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IDIOSYNCRATIC VOLATILITY TRANSMISSION BETWEEN VISEGRAD STOCK MARKETS – THE ROBUST QUANTILE ESTIMATES

Abstract: *This paper investigates the idiosyncratic volatility transmission effect between four stock markets of Visegrad group countries. The research process involves isolation of the global market noises from the empirical time-series, the use of an innovative NAGARCH-NIG model for conditional volatility creation and risk transmission measurement via a robust quantile regression model. We find that the highest volatility spillover effect exists between Prague, Warsaw and Budapest stock markets, whereas Bratislava stock market receives and transmits a very low level of volatilities towards other three markets, regarding both tranquil and crisis periods. The most likely reason for such findings is the fact that the Slovakian stock market has the lowest level of market capitalisation and the lowest average daily trading volumes. However, this makes the SAX index a very suitable investment instrument in combination with the other three indices, whereas the best combination is the SAX index with WIG.*

Keywords: *volatility transmission, GARCH, robust quantile regression, Visegrad group stock indices*

JEL classification: C21, G11, G32

1. Introduction

It is a known fact that financial globalisation has contributed significantly to the process of financial ties strengthening between regional stock markets. Volatility spillovers and macroeconomic news transmission are two prominent types of impact that emerging stock markets receive, according to Hanousek and Kočenda (2011). In addition, foreign institutional investors from around the world

DOI: 10.24818/18423264/57.1.23.16

that seek diversification opportunities are present in emerging equity markets in great deal, and their activities set a stage for rapid transfer of news between the markets. Ross (1989) asserted that synonymous for information transfer is volatility spillover effect, since changes in variance, and not the asset's price change, reflects the arrival of information in the market. He documented that the variance of price changes is directly related to the rate of information flow to the market. Knowing the exact volume of volatility transmission between the markets is very important for international risk hedgers, because if stronger international volatility linkages exist between stock markets, the benefits of international portfolio diversification may liquefy. Demiralay and Bayraci (2015) listed several factors that explain why it is important to understand the speed and scope of volatility transmission between stock markets. First, the existence of volatility spillover effect prompts a possibility to generate excess returns. Second, it can enhance risk predictions, producing more accurate asset pricing and value-at-risk assessments. Third, information about which stock market is transmitter and which one is recipient of volatility shocks can help portfolio managers in their tactical asset allocation efforts and construction of multi-asset portfolios. Last but not least, policymakers can use this knowledge to design a proper monetary policy mechanism that can successfully address financial stability issues.

The focal point of this paper is four stock markets of Visegrad group – the Czech Republic, Poland, Hungary and Slovakia, which is one coherent and integrated group of fast-growing emerging markets (see, e.g., Jasova, 2015; Hanus and Vacha, 2020). The primary reasons why we address the topic of volatility spillover between these economies is the fact that this effect is grossly underresearched in emerging European equity markets, according to Hanousek and Kočenda (2011). Therefore, there is plenty of room for our contribution in this field of research.

We try to put an emphasis on the accuarcy and reliability of the obtained results. To this end, we use several sophisticated and elaborate methodological approaches, which compose our procedure of three steps. First, we address the issue of endogeneity, which means that exogeneous variables are correlated with the error term. In order to resolve this problem, we isolate the global shock effect from the empirical series, following the procedure of Bali and Cakici (2008). In this way, we can observe only intrinsic characteristics of these markets, highlighting at the same time the idiosyncratic volatility transmission between the selected stock markets.

After the extraction of idiosyncratic residuals, in the second stage, we try to accurately measure volatilities of the selected time-series. Most commonly, researchers create conditional volatilities by using a simple type of GARCH model. However, the problems may occur in this procedure when empirical data have no-normal characteristics, such as strong asymmetry, skewness, and heavy tails. In order to address these issues, we combine relatively novel nonlinear asymmetric GARCH (NA-GARCH) model of Engle and Ng (1993), along with elaborate distribution functions – normal inverse gaussian (NIG) distribution. This approach is in contrast to the majority of studies that have used only the simple GARCH model with the ordinary normal distribution. Chen et al. (2008) explained that the major weakness of the GARCH-normal type model is that it assumes a specific functional form before any estimations are made, which, as a result, could yield biased coefficient estimates and standard errors.

