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Analysis of the Relationship between Market Volatility and Firms Volatility on the Polish Capital Market

A b s t r a c t. In this paper we investigate if the strength of firm-market volatility relationship has changed after subprime crisis on the Polish Capital Market. The empirical study concern the selected companies listed on the Warsaw Stock Exchange (WSE) from the construction and IT sectors in the 2004–2011 period. The volatility measures were computed on the basis of daily low and high prices for companies shares and WIG index. For each company ARFIMAX-FIGARCH model with additional exogenous variables, which represented market volatility, was estimated in the stable and the turbulent period. Conducted empirical studies have not shown that the negative shocks flowing from the American stock market through investors' behavior channel contributed to the increase in the fraction of firms of the construction and IT sectors listed on the WSE whose volatility is shaped by market volatility.

K e y w o r d s: ARFIMAX-FIGARCH, firm volatility, market volatility, subprime crisis, Warsaw Stock Exchange.

J E L Classification: G12; D40; C58.

Introduction

Volatility of prices of listed companies shares is the subject of interest not only to stock exchange investors but also companies which emit them. High volatility means high probability of change of company market value in the future and this in turn influences its competitiveness on the market. This is

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connected with the fact that high market value of an enterprise in relation to its book value is connected with a simultaneous high market share of a given subject (Grabowska, 2013). Enterprise competitiveness depends, among others, on the value for the shareholders and clients, financial capability, determining its ability to act and react quickly in the competitive environment and human potential and technologies used in implementing strategic changes (Feurer and Chaharbaghi, 1994). Moreover, the knowledge about linkages between market volatility and firm volatility is of great importance in risk management process and determining the investment portfolio structure, because it helps to understand the nature of individual firm volatility and identify this process determinants. It is not surprising that there exist many articles that were devoted to this issue. We may summarize some important facts about firm volatility on the basis of literature studies. As suggest Karolyi (2001) the existence of excessive volatility in stock prices undermines the usefulness of the information about the true value of the company. This clearly does not mean that high volatility is proof of the irrational behavior and inefficient markets and investors. No signals from the market to volatility of stock prices, affirms the conviction that it is the correct measure of risk. Interest in the subject matter of volatility, in particular, the possibility of its forecasting is related to the ability to reduce the risk of investment or achieving higher returns from investments. In the literature, there are already several well-documented facts concerning volatility. Chen and Lai (2013) and other researchers (Whaley, 2009; Simon, 2003; Giot, 2005; Peng and Ng, 2012) showed a significant feature, which is the asymmetry of volatility. Shin and Stulz (2000) decomposed shares risk into its market and firm-specific components in order to show that changes in market risk are positively correlated with changes in firm value, but changes in firm- specific risk are negatively correlated with changes in firm value. Campbell et al. (2001) used a disaggregated approach to study the volatility of common stocks at the market, industry and firm level. They proposed three variance components, which were estimated monthly using daily data, so their further analysis about volatility components were conducted on the basis of monthly frequency indicators and for this reason they could not consider the impact of volatility clustering effect on evaluation of risk measurement process. Phylatkis and Xia (2009) investigated the equity market comovement at the sector level and confirmed the sector heterogeneity of the contagion. They showed that investors might find the profitable sectors on the capital markets despite of the prevailing contagion on the market level. Chuliá and Torró (2011) estimated a conditional CAPM with multivariate GARCH-M structure in order to investigate an asymmetric volatility spillover effect between large and small firms in the Spanish stock market and they proved the existence of bidirectional relationship between these volatility processes with asymmetric influence of bad and good news for firm volatility. Sharma et al. (2011, 2014) showed that firms belonging to different sectors experienced different degrees of association with market volatility, what caused that in some cases firm volatility might be predicted on the basis of market volatility. They proved that commonality in volatility increases with the firm's size. Sequeira and Lan (2003) found that, the most significant component of aggregate volatility in the international market, with firm-level volatility forming the largest component of total volatility is unsystematic variance of the stock return. They also claim that volatility of the market-level is more important than the volatility of the sector-level in the explanation of the total volatility of stock return, which is also confirmed in earlier research conducted by Cavaglia et al. (2000) or Griffin and Karolyi (1998). That is why both managerial staff in enterprises and investors should be interested in knowing the strength and direction of relationships between shares volatility of particular enterprises and stock market volatility.

Previous studies on the volatility in the majority relate to market volatility. A small part of the study is devoted to the volatility of the firm-level. Volatility of asset prices is also often explained by the mechanism of transmission of crises and the related phenomenon of contagion (Baur, 2003; Corsetti et al., 2005; Claessens and Forbes, 2004; Le and David, 2014). Researchers examining the contagion effect on the capital market level concern only a chosen stock indices, which do not reflect the impact of the volatility of share prices of companies in different sectors. In such an approach the heterogeneity effect of the sectors selected within a given capital market and their various immunity to external shocks and different sensitivity to effects of a financial crisis are omitted (Phylatkis and Xia, 2009).

