Asymmetric Conditional Volatility Modeling: Evidence from Central European Stock Markets

Modelování podmíněné volatility pomocí asymetrických modelů: příklad ze středoevropských akciových trhů

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Abstract

This paper investigates the asymmetric response of equity volatility to return shocks. The effects of good and bad news on volatility in the Czech and Polish stock markets using asymmetric ARCH models before and during the global financial crisis of 2008-09 are examined. Moreover we generalize the news impact function to study asymmetric volatility under the ARCH-type models. The PX and WIG20 stock indexes were used as a proxy to the Czech and Polish stock markets to study the asymmetric volatility over 7 year's period. Commonly used asymmetric volatility models i.e. EGARCH and TGARCH models were applied. The PX and WIG20 returns series found to react to the good and bad news asymmetrically. The presence of the leverage effect would imply that the negative news has a greater impact on volatility than a positive innovation. We found that GARCH-class models with normal errors are not capable to capture fully the leptokurtosis in empirical time series, while GED and Student's *t* errors provide a better description for the conditional volatility.

Key words

Asymmetric volatility, leverage effects, GARCH models, news impact function, financial crisis

JEL Classification: C51, C52, C58

1. Introduction

Financial markets, due to their key role in the economies of countries, have been studied from different points of view. In this regard, one key aspect of the stock markets that has attracted much attention in financial literature is the analysis of the stock returns and its volatility. Ups and downs in prices are quite natural in stock market behavior. Volatility is a typical symptom of a highly liquid stock market. An increase in stock market volatility brings a large stock price change of growths or declines. Investors interpret a raise in stock market volatility as an increase in the risk of investment and consequently they shift their funds to less risky assets.

The fluctuation of stock prices not only is not destructive by itself but also is a sign of market efficiency in stock markets (Goudarzi, Ramanaraynan (2011)). The main problem with price fluctuations that affects the financial market efficiency is destructive excess volatility that ends crashes and or crisis in financial markets as we observed for example in 2008-2009 years.

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The relation between the equity volatility and return shock has long been an active research topic in the finance literature. It is generally agreed that there is an asymmetry in the relation, that is, a positive return shock has a smaller impact on future volatility than does a negative innovation of the same size. There are two explanations for this relationship: a leverage effect as changes in equity volatility increase following increases in financial leverage following negative returns and the volatility feedback effect.

While the volatility and its relationship with stock price in developed financial markets has been well studied, little attention has been paid towards an extensive study of the volatility of the emerging stock market in Europe like Czech Republic or Poland. It is now well known that equities from emerging capital markets have vastly different characteristics than equities from developed capital markets.

There are at least four distinguishing features of emerging market returns: higher sample average returns, low correlations with developed market returns, more predictable returns, and higher volatility (Bekaert and Wu, 2000). These differences may have important implications for decision making by investors and policy makers. Thus, put emphasis on developed markets finding may mislead policy makers in making proper decisions. For those reasons, the aim of this paper is to investigate the asymmetric relation between stock price and its volatility in emerging equity markets in Czech Republic and Poland.

We investigated and modeled volatility using two specified nonlinear asymmetric models, EGARCH (1, 1) and TGARCH (1, 1) and news impact curve. We found that both PX and WIG20 return series exhibit leverage effects. The rest of this paper is organized as follows. Section 2 deals with the GARCH-family asymmetric volatility models considered for this paper. The description of the data and the methodology are presented in section 3 .The empirical analysis and findings are presented in section 4 and section 5 concludes the paper.

2. Theoretical Background

One of the primary restrictions of GARCH-type models is that they force a symmetric response of volatility to positive and negative news. This arises since the conditional variance in GARCH model is function of the magnitudes of the lagged residuals and not their signs. However, it has been argued that a negative shock to financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude. In the case of equity returns, such asymmetries are typically attributed to leverage effects.

2.1 Asymmetric ARCH models

The asymmetric response of good and bad news to future volatility, or the leverage effect, is such that bad news should increase future volatility while good news should decrease future volatility. To model this phenomenon in this study we applied two models that allow analyzing the asymmetric shocks to volatility, the Exponential GARCH model and Threshold ARCH model.