The last stage of our three-fold procedure involves the measurement of the idiosyncratic volatility spillover effect from neighbouring stock markets to the recipient stock market, and this procedure is repeated for all selected indices. This estimation is done by inserting idiosyncratic conditional volatilities into the recently developed sophisticated econometric methodology – robust quantile regression (RQR) of Wichitaksorn et al. (2014). This complex and elaborate quantile regression technique uses a likelihood-based approach for the quantile parameter estimation, but in the estimation process it considers several relatively recently developed skewed distributions – Normal, Student-t, Laplace, contaminated Normal and Slash distribution. It is known that researchers that use traditional QR approach of Koenker and Bassett (1978) usually disregard the choice of proper density function, because QR estimates quantile parameters that make irrelevant the choice of the best-fitting distribution. However, if quantile regression is estimated under the optimal distribution function, then it increases robustness of the parameters, which is crucial for the reliability of results. In other words, it gives us the assurance that the obtained results are unbiased and trustworthy. More specifically, the robust QR methodology decreases the length of credible intervals and increases the accuracy of quantile estimates, compared to the traditional QR approach of Koenker and Bassett (1978). Applying RQR methodology, we can measure the volatility transmission effect across the quantiles, which provides us with accurate information regarding the magnitude of the spillover effect in the states of low, moderate, and high volatility conditions.

In addition to the introduction, the rest of the paper is structured as follows. The second section contains a review of the literature. The third section explains the methodologies used, whereas the fourth section presents dataset and auxiliary calculations. The fifth section is reserved for the robust quantile regression results. The sixth section discusses the findings and concludes.

2. Brief literature review

Many research papers analysed the risk spillover phenomenon between stock markets around the globe, while some of them are presented in the following. For instance, Li and Giles (2015) examined the linkages of stock markets across the USA, Japan, and six Asian developing countries: China, India, Indonesia, Malaysia, the Philippines, and Thailand, using an asymmetric BEKK-GARCH model. They disclosed that there is a significant unidirectional shock and volatility spillover effect from the US market to both the Japanese and the Asian emerging markets. Their results also indicated that the volatility spillovers between the US market and the Asian markets are stronger and bidirectional during the Asian financial crisis. Finta et al. (2017) researched the contemporaneous volatility spillover effects between the US and the UK equity markets, using high-frequency data. They found that when markets trade simultaneously increases, the US stock market volatility has a greater impact on the UK stock market volatility than the other way around. Nishimura et al. (2016) studied the effects of return and volatility spillover during periods in which trading hours in China and Japan overlap, using high-frequency data. Their results suggested a unidirectional influence of the Chinese stock market on Japanese markets in terms of returns. They explained that this result is likely attributable to restrictions on foreign investment in the Chinese market. On the other hand, they found no volatility spillover effects between the Chinese and Japanese markets. According to our best knowledge, only Demiralay and Bayraci (2015), using the generalised VAR methodology of Diebold and Yilmaz (2012), investigated volatility spillover phenomenon in three Visegrad countries – the Czech Republic, Poland and Hungary, and they also researched the effect *vis-à-vis* Germany, the US and Russia. They reported that strong volatility links exist among the CEEC, asserting that these markets were exposed to higher volatility in the periods of extreme market conditions; particularly, it applies for the US subprime mortgage crisis and the subsequent eurozone crisis.

3. Methodologies

3.1. Creation of idiosyncratic residuals

The first stage of our three-step procedure involves isolation of the common factor in the Visegrad stocks markets that is related to broader market developments, which contains the weight of a global systemic turbulence. By doing this, we can capture an idiosyncratic volatility that has only characteristic features of each of the examined stock markets. We refer to the papers of Bali and Cakici (2008) and Vo and Phan (2019), in order to properly decompose empirical returns into the market-related component and the idiosyncratic component. These authors extracted an idiosyncratic volatility by employing a single-factor model in the following way:

$$r_{i,t} = C + \Theta r_{m,t} + \epsilon_{i,t} \tag{1}$$

where $r_{i,t}$ and $r_{m,t}$ are returns of individual stock market (i) and global market (m). The global market is proxied by the US S&P500 index, which describes global developments more realistically. C and Θ are common regression parameters, while $\epsilon_{i,t}$ denotes regression residuals that are free of noises from the global market. These residuals are further used in the NA-GARCH model with NIG distribution in the process of idiosyncratic volatilities estimation.