The impact of the subprime crisis on individual segments of the Polish financial market were presented by Konopczak et. al. (2010). The analysis shows the local and global conditions that made the interaction of disorders associated with the global financial crisis on the Polish financial market was as strong as in developed markets. Empirical studies, including the period of the subprime crisis, conducted by Otola (2013), concerning the relationship between the WIG index and the S&P500 index, had to indicate whether negative shocks arising in the United States have been transferred to Polish Capital Market by stock exchange channel. The high volatility in the capital market, which has been observed in an unstable period is not only the result of the interdependence between the markets but the result of the financial contagion of Polish Capital Market. In this context, we rightly seem to conduct the further research on the volatility of the Polish Capital Market on the firm level.

Taking above into consideration we are interested in examining the direction and strength of relationship between firm-level volatility and market-level volatility on the Polish Capital Market in the period of pre- and post-subprime crisis. The aim of this paper is to investigating if the market volatility and firm volatility are related and if the strength of this relationship increase significantly in the turbulent period compared to the stable period. The empirical study concerns the selected companies listed on the Warsaw Stock Exchange from the construction and IT sectors in the period from 2 January 2004 to 31 December 2011. In this respect, our contribution to the literature is connected with the calibration of Sharma et al. model (2011, 2014) through introducing long memory dynamics and skewed fat-tailed distributions of innovations into the basic model describing the relationship between firm volatility and market volatility. Following Sadigue and Silvapulle (2001) and Kang and Yoon (2012) we expect that on the Polish capital market some investors reacted to new information immediately, whereas others postpone making the investment decision until they confirm the information. It causes that their actions form a non-linear pattern, which characterizes statistical persistence in a time series. We also taking into consideration the possible structural changes that may have affected the long memory property, so we divide the analyzed period into two sub-periods, taking the subprime financial crisis of July 2007 as the structural change point. The above considerations allow us to formulate the following hypothesis: *There is no significant increase in the fraction of firms from a given sector of Polish Capital Market whose volatility is strongly and positively related with market volatility in pre-crisis period compared with post-crisis period.*

The remainder of the paper is organized as follows. Section 2 describes the methodology, data properties are presented in section 3. In Section 4 we verify the hypothesis about the commonality in volatility in stable and turbulent period. And finally, Section 5 concludes the paper.

2. Methodology

We have modified the model of Sharma et al. (2011, 2014), which describes the relationship between firm volatility and stock market volatility by capturing the possible long memory effect in both firm and market volatility process. Theoretical frames of the volatility model determines Capital Asset

Pricing Model (CAPM) and Fractionally Integrated Generalized Autoregressive Conditional Heteroscedasticity (FIGARCH).

In empirical research presented in the paper the authors use the following regression equation, in which firm volatility is conditioned by previous and present market volatility and also by present return on investment into the market portfolio and squared return of market index (Sharma et al., 2011):

$$V_{f_i,t} = \alpha_{0i} + \alpha_{1i}V_{m,t} + \alpha_{2i}V_{m,t-1} + \alpha_{3i}R_{m,t} + \alpha_{4i}R_{m,t}^2 + \varepsilon_{it}, \quad (1)$$

where: V_m – stock market volatility, V_{f_i} – share volatility of *i*-nth company (i=1, 2, ..,N), $R_{m,t}$ – logarithmic return of stock market index.

Sharma et al. (2011) incorporated market return and squared market return factors into above equation in order to control for possible spurious dependence between returns and volatility measures.

Price range estimators are used as volatility estimators that are computed on the basis of full publicly available set of information about financial instrument prices what make them more efficient than volatility estimators calculated as the squared return (Fiszeder and Perczak, 2013; Molnár, 2012; Sharma et al., 2014):

- daily volatility estimator created by Parkinson (1980):

$$V1 = 0.361 \cdot [\ln(PH_{it}) - \ln(PL_{it})]^2, \quad (2)$$

  where: PH_{it} – highest price of *i*-nth financial instrument on *t* day, PL_{it} – lowest price of *i*-nth financial instrument on *t* day;

- daily volatility estimator proposed by Garman and Klass (1980):

$$V2 = 0.5 \cdot [\ln(PH_{it}) - \ln(PL_{it})]^2 - [2\ln 2 - 1][\ln(PC_{it}) - \ln(PO_{it})]^2, \quad (3)$$

  where: PC_{it} – closing price of *i*-nth financial instrument on *t* day, PO_{it} – opening price of *i*-nth financial instrument on *t* day;

- daily volatility estimator defined by Rogers and Satchell (1991):

$$\begin{aligned} V3 = {} & [\ln(PH_{it}) - \ln(PO_{it})][\ln(PH_{it}) - \ln(PC_{it})] + \\ & + [\ln(PL_{it}) - \ln(PO_{it})][\ln(PL_{it}) - \ln(PC_{it})]. \end{aligned} \quad (4)$$