Nelson (1991) proposed a GARCH-class model named Exponential GARCH that allows for asymmetric effects and therefore solves one of the important shortcomings of the symmetric models. While the GARCH model imposes the nonnegative constraints on the parameters, EGARCH models the log of the conditional variance so that there are no restrictions on these parameters:

$$\log\left(\sigma_t^2\right) = \omega + \sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{p} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}. \tag{1}$$

Note that the left-hand side is the logarithm of the conditional variance. This implies that the leverage effect is exponential and that forecast of the conditional variance is guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma_i < 0$. Bad news can have a larger impact on volatility, and the value of γ_i would be expected to be negative. Thus EGARCH basically models the log of the variance as a function of the lagged logarithm of the variance and the lagged absolute error from the regression model. It allows the response to the lagged error to be asymmetric.

Another extension of the classic GARCH model that allows for leverage effects is the Threshold-GARCH or TGARCH. The idea of TGARCH model is to divide the distribution of the innovations into disjunctive intervals and then approximate a piecewise linear function for the conditional standard deviation or the conditional variance respectively.

Zakoian (1994) extend this preliminary Threshold model by including the lagged conditional standard deviations as a regressor, which is known as the TGARCH model.

TGARCH is therefore estimated with the following equation:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i S_{t-i} \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2, \quad (2)$$

where

$$S_{t-i} = \begin{cases} 1 \text{ if } \varepsilon_{\text{t-i}} < 0 \\ 0 \text{ if } \varepsilon_{\text{t-i}} \geq 0. \end{cases} \quad (3)$$

In other words, depending on the y_i being above or under the threshold value (which equals zero), ε_{t-i}^2 will have different effects on the conditional variance σ_t^2, as it follows:

- When ε_{t-i} is positive, total effects are given by $\alpha_i \varepsilon_{t-i}^2$;
- When ε_{t-i} a negative, total effect is are given by $(\alpha_i + \gamma_i)\varepsilon_{t-i}^2$.

This is why in the case of TGARCH we expect γ_i to be positive, so that bad news would have a more powerful effect on volatility than good news. To accept the null hypothesis of no leverage effect in TGARCH model, the γ_i coefficient must be negative. In other words, if the γ_i coefficient is not negative there is evidence of leverage effects in the series.

2.2 News Impact Curve

In addition to analytical expressions of leverage effect is appropriate and useful to express it graphically as well. Suitable way of graphic expression of leverage effect is the use of news impact curve. News impact curves have been introduced by Engle and Ng (1993) to represent the response of volatility to a shock on the asset return. In their context, the news impact curve measures the effect of a news at date *t*-1 on volatility at date *t,* while the information dated earlier is held constant, evaluated at the level of the unconditional variance of the asset return.

3. Data and Methodology

Empirical analysis is performed on daily data of PX and WIG20 indexes in period from 2004 till 2010, it includes total of 1825 observations. This period was chosen purposely, to investigate changes of the Czech and Polish equity markets volatility during time with a special emphasis on the resolution of behavior in the time before and during the global financial crisis in 2008-2009. We have 7 years long time series of the closing rates of PX and WIG20 indexes. Those time series were obtained from www.pse.cz and www.wse.com.pl.

The PX is a weighted index containing the most liquid titles with weights changing according to the market capitalization. At the present time, the actual number of the basic issues is variable. WIG20 index is based on the value of portfolio with shares in 20 major and most liquid companies in the main stock market.

The returns r_t at time *t* were defined in the logarithm of PX and WIG20 indices *p*, that is, $r_t = \log\left(p_t - p_{t-1}\right)$.Visual inspection of the plot of daily values and returns series of both indices proved very useful, for details see Figure 1 and Figure 2.

As it has been empirically confirmed, crises are not devoted to developed markets only. Emerging markets includes Czech Republic and Poland isn't excluded from this rule and may face such instability sometime. Following the spread of bad news about U.S financial crisis the Central European equity markets, Czech and Polish ones included, have seen a more than 60 percent decline in both selected indexes, please see Figure 1. This happened primarily due to the withdrawal by foreign portfolio investors between September and December 2008 and its psychological impact on national investors.