3.2. Estimation of idiosyncratic conditional volatilities

In order to estimate conditional volatilities as accurate as possible, we couple NA-GARCH model with normal inverse gaussian (NIG) distribution[1]. To avoid autocorrelation bias, we consider the AR(1) specification in the mean equation. The error term (ε_t) in the mean equation follows the $\varepsilon_t \sim NIG(0, h_t)$ process. Equation (2) presents the mathematical formulation of the NA-GARCH model.

$$\sigma_t^2 = c + \omega_2 \sigma_{t-1}^2 + \omega_1 \sigma_{t-1}^2 (\varepsilon_{t-1}^2 - \omega_3)^2 \quad (2)$$

where σ_t^2 is conditional variance, constant term is denoted by c, while ω_1, ω_2 and ω_2 are estimated parameters. In particular, ω_1 captures the persistence of volatility, ω_2 gauges an ARCH effect, while ω_3 measures asymmetric response of volatility to positive and negative shocks. Equation (3) presents unconventional heavy-tailed distributions – normal inverse Gaussian distribution (NIG) of Barndorff-Nielsen (1997). The NIG distribution can recognise heavier tails than the conventional distribution that are often skewed and asymmetric, which can contribute to a more precise measurement of idiosyncratic conditional volatilities.

$$f(x) = \frac{\delta\alpha \exp\left(\delta\sqrt{\alpha^2-\beta^2}\right) K_1\left(\alpha\sqrt{\delta^2+(x-\mu)^2}\right) \exp\left(\beta(x-\mu)\right)}{\pi\sqrt{\delta^2+(x-\mu)^2}}; \quad x \to \pm\infty \quad (3)$$

where $\delta > 0$ and $0 < |\beta| \leq \alpha$. Scale and location are determined by the μ and δ parameters, respectively. Shape and density are controlled by α and β parameters, respectively. K_1 is modified Bessel function of the third kind. Symmetric distribution happens if $\beta = 0$.

3.3. Robust quantile regression methodology

Considering general quantile regression, Yu and Moyeed (2001) introduced a Bayesian modelling approach by using the asymmetric Laplace distribution (ALD). ALD has the zero-quantile property and a useful stochastic representation, but it is not differentiable at zero, which could cause problems of numerical instability, according to Morales et al. (2017). Therefore, setting a quantile regression model through the classical or Bayesian framework with the Laplace density is a pretty strong assumption. In order to resolve this deficiency, Wichitaksorn et al. (2014) proposed a generalised class of skew densities (SKD) for the analysis of QR that provides competing solutions to the ALD-based formulation. In particular, the procedure of the robust skew density class distributions construction involves mixing a skew-normal distribution of Fernandez

[1] Estimation was done via the 'rugarch' package in 'R' software.

and Steel (1998) and the symmetric class of scale mixture of normal distributions of Andrews and Mallows (1974). According to Morales et al. (2017), y has a skewed distribution (SKD) with location parameter μ, scale parameter σ, skewness parameter p and weight function $\kappa(\cdot)$, if y can be presented stochastically as $y = \mu + \sigma\kappa(U)^{1/2}Z$, where Z follows skewed normal distribution (SKN), $Z \sim SKN(0,1,p)$. If U is integrated out, then the marginal probability density function (pdf) of y is given as in equation (4):

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

From the expression (4), several skewed and thick-tailed distributions can be built, taking into account different specifications of the weight function $\kappa(\cdot)$ and $pdf\ h(u|\nu)$. These functions are Student-t, Laplace, slash distribution and contaminated Normal distribution. Their mathematical presentations are given in Table 1.

Table 1. Mathematical presentation of skewed distributions

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

Our goal is to measure the complex dependence structure between idiosyncratic volatilities of Visegrad group stocks, using robust quantile regression[2] approach. Therefore, the multivariate conditional quantile function (Q), assuming dependent variable (y) at quantile τ, corresponding regressors (x) and some form of distribution function (F_u) of the errors, can be defined for every index as in equations (5) to (8):

$$Q_{y(PX)}(\tau|x) = \varpi_0 + \varpi_1 x_{WIG} + \varpi_2 x_{BUX} + \varpi_3 x_{SAX} + F_u^{-1}(\tau) \quad (5)$$

$$Q_{y(WIG)}(\tau|x) = \varpi_0 + \varpi_1 x_{PX} + \varpi_2 x_{BUX} + \varpi_3 x_{SAX} + F_u^{-1}(\tau) \quad (6)$$

$$Q_{y(BUX)}(\tau|x) = \varpi_0 + \varpi_1 x_{PX} + \varpi_2 x_{WIG} + \varpi_3 x_{SAX} + F_u^{-1}(\tau) \quad (7)$$