Originally, the Parkinson, Garman-Klass, Rogers-Satchell volatility measures of financial instruments prices are the estimators of unconditionally volatility for the geometric Brownian motion determined for time interval [0, *T*]. Therefore, all of analysed here estimators are derived under the assumptions of continuous sampling, no bid-ask spread and constant volatility. Moreover, in the case of the Parkinson and Garman-Klass estimators an additional assumption refers to zero drift. It is worth attracting attention on some properties of range-based volatility estimators, especially in the case when one day is used as a unit of time. It was proved that the Garman-Klass estimator characterized by the highest efficiency in the case when the assumption of zero drift was met. The efficiency of range- based volatility estimators for zero drift are as follow: the Parkinson – 4.9, the Garman-Klass – 7.4, the Rogers-Satchell – 6.0 and they are significantly higher than the efficiency of simply volatility estimator (based on squared daily returns) equals by definition 1 (Molnár, 2012). For daily financial time series, mean return is often much smaller than its standard deviation, which is in line with the assumption of zero drift. Fiszeder and Perczak (2013) derived the expected values of the Parkinson and Garman-Klass estimators for the arithmetic Brownian motion with non-zero drift and they proved the unbiasedness of the Parkinson and Garmann-Klass estimators for the process with a zero drift and of the Rogers-Satchell estimator for any drift. It is worth stressing that the square root of any range-based volatility estimators is a biased estimator of standard deviation of a Brownian motion, but this bias is rather small (3–4%) compared to bias of the square root of the simply volatility estimator (25%). The questionable issue is the use of the range-based volatility estimators for the standardization of the returns. It was shown that returns normalized by means of the Garman-Klass estimator were approximately normally distributed. Another disadvantage concerning the use of range estimators in practice is failure to comply with the assumptions of continuous sampling. Prices are observed at discrete points in time (vector of PO_t, PH_t, PL_t, PC_t for each day) and it causes that the observed high price is below the true high price and observed low price is above the true low price. Bid-spread effect works in the opposite direction. These two effects are small for liquid stocks (Molnár, 2012). A debatable question is also the adjustment of range-based volatility estimators for the opening jumps, resulting from the situation that most of the assets are not traded continuously for 24h a day (Molnár, 2012; Fiszeder and Perczak, 2013).

Sharma et al. (2014) limited their empirical studies to modelling the firm volatility shocks (ε_i error term) by using GARCH(1,1) model with the conditional normal distribution of innovations. In the above equation the authors used full available on a given day information on the market portfolio (opening price, the lowest and the highest price, closing price), which will allow us to eliminate the effect of influencing the research results with one type of data only – closing price. For each analyzed series of share prices volatility of the given enterprises the ARFIMA(P,D,Q)-FIGARCH(p,d,q) models were chosen individually in accordance with the following stages:

- specification of the equation describing the relation between market volatility and firm volatility (1), adjusted for possible autocorrelation dependencies occurring in the company share volatility series;
- specification of the conditional variance equation describing the ARCH effect in the series of residuals from the equation (1) and the selection of the form of innovation density function.

The fractionally integrated autoregressive moving average process (ARFIMA) is more flexible econometric tool for modelling the conditional mean process than ARMA model in the situation when it exhibits long memory properties. Similarly, the fractionallly integrated generalized autoregressive conditional heteroskedasticity process, constituting a generalization of the GARCH model, enables for capturing the persistence in the conditional variance process (Bollerslev and Mikkelsen, 1996). However, market shocks have a simultaneous impact on the conditional mean and conditional variance. Therefore, some recent empirical studies have focused on the analyzing the relationship between the conditional mean and the conditional variance of the process that simultaneously exhibits long memory properties (Beine et al., 2002; Fiszeder, 2009; Kang and Yoon, 2012). The ARFIMA(P,D,Q)-FIGARCH(p,d,q) model is defined in the following way (Arouri et al., 2012):

$$\begin{aligned} &\psi(L)(1-L)^D(y_t-\mu_t)=\theta(L)\varepsilon_t \\ &\varepsilon_t=\eta_t\sqrt{h_t} \\ &\alpha(L)(1-L)^d\varepsilon_t^2=\omega+[1-\beta(L)]\vartheta_t \\ &\vartheta_t=\varepsilon_t^2-h_t, \end{aligned} \tag{5}$$

where: L denotes a lag operator;

$(1-L)^D=\sum_{j=0}^{\infty}\binom{D}{j}\cdot(-1)^jL^j=\sum_{j=0}^{\infty}\frac{\Gamma(j-D)}{\Gamma(j+1)\Gamma(-D)}L^j$ – differential filter of D order, where, $\Gamma(\cdot)$ denotes gamma function;

$\psi(L)=1-\psi_1L-...-\psi_PL^P$, $\theta(L)=1+\theta_1L+...+\theta_QL^Q$ are respectively lags polynomials for the autoregressive part of P order and moving average of Q order, whose all roots lie outside the unit circle, ψ_i, θ_i are the model parameters; $(1-L)^d=\sum_{s=0}^{\infty}\binom{d}{s}\cdot(-1)^sL^s=\sum_{s=0}^{\infty}\frac{\Gamma(s-d)}{\Gamma(s+1)\Gamma(-d)}L^s$ – differential filter of d order; $\alpha(L)=1-\alpha_1L-...-\alpha_qL^q$, $\beta(L)=1+\beta_1L+...+\beta_pL^p$ are respectively lags polynomials for the ARCH part of q order and GARCH part of p order, all the roots of $\alpha(L),[1-\beta(L)]$ lie outside the unit circle, α_i, β_i are the model parameters; η_t is an innovations series, $\eta_t \sim i.i.d(0,1)$.

