	0.7630***	0.2878***
	(0.0037)	(0.0197)	(0.0439)
g21	-0.0323	-0.1103***	0.0417
	(0.0139)	(0.01432)	(0.0582)

Coefficient	Brent Oil - BUX	Gold price - BUX	Baltic Dry index - BUX
g22	0.9406*** (0.0073)	0.9071*** (0.0119)	0.9521*** (0.0060)

*** significant at 1%, ** significant at 5%, * significant at 10%.

Source: Authors' own research.

Table 4. The bi-variate GARCH – BEKK (1,1) model for volatility spillover to Polish stock market

Coefficient	Brent Oil - WIG	Gold price - WIG	Baltic Dry index - WIG
c11	0.2802*** (0.0226)	0.8076*** (0.0281)	1.5233*** (0.0457)
c12	0.0098 (0.03672)	0.0562*** (0.0140)	-0.0389 (0.0455)
c22	0.1918*** (0.0187)	0.2123*** (0.0231)	0.1522*** (0.0189)
a11	0.3375*** (0.0132)	-0.1669*** (0.0096)	0.8526*** (0.0309)
a21	-0.0498 (0.0313)	0.1784*** (0.0200)	0.1314*** (0.0379)
a22	0.2358*** (0.0101)	0.2713*** (0.0128)	0.2162*** (0.0088)
g11	0.9364*** (0.0044)	0.7279*** (0.0211)	0.2805*** (0.0434)
g21	0.0188 (0.0166)	-0.0863*** (0.01213)	0.0705 (0.0689)
g22	0.9533*** (0.0055)	0.9377*** (0.0128)	0.9643*** (0.0038)

*** significant at 1%, ** significant at 5%, * significant at 10%.

Source: Authors' own research.

Table 5. The bi-variate GARCH – BEKK (1,1) for volatility spillover to Romanian stock market

Coefficient	Brent Oil - BET	Gold price - BET	Baltic Dry index - BET
c11	0.2344*** (0.0214)	0.6201*** (0.0377)	1.5808*** (0.0434)
c12	-0.0337 (0.0603)	0.0271** (0.0107)	-0.0311 (0.0494)
c22	0.4301*** (0.0171)	0.3124*** (0.0169)	0.2574*** (0.0017)
a11	0.2686*** (0.0119)	0.1398*** (0.0087)	0.8551*** (0.0294)
a21	0.1195** (0.0539)	0.1937*** (0.0256)	0.1673*** (0.0518)
a22	0.4912*** (0.0187)	0.4816*** (0.0133)	0.3824*** (0.0157)
g11	0.9556***	0.8421***	-0.2249***

Coefficient	Brent Oil - BET	Gold price - BET	Baltic Dry index - BET
	(0.0033)	(0.0197)	(0.0453)
g21	0.0045	-0.1183***	0.0886
	(0.0407)	(0.0128)	(0.1202)
g22	0.7465***	0.8235***	0.8871***
	(0.0132)	(0.0099)	(0.0092)

*** significant at 1%, ** significant at 5%, * significant at 10%.

Source: Authors' own research.

Conclusion

This paper aims to study the spillover effect or contagion effect of volatility from oil, gold and bulk shipping markets to eastern-European stock markets: Czech Republic, Hungary, Poland and Romania. In recent periods, the further advance of globalization and the rapid development in international linkages play an increasingly notable role in the transmission mechanism of shocks. The analysis of spillover effects at economic and financial markets has particular importance for investors mainly in risk hedging strategies and portfolio diversification. To address this research question, we implement a bivariate generalized autoregressive conditional heteroskedasticity model using the BEKK methodology, most exactly GARCH – BEKK (1,1). This multivariate time series model is widely used in literature, commonly in economics, finance and capital markets to assess different levels of spillover or contagion effects.

The results suggest that these indicators have a long-term memory of volatility and also previous shocks play an important role in volatility in these emerging markets. As regards the interconnection between these markets, the conditional volatility of index returns is negatively influenced by the volatility of the gold market, while for the other two markets the estimated coefficients are not statistically significant.

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