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

$$Q_{y(SAX)}(\tau|x) = \varpi_0 + \varpi_1 x_{PX} + \varpi_2 x_{WIG} + +\varpi_3 x_{BUX} + F_u^{-1}(\tau) \quad (8)$$

where ϖ_0, ϖ_1, ϖ_2, ϖ_3 are the parameters to be estimated. The quantile regression estimation of the particular quantile parameter β_τ can be achieved by minimisation of equation (9):

$$\hat{\beta}(\tau) = \text{argmin} \sum_{i=1}^{n} \rho_\tau(y_i - x_i^{\prime}\beta); \quad \beta \in \Re \quad (9)$$

where $\tau \in (0, 1)$ is any quantile of interest, while $\rho_\tau(z) = z(\tau - I(z < 0))$ and $I(\cdot)$ stands for the indicator function. It is very important to emphasise that connection between the minimisation of the sum in equation (9) and the maximum likelihood theory exists. More specifically, minimisation of equation (9) is equivalent to maximisation of the likelihood function when data follows some form of distribution densities, observed in the family of zero conditional quantile skewed distributions, as presented in Table 1.

4. Dataset and auxiliary calculations

This paper uses daily closing prices of four Visegrad group indices – PX (the Czech Republic), WIG (Poland), BUX (Hungary), and SAX (Slovakia). The sample covers the period between January 2003 and September 2021, whereby all time series are collected from the *stooq.com* website. We transform the empirical closing prices (P) of the selected stock indices into log returns (r) according to the expression $r_{i,t} = 100 \times \log(P_{i,t}/P_{i,t-1})$, where i stands for particular stock index. Due to the unavailability of some empirical data, we synchronise all stock indices according to the existing observations. Table 2 contains stylised facts of the empirical time-series.

Table 2. Statistical properties of the idiosyncratic residuals of the selected indices

	Mean	St. dev.	Skewness	Kurtosis	JB	LB(Q)	LB(Q^2)
PX	0.014	1.317	-0.595	20.516	51817.8	0.000	0.000
WIG	0.033	1.176	-0.435	6.840	2724.1	0.000	0.000
BUX	0.040	1.458	-0.123	10.496	9857.2	0.000	0.000
SAX	0.023	1.130	-0.950	21.343	58394.5	0.000	0.000

Notes: JB stands for values of Jarque-Bera coefficients of normality, LB(Q) and LB(Q2) tests denote p-values of Ljung-Box Q-statistics of level and squared residuals for 20 lags.

It can be seen that all indices have positive daily average return, whereby BUX has the highest average return, while SAX follows. It is also noticeable that these returns are more left-asymmetric, fat-tailed, and high-peaked than the Gaussian distribution. LB(Q) and LB(Q^2) tests suggest the presence of autocorrelation and heteroscedasticity, which means that the usage of the AR(1)-NA-GARCH model might be appropriate. Figure 1 presents estimated conditional volatilities of four indices, created by the NA-GARCH model with NIG distribution. These time-series serve as measures of risk, which are subsequently embedded in the RQR model.

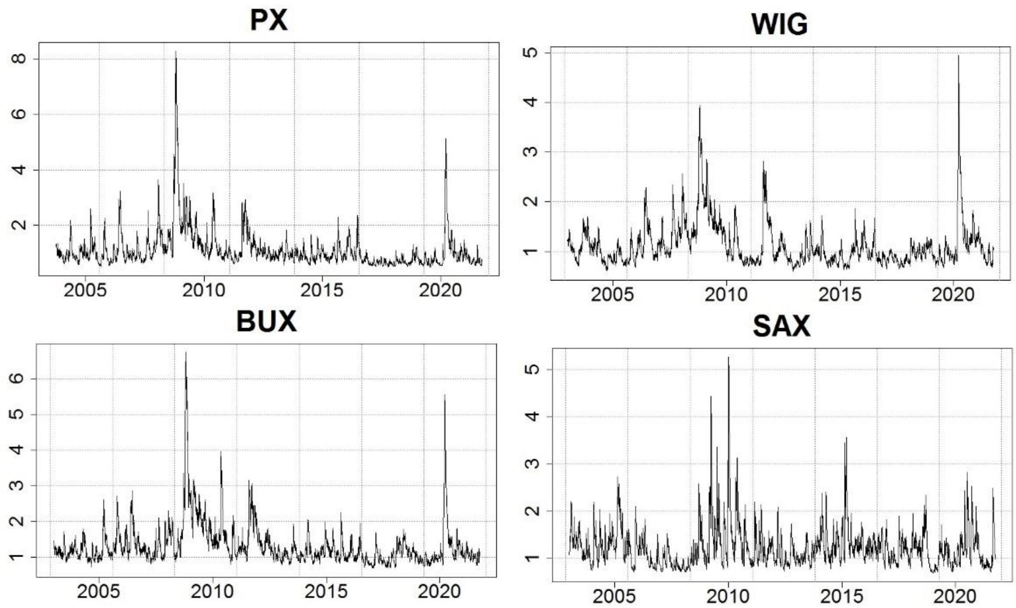


Figure 1. Graphical illustration of estimated idiosyncratic conditional volatilities