On the basis of D parameter value one can identify the memory type of the process (Hosking,1981):

- $D \in (-0.5; 0)$ means that the process exhibits negative dependencies between distant observations (anti-persistence, but stationary process),
- $D \in (0; 0.5)$corresponds to the long-memory stationary process,
- $D = 0$ means reduction of the ARFIMA(P,D,Q) to the stationary ARMA(P,Q) model (short memory process),
- $D \geq 0.5$ indicates a non-stationary process (in particular for $D = 1$ the process follows a unit root process – ARIMA(P,1,Q) model).

For the FIGARCH model the influence of current shocks for volatility forecasts decreases to zero, but at a slower rate than for GARCH processes. Moreover, the autocorrelation function of FIGARCH squared residuals decreases at a hyperbolic rate to zero, which indicates long memory in volatility of series described by this class models. The existence of long memory in volatility process may be recognized on the basis of estimated value of d parameter (Fiszeder, 2009):

- $d \in (0; 1)$ means that volatility process exhibits long memory property,
- $d = 0$ means reduction of the FIGARCH(p,d,q) to the GARCH(p,q) process for which the influence of current volatility on forecasts of conditional variance decays at fast rate (also short memory process in sense of "influence of current volatility for the *true* conditional variance process"),
- $d = 1$ means reduction of the FIGARCH(p,d,q) to the IGARCH(p,q) process for which current volatility has permanent impact on forecasts of conditional variance (short memory in above explained sense).

This class of models is estimated by using the quasi-maximum likelihood (QML) estimation method, based on the following log-likelihood function (under the assumption about Gaussian distribution of innovations) (Fiszeder, 2009; Kang and Yoon, 2012):

$$LL_{Gaussian} = -\frac{1}{2}T\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}[\ln(h_t) + \eta_t^2], \tag{6}$$

where T denotes the number of observation.

It is worth stressing that one of stylized facts of high – frequency time series of financial prices is excess kurtosis and skewness of returns distributions (Fiszeder, 2009; Laurent, 2013; Włodarczyk, 2010). In order to capture the excess kurtosis and fat-tailed effect in the residuals, the Student t-distribution may be used as the innovation distribution in ARFIMA-FIGARCH model, and then the log-likelihood function is defined as follows (Kang and Yoon, 2012; Laurent, 2013):

$$LL_{Student} = T\left\{\ln\Gamma\left(\frac{\nu+1}{2}\right) - \ln\Gamma\left(\frac{\nu}{2}\right) - \frac{1}{2}\ln[\pi(\nu-2)]\right\} - \\ -\frac{1}{2}\sum_{t=1}^{T}\left[\ln(h_t) + (1+\nu)\left[\ln\left(1+\frac{\eta_t^2}{\nu-2}\right)\right]\right], \tag{7}$$

where $2 < \nu \leq \infty$.

Parameter ν measures the degree of fat tails of the density function and the lower its values is, the fatter tails of distribution are. The latest specification of ARFIMA-FIGARCH models, which be considered in this work, allows for both the excess skewness and kurtosis of residuals by using the skewed Student t-distribution. In this case the log-likelihood function is as follows (Kang and Yoon, 2012; Laurent, 2013):

$$LL_{SkewedStudent} = T\left\{\ln\Gamma\left(\frac{\nu+1}{2}\right) - \ln\Gamma\left(\frac{\nu}{2}\right) - \frac{1}{2}\ln[\pi(\nu-2)] + \ln\left(\frac{2}{k+\frac{1}{k}}\right) + \ln(\sigma_S)\right\} - \\ -\frac{1}{2}\sum_{t=1}^{T}\left[\ln(h_t) + (1+\nu)\left[\ln\left(1+\frac{(\sigma_S\eta_t+\mu_S)^2}{\nu-2}k^{-2I_t}\right)\right]\right], \tag{8}$$

where:

$$I_t = \begin{cases} 1 & \text{if } \eta_t \geq -\mu_S/\sigma_S \\ -1 & \text{if } \eta_t < -\mu_S/\sigma_S \end{cases}, \tag{9}$$

is the indicator function, which is determined on the basis of the mean *(μ_S)* and standard deviation (σ_S) of the skewed Student *t*-distribution (Kang and Yoon, 2012; Laurent, 2013):

$$\mu_S = \frac{\Gamma\left(\frac{\nu-1}{2}\right)\sqrt{\nu-2}}{\sqrt{\pi}\,\Gamma\left(\frac{\nu}{2}\right)}\left(k-\frac{1}{k}\right), \tag{10}$$

$$\sigma_S^2 = \left(k^2 + \frac{1}{k^2} - 1\right) - \mu_S^2. \tag{11}$$

The value of the asymmetry parameter ln(k) determined the type of skewness, that is, if $\ln(k) > 0$, the density is right skewed and if $\ln(k) < 0$, the density is left skewed.

3. Data Description

Empirical research were conducted for the chosen companies from construction and IT sector listed on the main market of the Warsaw Stock Exchange whereas restrictive provisions which these companies had to meet in order to be able to exist on it. To the research 17 companies from the construction sector were chosen in the stable period and during a turbulent three more. The IT sector study involved 10 companies during the stable period and 20 in a turbulent period. The authors excluded from the research sample enterprises which in the given sub-period withdrew from the market or their debuts took place in the course of the given sub-period. Data were obtained from the Notoria Service and consist of 2013 daily observations of high, low, open and close prices for analyzed companies from January 2, 2004 to December 30, 2011.