Figure 1: PX and WIG20 values (2004-2010)

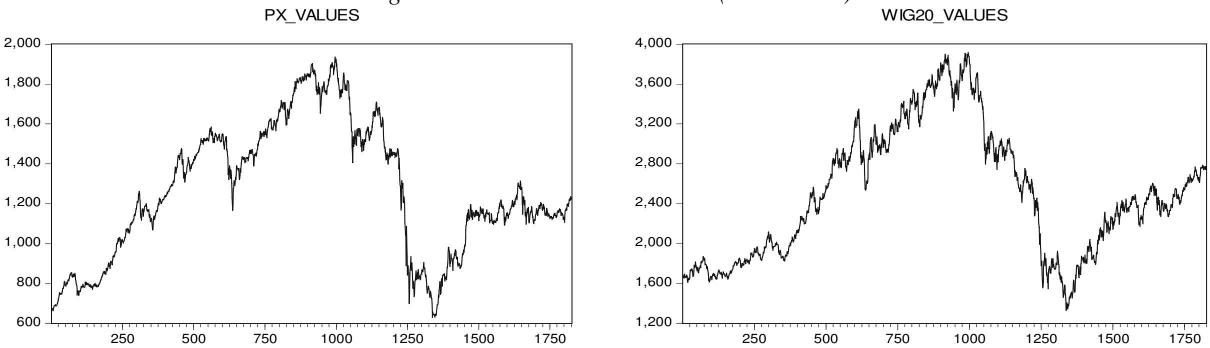
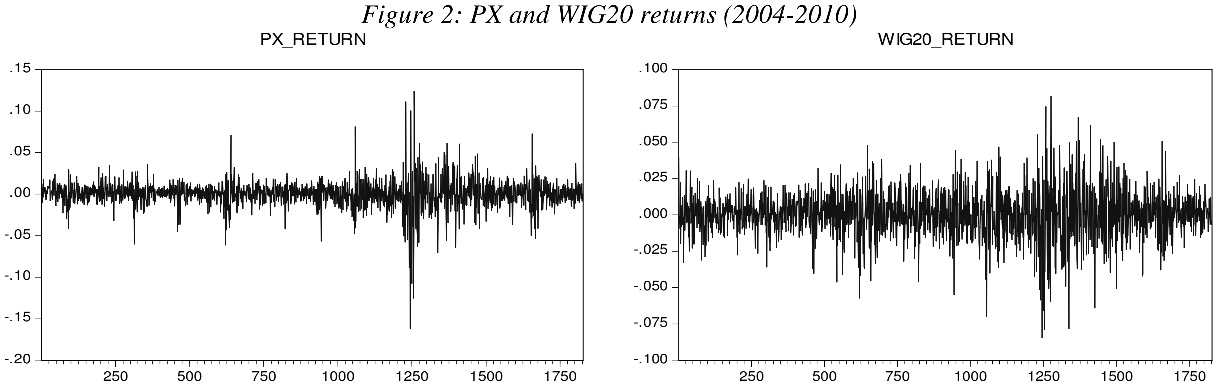


Figure 2: PX and WIG20 returns (2004-2010)



It can be seen that from Figure 2 that return fluctuates around mean value that is close to zero. Volatility is low for certain time periods and high for other periods. The movements are in the positive and negative territory and larger fluctuations tend to cluster together separated by periods of relative calm. The volatility of PX and WIG20 indexes was highest in 2008. Thus Figure 2 show volatility clustering where large returns tend to be followed by small returns leading to continuous periods of volatility and stability. Volatility clustering implies a strong autocorrelation in squared return. Since the volatility was highest in 2008 when the values of both indexes reached the minimum values in investigated period we divided the basic period 2004-2010 into two testing period. First period was defined from 2004 to the end of July 2007 and the second one started at the beginning of June 2007 and finished by the end of 2010. Our goal is to investigate and compare the behavior of asymmetric response of equity volatility on return shocks in both periods.

	PERIOD: 2004-2007		PERIOD: 2007-2010	
	PX_1	WIG20_1	PX_2	WIG20_2
Mean	0,001158	0,000949	-0,000481	-0,000340
Standard Deviation	0,010739	0,012702	0,020826	0,019193
Skewness	-0,565329	-0,330524	-0,416504	-0,149600
Kurtosis	8,609567	4,522922	13,24761	5,111533
Jarque-Bera	1245,698*	104,8534*	4012,480*	172,638*

*Significant at 0,05.