After creating the optimal conditional volatilities, we intend to determine which SKD fits the best to the particular dependent variable in the robust QR framework. Table 3 presents the AIC values for estimated RQR models under five different skewed distributions – Normal, Student-t, Laplace, contaminated Normal and Slash distribution, for every selected index. We fit five models with different distribution functions, performing a median regression ($\tau^{0.5}$).

Table 3. Estimated AIC values for the quantile regression under different SKD

Indices					
	Normal	Student-t	Laplace	Slash	Cont. Normal
PX	6622.0	238.7	466.9	238.3	942.7
WIG	3401.2	-1786.9	-1703.4	-1775.7	-1712.3
BUX	5017.9	-446.2	-384.34	-433.7	-254.6
SAX	8567.8	1864.1	2190.5	1815.9	2699.2

Note: Greyed numbers indicate the lowest AIC value.

According to AIC measures, it can be seen that the best RQR model is with the Student-t distribution in the cases of WIG and BUX, while for PX and SAX, the best RQR model is estimated with the Slash distribution. In order to be parsimonious, we present in Figure 2 only model residuals with the theoretical shape of every distribution function in which the PX index is a dependent variable. Visual presentation of fitted model residuals for all other indices can be obtained by request. Figure 2 suggests that the Slash and Student-t distributions are two of the best fitting functions, whereas Table 3 gives very tiny advantage to the Slash distribution in the case of PX. Therefore, following the results in Table 3, all robust quantile parameters are assessed with the Student-t or Slash RQR, and the results are presented in the next section.

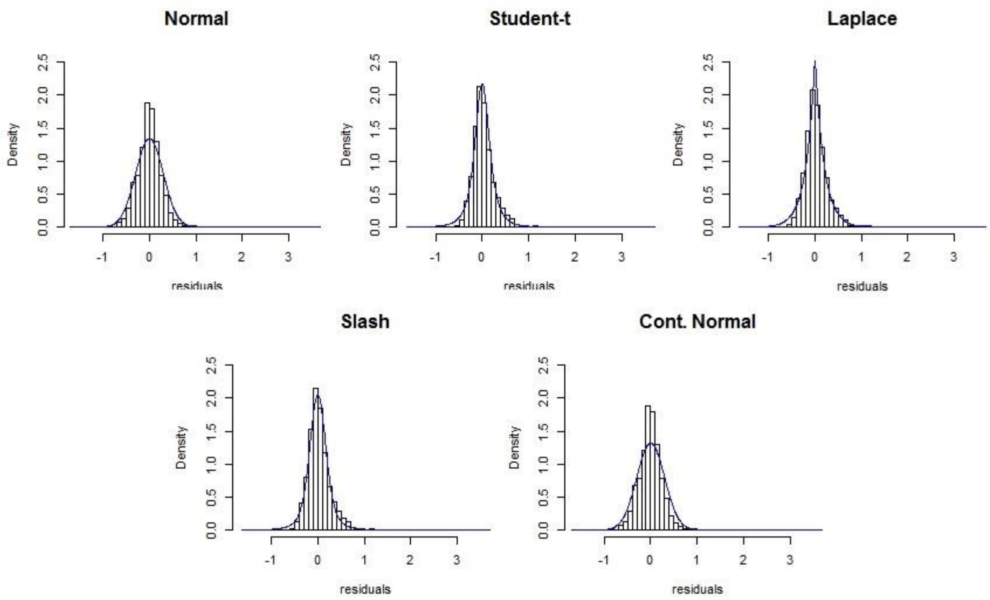


Figure 2. Fitted distributions of the estimated PX residuals

5. Results of estimated robust quantile parameters

This section presents the results of the estimated seven robust quintile parameters that range from 0.05 to 0.95. Sine we operate with volatilities in the RQR model, then we can distinct between calm ($\tau^{0.05}$ and τ^{20}), moderate (τ^{35}, τ^{50} and τ^{65}) and turbulent (τ^{80} and τ^{95}) periods. The results in Table 4 describe magnitude of idiosyncratic volatility transmission between four Central and