The starting point is determining the breakthrough on the basis of which it is possible to distinguish two sub-periods: the stable period which corresponds to low stock market volatility and the turbulent period characterized by high market volatility. First symptoms of growing volatility of main indexes of American market (DJIA, NASDAQ, S&P500) can be observed in July and August of 2007. They are accompanied by bankruptcy of two hedging funds of Bear Stearns bank connected with the mortgage market in the USA (July 2007), as well as the insolvency of three funds of the French bank BNP Paribas investing in the bonds market secured with mortgages subprime (9 August 2007) (Otola, 2013; Burzała, 2013; Dungay et al., 2011). The analyzed period was divided into two sub-samples:

- the stable period (02.01.2004–25.07.2007) – 899 observations;
- the turbulent period (26.07.2007–31.12.2011) – 1114 observations.

Due to the prolonging period of instability on the European financial market, caused not only by the occurrence of the subprime crisis, but also the debt crisis in the peripheral countries of the EU zone, the turbulent period in the present analysis was lengthened to the end of the year 2011.

Selection of sectors was conducted on the following basis. The construction sector is most connected with the country's economy and most susceptible to GDP changes. It is also most strongly represented sector on the Polish stock market. Moreover, since 2004 Poland as a member of the European Union has been receiving financial resources within European funds to improve the living conditions of inhabitants. In the course of the second programming period (2007–2013) Poland received about 242,3 billion PLN, the part of which was destined for public infrastructural investments, both in the scope of road construction as well as other public facilities. About 48% of allocated within structural funds resources were used to execute the Infrastructure and Environment Programme. Additionally, the decision of UEFA in the II quarter of 2007 to give the right to organize the European Football Championship – Euro 2012 in Poland and Ukraine was also connected with the necessity to complete numerous construction investments in short time. According to the Central Statistical Office since the year 2005 the construction sector was the fastest growing sector of Polish economy. Moreover, this sector is the most abundantly represented sector on the Warsaw Stock Exchange. We claim that there is no significant increase in the fraction of firms, belonging to the construction sector, whose volatility is shaped by market volatility in the turbulent period compared to the stable period. Thus, one can expect that external shocks transmitted on the stock market in Poland in the subprime crisis period and the debt crisis in the Euro zone should not be noticeable by the enterprises of this sector. Claessens and Forbes (2004) emphasised the importance of investor reactions in the contagion process in the liquidity risk context. Referring to this theory one can expect that investors having in mind good development perspectives resulting from a substantial financing of this sector with structural funds should not withdraw capital located in the stocks of construction companies.

The second select sector, namely IT, may be considered as the one based on knowledge, most intellectual and innovative one. The IT sector may be divided into three groups due to the form of conducted activity:

- production of IT equipment (among others Comp, Elzab, Novitus);
- software related services (among others Asseco Poland, Comarch, Sygnity);
- distribution of IT solutions (among others Arcus, B3System, NNT System).

Comparing it with the construction sector one should notice that in the analyzed period a lot of enterprises from the IT sector put on acquiring capital to conduct activity through emission of shares (see table 1). The resources acquired from the shareholders for development of this sector are used not only on tangible investments but also investments in intellectual capital. Moreover, development of new and growth of awareness of needs in the scope of IT also in the sector of Small and Medium Enterprises, the use of structural funds to liquidate disproportions in access to tele-informatic technologies in rural areas are only some of the factors conditioning continuity of operations of this sector companies. The IT sector is perceived in the world as one of the most perspective ones, the one which creates new innovative products, such as for example mobile product applications or development of cloud services. Customers of products and services of the IT sector are primarily enterprises from the public administration sector that to a large extent use for this purpose the resources from the European funds. More important customers of services and products from the IT sector are enterprises operating in the banking and tele-communication sectors. Such a perception of the IT sector by the investors should contribute to the fact that the enterprises listed on the stock market should show resistance to shocks coming from the market. Thus, in our opinion commonality in volatility did not increase significantly in the turbulent period compared to the stable period in the IT sector on the Polish Capital Market.

Table 1. Descriptive statistics for volatility measures – stable period

Variable	Minimum	Mean	Maximum	Standard deviation	Skewness	Kurtosis
V1_WIG	0.0004	0.008	0.157	0.012	5.577 [0.000]	47.622 [0.000]
V2_WIG	0.0003	0.008	0.195	0.011	7.348 [0.000]	85.857 [0.000]
V3_WIG	0	0.008	0.269	0.013	9.764 [0.000]	147.92 [0.000]
V1_Construction	0.013	0.136	1.303	0.130	3.042 [0.000]	14.837 [0.000]
V2_Construction	0.011	0.131	1.786	0.146	4.248 [0.000]	28.550 [0.000]
V3_Construction	0.006	0.158	3.506	0.241	5.418 [0.000]	47.534 [0.000]
V1_IT	0.009	0.116	1.046	0.119	2.759 [0.000]	10.424 [0.000]
V2_IT	0.010	0.084	1.397	0.081	6.675 [0.000]	78.417 [0.000]
V3_IT	0.011	0.092	2.179	0.103	10.018 [0.000]	165.52 [0.000]

Note: all volatility series were scaled by 100, p-value in brackets.