Table 1: Descriptive statistics of PX and WIG20 returns

Table 1 presents the summary statistics (mean, standard deviations, skewness, kurtosis, and Jarque-Bera normality test) for daily stock returns. The skewness coefficient is negative all four time series, suggesting that the all series have a long tail while kurtosis is very high in all cases which reflect that all distributions are highly leptokurtic. As expected, the Jarque-Bera test rejects normality at the 5% level for all series.

4. Empirical Analysis and Model Estimates

As Table 2 shows ARCH-LM test was statistically significant which indicates the presence of ARCH effect in the residuals of mean equation of all PX and WIG20 series. The ARCH type models were estimated for PX and WIG20 returns series using maximum likelihood method. The information criterion such as AIC was used and a set of model diagnostic tests were applied to choose the volatility models which represent the conditional variance of the PX and WIG20.

ARCH-LM test up to 10 lags							
PX_1 (2004-2007)				WIG20_1 (2004-2007)			
F-statistics	9,4859	Prob.	0,0000	F-statistics	6,1174	Prob.	0,0000
PX_2 (2007-2010)				WIG20_2 (2007-2010)			
F-statistics	34,4535	Prob.	0,0000	F-statistics	14,2212	Prob.	0,0000

Table 2: ARCH-LM test for PX an WIG20 returns

Further, we test for asymmetric effects on conditional volatility in the four series investigated. The potential presence of leverage effect can be calculated as the correlation of lagged returns and a measure of future volatility; see, for example Cont (2001), who defines the leverage effect of lag τ as $L(\tau) = Corr\left(r_{t-\tau}, r_t^2\right)$, where *Corr* (*a*, *b*) is the linear correlation between *a* and *b*, and r_t^2 is used as a measure of volatility at time *t*. We test for asymmetric effects on conditional volatility in the four financial series investigated. A negative value for this correlation coefficient provides evidence for potential leverage effects. Table 3 presents estimates of this coefficient for the four time series. We notice that the correlation between r_t^2 and r_{t-1} has a small negative value in all cases, indicating weak evidence for asymmetry. Asymmetric GARCH models could therefore perform well in explaining conditional volatility for the four analyzed series.

Period	Series	Corr (r_{t-1}, r_t^2)
2004-2007	PX_1	-0,10161
	WIG20_1	-0,04524
2007-2010	PX_2	-0,08222
	WIG20_2	-0,02986

Table 3: Testing for asymmetric effects on conditional volatility

Furthermore, we estimate a series of asymmetric GARCH-family models to explain conditional variance and volatility clustering for each of the four series: EGARCH (1, 1) and TGARCH (1, 1). Parameter estimates are reported in Table 4 and Table 5.

At first the EGARCH (1, 1) and TGARCH (1, 1) models were estimated for PX returns series using the maximum likelihood estimator assuming the Gaussian standard normal distribution. The estimation results of EGARCH (1, 1) and TGARCH (1, 1) models for index PX are shown in Table 4. The conditional means are significant in all estimated models. For the EGARCH (1, 1) and TGARCH (1, 1) models the persistence in volatility was very long and explosive suggestive of an integrated process. The asymmetric effect captured by the parameter estimate γ was positive and significant in the TGARCH (1, 1) suggesting the presence of leverage effect in both periods. Similar results have been obtained by EGARCH (1, 1) model. The asymmetric term was negative and significant suggesting leverage effects.

	PERIOD: 2004-2007				PERIOD: 2007-2010			
MODELS	COEFF.	VALUE	Prob.	AIC	COEFF.	VALUE	Prob.	AIC
TGARCH(1,1)	intercept	0,0001	0,0000	-6,428	intercept	0,0001	0,0009	-5,453
	ARCH	0,0331	0,0459		ARCH	0,0971	0,0002	
	GARCH	0,6961	0,0000		GARCH	0,8225	0,0000	
	GAMMA	0,3103	0,0000		GAMMA	0,1272	0,0000	
EGARCH(1,1)	intercept	-1,0961	0,0000	-6,419	intercept	-0,4717	0,0000	-5,443
	ARCH	0,2166	0,0000		ARCH	0,2984	0,0000	
	GARCH	0,8992	0,0000		GARCH	0,9706	0,0000	
	GAMMA	-0,1271	0,0000		GAMMA	-0,0798	0,0000	

Table 4: Estimated asymmetric volatility models for PX returns

After detecting the presence of leverage effects in the series using TGARCH (1, 1) and EGARCH (1, 1), the Akaike information criterion (AIC) was applied to select the fittest model to the data. The model with lowest value of AIC fits the data best. The study concluded that TGARCH (1, 1) is adequately indicates the volatility asymmetry in the PX in both investigated periods. For instance, in crises period it is clear that the good news has an impact of 0,0971 magnitude and the bad news has an impact of 0,0971+0,1272 = 0,2253.