Eastern European stock indices of Visegrad group, while Figure 3 depicts the quantile plots. It can be seen in Figure 3 that the credible intervals of all estimated quantile parameters are very narrow, which indicates that all RQR parameters are highly statistically significant. The estimated quantiles gauge the multidirectional volatility spillover effect, meaning that each market is observed as transmitter and receiver of volatility shocks, which can give us a clue whether some market dominates all other or not. It can be seen in Table 4 that the majority of estimated QR parameters are highly statistically significant, regardless of whether we talk about lower or higher quantile parameters. It suggests that significant risk transmission effect exists among these four markets in both tranquil and crisis periods. In addition, it is interesting to note that RQR parameters increase in higher quantile parameters, which is a clear indication that volatility transmission is stronger in turbulent times. This is not surprising, since many researchers reached a similar conclusion. For instance, Beirne et al. (2013) observed 41 emerging markets and reported that volatility transmission increases during market turmoil from mature to emerging equity markets, whereas they found an evidence that spillovers from mature markets appear to be present only during turbulent episodes. Wang et al. (2018) investigated volatility spillover phenomenon from the US stock market to several developed stock markets of Japan, Germany, France, United Kingdom and Canada. They found that the time-varying spillover effect was stronger when the US economy was in recession.

We divide Table 4 into four panels, whereby each panel contains the results of the recipient market that endures volatility shocks from the other three markets. Panel A observes the Czech index (PX) as a dependent variable, and it can be seen that the WIG and BUX indices have a much stronger volatility spillover influence on the PX index across the quantiles, compared to the influence of the Slovakian index (SAX). The effect of the Slovakian index is very low, and does not exceed 5%, taking into account all market circumstances. As a matter of fact, we find that the strongest effect amounts 4.8% in τ^{65} quantile, which describes moderate market conditions, whereas during periods of economic turbulence that is portrayed by τ^{95} quantile, the transmission effect is nonexistent. On the other hand, volatility spillover from Polish and Hungarian indices goes around 30% when the Czech market is very calm, and it gradually progresses as the Czech market enters more stressful periods, going even beyond 70% in some instances. More specifically, the volatility spillover effect of the Polish stock market is stronger during calm and moderate market conditions (from τ^{20} to τ^{50} quantiles), and it amounts between 45-51%, while from τ^{65} quantile onwards, stronger effect has the BUX index, going beyond 70% when Czech stock market is under severe stress.

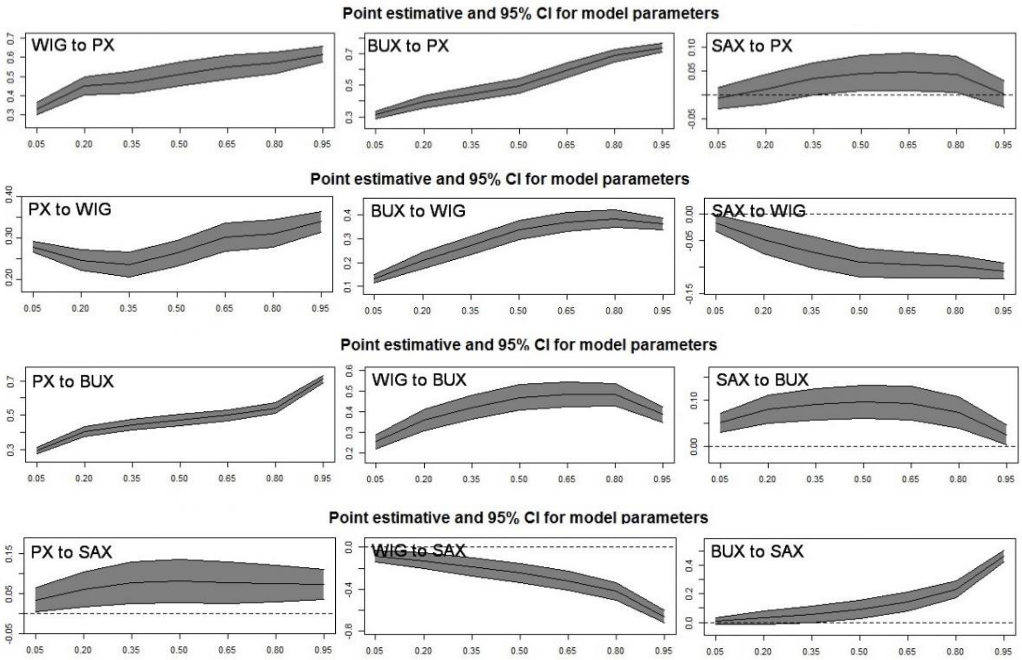
Table 4. Estimated robust quantile regression parameters