On the basis of daily information on four price categories (open, close, high and low) of the WIG stock index and shares of particular companies the authors determined volatility series in the stable and turbulent period according to the price range volatility measures (2)–(4). For each sector the authors estimated series of average firm volatility in each of the analyzed sub-periods and then on their basis they determined descriptive statistics (Tables 1–2).

Table 2. Descriptive statistics for volatility measures – turbulent period

Variable	Minimum	Mean	Maximum	Standard deviation	Skewness	Kurtosis
V1_WIG	0.0002	0.015	0.373	0.028	6.125 [0.000]	53.180 [0.000]
V2_WIG	0.0002	0.013	0.305	0.027	6.340 [0.000]	50.279 [0.000]
V3_WIG	0	0.013	0.357	0.029	6.651 [0.000]	55.075 [0.000]
V1_Construction	0.012	0.205	2.481	0.351	2.176 [0.000]	3.837 [0.000]
V2_Construction	0.010	0.120	3.394	0.195	7.707 [0.000]	103.24 [0.000]
V3_Construction	0.010	0.100	3.623	0.253	10.149 [0.000]	112.55 [0.000]
V1_IT	0.061	0.289	1.224	0.170	1.861 [0.000]	4.802 [0.000]
V2_IT	0.011	0.092	0.571	0.075	2.919 [0.000]	11.721 [0.000]
V3_IT	0.010	0.104	0.697	0.084	2.626 [0.000]	9.510 [0.000]

Note: all volatility series were scaled by 100, p-value in brackets.

One can observe that the average volatility in the IT sector was relatively lower than in the construction sector for all three measures. A similar dependence can be observed for the maximum value of each volatility measures evaluated for the firms in both sectors. It is worth emphasizing that in the stable period market volatility was substantially lower than volatility of firms in both sectors, comparing volatility range determined in accordance with the three analyzed measures. Also determined skewness and kurtosis indicate sector differentiation of the volatility process, which may indicate heterogeneity of the construction and IT sectors on the Warsaw Stock Exchange. Similar conclusions were formulated for the American stock exchange in the paper of Sharma, Narayan and Zheng (2014).

The determined average statistics for the series of firm and market volatility took higher values in the turbulent period in comparison with the stable period. Also in this period market volatility was substantially lower than the firm volatility in both sectors. Due to high kurtosis and skewness of the volatility series determined in accordance with the Rogers and Satchel formula only volatility calculated according to the Parkinson method has been included in the further part of the analysis. Shaping of daily volatility for the

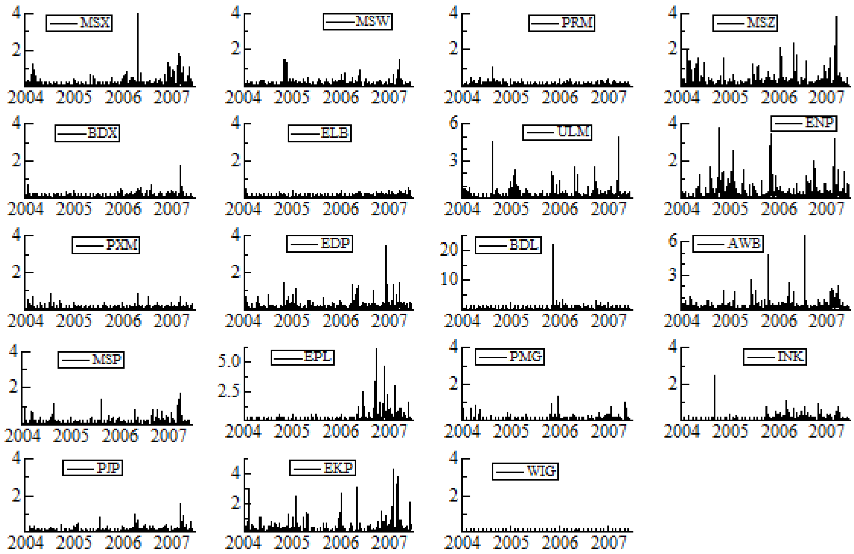

Figure 1. Shaping of daily volatility for the companies from the construction sector in the stable period[1]

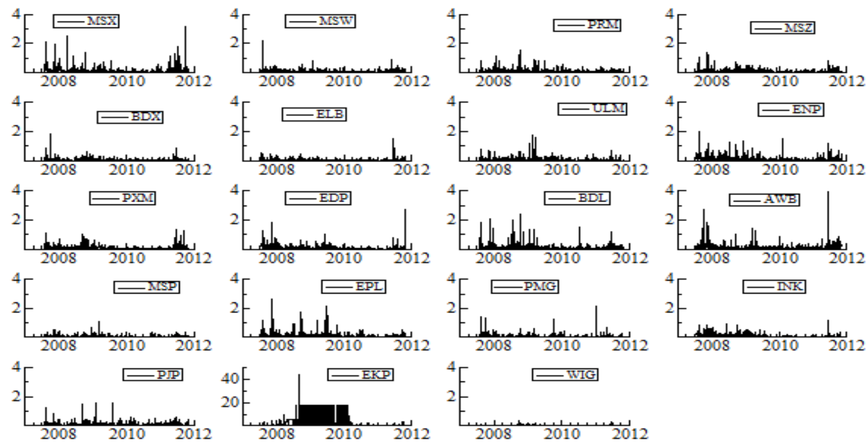

Figure 2. Shaping of daily volatility for the companies from the construction sector in the turbulent period[2]

[1] Explanations of used abbreviations for listed companies can be found in Table 5.
[2] Explanations of used abbreviations for listed companies can be found in Table 6.