	PERIOD: 2004-2007				PERIOD: 2007-2010			
MODELS	COEFF.	VALUE	Prob.	AIC	COEFF.	VALUE	Prob.	AIC
TGARCH(1,1)	intercept	0,0001	0,0348	-5,957	intercept	0,0001	0,0155	-5,292
	ARCH	0,0630	0,0006		ARCH	0,0099	0,4665	
	GARCH	0,9371	0,0000		GARCH	0,9283	0,0000	
	GAMMA	-0,0276	0,1401		GAMMA	0,1097	0,0000	
EGARCH(1,1)	intercept	-0,2013	0,0033	-5,955	intercept	-0,2249	0,0000	-5,302
	ARCH	0,0978	0,0000		ARCH	0,1229	0,0000	
	GARCH	0,9856	0,0000		GARCH	0,9841	0,0000	
	GAMMA	0,0204	0,1504		GAMMA	-0,1028	0,0000	

Table 5: Estimated asymmetric volatility models for WIG20 returns

In the case of index WIG20 the results differ as shown in Table 5. In the first investigated period there was statistically significant parameter γ in the case of neither EGARCH (1, 1) model nor TGARCH (1, 1) model. It means that the leverage effect hasn´t been confirmed on the Polish market in the pre-crisis period. The influence of positive and negative news on volatility was therefore symmetrical. In the crisis period, there was on the contrary statistically significant parameter γ in the case of estimation by using both EGARCH (1, 1) and TGARCH (1, 1) models. The negative news thus during the crisis affects the volatility of the Polish market more significantly than positive news.

The results of diagnostic tests showed that the models are correctly specified. The ARCH-LM tests were insignificant which confirms the sufficiency of asymmetric models in modeling the serial correlation structure in the conditional mean and variance. Overall, using AIC and Log likelihood function as model selection criteria the preferred model was the TGARCH (1, 1) in case of PX return in both period. In case of WIG20 returns the EGARCH (1, 1) model fits in best way in crisis period.

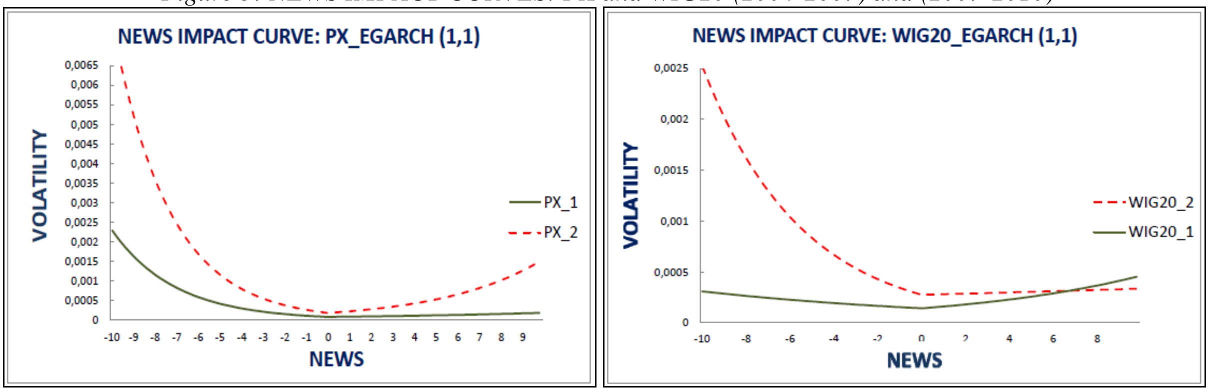
Model	AIC	Log-likelihood	AIC	Log-likelihood	AIC	Log-likelihood
PX_1	Normal Distribution		Student ‘s Distribution		GED	
EGARCH (1,1)	-6,419	2935,704	-6,497	2971,672	-6,479	2964,045
TGARCH (1,1)	-6,428	2939,282	-6,501	2973,732	-6,484	2966,102
WIG20_1	Normal Distribution		Student ‘s Distribution		GED	
EGARCH (1,1)	-5,955	2723,551	-5,977	2734,534	-5,988	2739,372
TGARCH (1,1)	-5,957	2724,502	-5,978	2734,816	-5,989	2739,836
PX_2	Normal Distribution		Student ‘s Distribution		GED	
EGARCH (1,1)	-5,443	2489,602	-5,464	2500,210	-5,465	2500,840
TGARCH (1,1)	-5,453	2494,470	-5,473	2504,546	-5,474	2505,039
WIG20_2	Normal Distribution		Student ‘s Distribution		GED	
EGARCH (1,1)	-5,302	2425,141	-5,114	2340,674	-5,314	2431,672
TGARCH (1,1)	-5,292	2420,646	-5,303	2426,710	-5,307	2428,604