		Estimated robust quantiles						
		0.05	0.20	0.35	0.50	0.65	0.80	0.95
Panel A. Dependent variable – PX								
β_1	Constant	-0.026	-0.140	-0.166***	-0.204***	-0.269***	-0.282***	-0.166***
β_2	WIG	0.331***	0.451***	0.467***	0.512***	0.549***	0.572***	0.616***
β_3	BUX	0.312***	0.396***	0.446***	0.495***	0.596***	0.689***	0.738***
β_4	SAX	-0.006	0.012	0.034*	0.045*	0.048*	0.043*	0.001
Panel B. Dependent variable – WIG								
β_1	Constant	0.277***	0.380***	0.436***	0.431***	0.432***	0.490***	0.628***
β_2	PX	0.279***	0.247***	0.236***	0.264***	0.302***	0.310***	0.340***
β_3	BUX	0.132***	0.209***	0.271***	0.337***	0.370***	0.385***	0.362***
β_4	SAX	-0.016*	-0.048***	-0.072***	-0.091***	-0.095***	-0.099***	-0.107***
Panel C. Dependent variable – BUX								
β_1	Constant	0.319***	0.176***	0.149***	0.150***	0.195***	0.285***	0.519***
β_2	PX	0.298***	0.407***	0.447***	0.472***	0.501***	0.542***	0.710***
β_3	WIG	0.254***	0.360***	0.419***	0.468***	0.483***	0.481***	0.385***
β_4	SAX	0.051***	0.080***	0.091***	0.096***	0.093***	0.073***	0.024***
Panel D. Dependent variable – SAX								
β_1	Constant	1.114***	1.189***	1.288***	1.397***	1.518***	1.652***	1.860***
β_2	PX	0.034*	0.060**	0.078**	0.081**	0.077**	0.076**	0.072***
β_3	WIG	-0.081***	-0.128***	-0.184***	-0.246***	-0.321***	-0.419***	-0.660***
β_4	BUX	0.011	0.034	0.055*	0.091**	0.146***	0.230***	0.467***

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

Panel B highlights the Polish case. It is obvious that the WIG index endures much less volatility shocks from the Czech and Hungarian markets in comparison with the effect that the PX index endures from Polish and Hungarian markets. In particular, the amount of volatility shocks that WIG index receives from the PX index is almost half the size that PX index experiences from WIG index. We find that the strongest spillover effect from the Czech market is 34%, while the highest transmission effect from the Hungarian market goes around 39% in τ^{80} quantile. As in the Czech case, we also find a very weak spillover effect that comes from the SAX index, but in this case, the quantile parameters are negative, which indicates that an increase in volatility in the Slovakian market actually decreases volatility in the Polish stock market. This finding is important for the hedging efforts of investors who combine the WIG and SAX indices in a single portfolio.

As for the Hungary case, we reveal that the PX index has the strongest volatility spillover effect on the BUX, while the WIG index follows. More specifically, the transmission effect of the Prague market is 54% in τ^{80}, whereas from the Warsaw market it goes around 48%. The significant discrepancy exists when we observe the highest quantile. In this case, the magnitude of the volatility spillover effect from the Czech market is almost twice the size in comparison with the Polish market. We report that the BUX index receives the highest spillover effect from the SAX in comparison to the PX and the WIG indices, albeit this effect is also very small and does not go beyond 10%. It is interesting to note that the BUX index receives the strongest effect from SAX in moderate market conditions, which is depicted by the median quantile, while this effect gradually subsides with the increase of quantiles.



Note: X axis represents estimated quantiles, while Y axis denotes their value.

Figure 3. Plots of estimated robust quantile parameters

Taking into account the PX, the WIG and the BUX index, we can say that our results are in line with the study of Hanousek and Kočenda (2011), although these authors researched return, and not volatility spillover effect as we do. In particular, they argued that the Budapest stock market produces the strongest spillover effects toward the other two markets, which coincides very well with our results. They explained that a possible reason could be the fact that the largest volume of trade, conducted by foreign investors, happens in Budapest, while Prague and Warsaw follow.