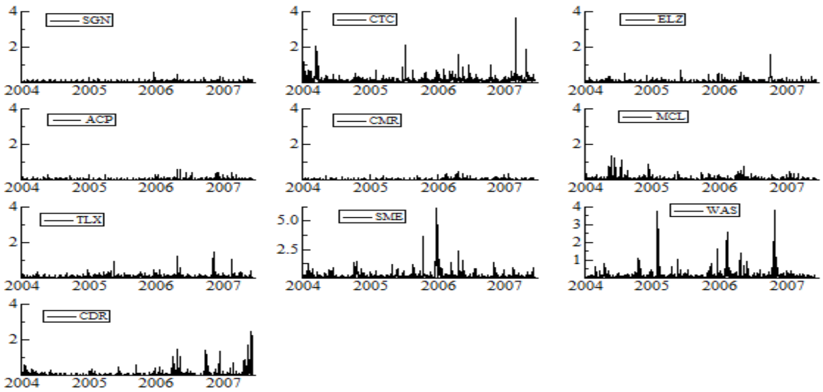

Figure 3. Shaping of daily volatility for the companies from the IT sector in the stable period[3]

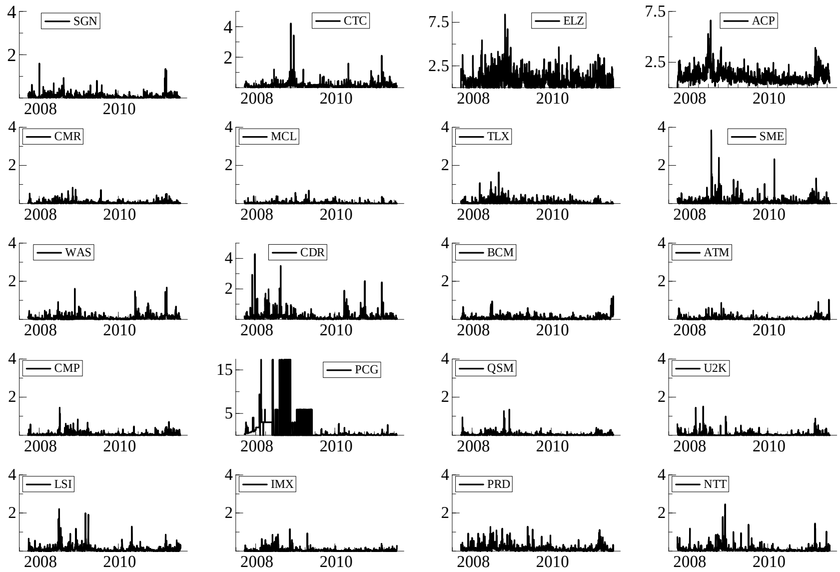

Figure 4. Shaping of daily volatility for the companies from the IT sector in the turbulent period[4]

[3] Explanations of used abbreviations for listed companies can be found in Table 7.
[4] Explanations of used abbreviations for listed companies can be found in Table 8.

companies from the construction and IT sectors in the stable and turbulent periods show Figures 1–4.

In the stable period the biggest range of daily share price volatility fell for Budopol SA company. High daily spread of volatility was also characteristic for such companies as: Awbud SA, Energopol Południe SA, Ulma Construccion SA. In the turbulent period two companies Elkop SA and Erbud SA were characterized by very high daily volatility spread.

In the stable period the highest spread in daily volatility was observed for the companies: Simple SA, Wasko SA and Calatrava Capital SA. In the turbulent period a high daily spread of volatility was observed in the companies: ZUK Elzab, Asseco Poland SA, CD Project Red SA, Calatrava Capital SA, Simple SA, PC Guard SA, LSI Software SA, NTT System SA.

The presented above descriptive statistics for enterprises listed on the Warsaw Stock Exchange from the construction and IT sectors let us notice differences both between sectors as well as the stable and turbulent periods.

4. Verifying the Hypothesis about the Commonality in Volatility in Stable and Turbulent Period

Time series volatility V1 of share prices of enterprises from the construction and IT sectors in the stable period i.e. 02.01.2004.–25.07.2007 and the turbulent one 26.07.2007–31.12.2011 were subject to modelling in order to verify the occurrence of significant relationships between firm volatility and WIG index volatility. Due to the characteristic properties of volatility time series, which were the subject of modelling: skewness, high kurtosis, fat-tailed distribution, autocorrelation dependencies (Box-Pierce test), occurrence of long memory effect (GPH test), occurrence of volatility clustering effect (Engle test, McLeod and Li test) (see Table 3), for each volatility series individual specification of the model in the form (5)–(8) were selected with t-Student distribution or skewed t-Student distribution (Laurent, 2013).