Table 6: Information criteria and log-likelihood function for re-estimated asymmetric volatility models

Further, we re-estimate the models after having eliminated the restrictive assumption that the error terms follow a normal distribution. In order to accomplish this goal, we assume that residuals follow successively a Student´s distribution and also a Generalized Errors Distribution (GED), two of the distributions capable of incorporating fat tails usually present in empirical distributions. Therefore, we estimate the best fitted asymmetric GARCH-family model for each of the four time series considering first that the residuals follow a Student´s distribution, and after that a GED. Table 6 presents AIC and Log likelihood functions in all cases. In most models the assumption of GED of errors gives us better estimates.

Finally, the news impact curve for EGARCH (1, 1) model for PX and WIG20 return series also in most cases confirmed the existence of leverage effects in the PX and WIG20 returns series. The plots of news impact curve are as Figure 3.

Figure 3: NEWS IMPACT CURVES: PX and WIG20 (2004-2007) and (2007-2010)



As Figure 3 indicates, the effects of news on volatility of PX return series is asymmetric in both investigated periods, while in times of crisis, this effect is significantly larger than in the pre-crisis period. In other words the bad news has more effects on volatility than good news. The behavior of WIG20 return series is different. While in the pre-crisis period, the asymmetric impact of news in volatility was not empirically observed, this occurs only in times of crisis, and moreover the size of the measured volatility is lower than for index PX.

5. Conclusion

The volatility of PX and WIG20 stock returns have been investigated and modeled using two nonlinear asymmetric models, EGARCH (1, 1) and TGARCH (1, 1) and news impact curve. We found that PX and WIG20 returns series exhibit leverage effects and in addition to leverage effects exhibit other stylized facts such as volatility clustering and leptokurtosis associated with stock returns on developed stock markets. Further, we found that TGARCH (1, 1) can be suitable representative of the asymmetric conditional volatility process for daily returns series of PX in both investigated periods. In case of WIG20 returns we found that EGARCH (1, 1) can be appropriate representative of the asymmetric conditional volatility process in crises period while in crises period leverage effect wasn´t confirmed at all.

All the results are in harmony with theoretical expectations. EGARCH models show a negative and significant γ parameter for all the series if the values are statistically significant. Thus past negative shocks have a greater impact on subsequent volatility than positive shocks do. TGARCH leverage effects are positive and significant for three series, attesting that bad news increase volatility.

While a certain reasonable level of volatility is certainly a natural and desirable, as it reflects the impact of new information on the markets from some level of volatility can be damaging. In this case, stock price already on the market usually does not reflect the real price of the underlying asset. Excessive volatility can lead to inefficient resource allocation, and upward pressure on interest rates is due to the excessive uncertainty in the equity markets.

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Summary

Tento článek je věnován analýze asymetrické reakce akciových trhů na nové informace. V příspěvku jsou analyzovány účinky pozitivních a negativních zpráv na volatilitu akciových trhů v České republice a Polsku za použití asymetrických modelů EGARCH a TGARCH v období před a během globální finanční krize v letech 2008-09. Výnosy indexů PX a WIG20 byly využity jako ukazatel pro českou a polskou burzu ke studiu asymetrických vlivů nových zpráv na volatilitu ve zkoumaných obdobích. Asymetrie vlivu informací byla potvrzena na obou zkoumaných trzích, v případě polského trhu však pouze během krizového období.