Panel D in Table 7 shows that the case of the SAX index is the most peculiar one compared to all other indices, meaning that it does not follow an established pattern that characterises all other indices. The results indicates that unlike all other indices that transmit and receive fair amount of volatilities between each other, the SAX index experiences relatively low volatility spillover effect from other three markets. In particular, the effect of the PX index hardly exceeds 8% at its most. The effect of the WIG is negative, while the negative robust quantile parameters grow stronger as turbulence in the Slovakian market increases. In fact, quantile parameters from τ^{65} to τ^{95} are quite large, having a value between -32% and -66%, which creates excellent hedging opportunities for investors, even during very volatile market conditions in the Bratislava market. However, it seems that the Slovakian market has the closest ties with the Hungary market, since the SAX index receives the highest amount of volatility from Budapest. Up to the median quantile, it does not reach 10%, but as the quantiles grow larger, the effect doubles with the increase of every quantile. We find that the highest volatility transmission effect of the BUX happens when the Slovakian market is in a mode of very high volatility (τ^{95} quantile), and this average effect amounts almost 47%, which is relatively large.

Table 5. Market capitalisation and average daily trading volumes

	Czech Republic	Poland	Hungary	Slovakia
Market capitalisation♣	40,912	138,691	22,553	4,801
Average daily trading volumes♦	2,127,563	46,000,789	2,664,020	377

♣ Market capitalisation is presented in millions of USD;
source: www.indexmundi.com/facts/indicators/CM.MKT.LCAP.CD/rankings
♦ Average daily trading volumes are observed for pre-pandemic 2019; Source: stooq.com

The possible explanation why the SAX index is so resistant to the shocks from other markets may lie in the intrinsic characteristics of the Slovakian stock market. Namely, Table 5 presents the market capitalisation and average daily trading volumes of four stock markets. It can be seen that the Slovakian stock market is significantly underdeveloped in comparison to other three markets. Not only does Bratislava Stock Exchange (BSE) have the smallest capitalisation, but this market is severely illiquid, which is depicted by the average daily trading volume. This indicator suggests that the average daily number of transactions in 2019 is only 377, which is a very low number. This fact is the main reason why the spillover effect from and towards BSE is so low.

6. Discussion and conclusions

This paper tries to determine the level of the cross-market idiosyncratic volatility spillover effect that exists between the four Visegrad stock markets. For this task, we first cleanse empirical time series from the global market noise. Afterwards, we estimate the NA-GARCH-NIG model to generate idiosyncratic conditional volatilities, and then these volatilities are inserted in a robust quantile regression model, which produces very reliable estimates.

According to the findings, we report that the majority of the estimated RQR parameters are highly statistically significant, and they are growing with the increase of the quantiles. This means that the volatility transmission effect is more intense in the periods of increased market turbulence, which is very much in line with the previous studies. RQR parameters indicate that the highest spillover effect exists between Prague, Warsaw, and Budapest stock markets, whereas Bratislava stock market receives and transmits very low level of volatilities towards other three markets. The rationale for such results probably lies in the fact that Slovakian stock market is the least developed, meaning that it has the lowest level of market capitalisation and the lowest average daily trading volumes. The high illiquidity of the Slovakian stock market is most likely the main culprit for the low levels of transmission exist between the Slovakian stock markets and the other three markets.

The results of this paper can be used by investors who combine Visegrad stock indices in a single portfolio. These findings are important, because if volatility from one financial market transmits to another in high intensity, then assets from such markets cannot be included in the same portfolio with the other asset. According to Table 4, the best combination of indices in a portfolio would be the pair WIG-SAX, and the reasons are twofold. First, Table 4 suggests that the RQR spillover parameters between the WIG and the SAX are negative, which means that increase of volatility in one market reduces volatility on the other market. Therefore, combining the WIG and the SAX indices is good for hedging purposes. Second, Table 2 indicates that the WIG index has a relatively high average daily rate of return that amounts to 0.033%, which means that the portfolio with the WIG index would also produce relatively high portfolio returns. Therefore, investment in these indices could serve as some kind of safe haven for investors in the periods of global market unrest, i.e., in the periods when all other financial and commodity markets record increased volatility with the heightened level of volatility transmissions between them.

On the other hand, the worst index to find in a portfolio is PX. This index has the lowest average daily rate of return, amounting only 0.014%, according to Table 2. It means that portfolio with PX would also yield a relatively low level of earnings. Besides, the PX index receives and transmits a significant level of volatility spillover shocks toward the WIG and the BUX indices, and this is particularly conspicuous in the periods of increased market turmoil. This fact does not favour the PX index to be either primary or auxiliary investment instrument in a portfolio with the WIG and the BUX indices, whatsoever.

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