Additionally, in the conditional mean equation is assumed that the firm volatility is dependent on previous, present and future market volatility and also expected daily change of the WIG index and the squared WIG index return. The choice of the final form of the firm volatility model has been performed on the basis of :

- evaluating significance of the model parameters estimations;
- minimizing information criteria of Akaike'a (AIC) and Bayesian Schwarz (SC);

– test results of standardized models residuals which verified the correctness of the model dynamic specification: Box-Pierce test, Engle test, McLeod and Li test;
– Nyblom test for checking the constancy of model parameters over time;
– Engle and Ng set of tests for existing leverage effect and investigating possible misspecification of the conditional variance equation (FIGARCH vs. FIEPARCH), with in particularly covered Negative Sign Bias test and Positive Sign Bias test for verifying the effect of negative and positive shocks on the conditional variance (Laurent, 2013).

Table 3. Descriptive statistics and diagnostic tests for volatility series of MSW in stable period

Parameter/Test	Value of statistics
Mean	0.868
Standard deviation	1.410
Minimum	0
Maximum	14.537
Skewness	5.239 [0.000]
Kurtosis	38.493 [0.000]
Jarque-Bera statistics	59616 [0.000]
ADF statistics	–6.588
D-GPH statistics	0.259 [0.000]
Q Box-Pierce statistics	
Q(5)	71.1948 [0.000]
Q(10)	120.783 [0.000]
Q(20)	145.085 [0.000]
Q(50)	172.831 [0.000]
Q McLeod-Li statistics	
Q(5)	117.096 [0.000]
Q(10)	182.624 [0.000]
Q(20)	204.178 [0.000]
Q(50)	214.615 [0.000]
Engle LM statistics	
ARCH(1–1)	46.606 [0.000]
ARCH(1–2)	25.877 [0.000]
ARCH(1–5)	23.281 [0.000]
ARCH(1–10)	15.902 [0.000]
ARCH(1–20)	9.590 [0.000]

Note: p-value in brackets.

Below we present the detailed results of the estimation of ARFIMAX-FIGARCH model with t-Student innovations for the chosen enterprise from the construction sector – Mostostal Warszawa SA (MSW; see Table 4a–4b).

Table 4a. Estimation results of ARMAX(1,2)-GARCH(1,1) for MSW in stable period

Parameter	Parameter estimates		
Cst(M)	0.223 [0.000]		
$V_{m,t}$_WIG	**0.369 [0.374]**		
AR(1)	0.858 [0.000]		
MA(1)	–0.712 [0.000]		
MA(2)	–0.049 [0.044]		
Cst(V)	0.221 [0.025]		
ARCH1	0.165 [0.003]		
GARCH1	0.757 [0.000]		
Df-Student	2.258 [0.000]		
AIC	2.029	SC	2.072

Note: p-value in brackets.

Table 4b. Diagnostic residuals tests for MSW

Test	Estimates of the test statistics
Q Box-Pierce statistics for standardized residuals	
Q(5)	8.183 [0.037]
Q(10)	11.812 [0.107]
Q(20)	19.714 [0.289]
Q(50)	54.719 [0.205]
Q Box-Pierce statistics for squared standardized residuals	
Q(5)	0.660 [0.883]
Q(10)	0.916 [0.999]
Q(20)	2.187 [0.999]
Q(50)	3.857 [0.999]
Engle LM statistics	
ARCH(1–2)	0.035 [0.965]
ARCH(1–5)	0.128 [0.986]
ARCH(1–10)	0.088 [0.999]
Jarque-Bery for normality	27151 [0.000]
Joint Nyblom test of stability	1.2021
Nyblom for Cst(M)	0.1501
Nyblom for $V_{m,t}$_WIG	0.0541
Nyblom for AR(1)	0.0577
Nyblom for MA(1)	0.0505
Nyblom for MA(2)	0.0803
Nyblom for Cst(V)	0.1432
Nyblom for ARCH1	0.2187
Nyblom for GARCH1	0.2149
Nyblom for Df-Student	0.0712
Sign Bias Test	0.899 [0.369]
Negative Sign Bias Test	0.381 [0.703]
Positive Sign Bias Test	0.275 [0.783]
Jointly Engle–Ng test	2.227 [0.527]

Note: p-value in brackets, p-value (5%) = 0.47 for individual Nyblom test.

It is worth emphasizing that for each estimated model for the Mostostal Warszawa company, the parameters indicating the strength and direction of dependencies between enterprise volatility and market volatility was statistically insignificant.

The results summarizing estimation of ARFIMAX-FIGARCH class models with included variables describing volatility of the stock market for particular companies from the construction sector in the stable period and turbulent period have been presented in Tables 5–6.

The analysis of data included in Table 5 allows us to formulate the following conclusions. In case of Energopol-Południe and Budopol-Wrocław enterprises the relationship between the market volatility and volatility of their share prices was statistically insignificant. For the remaining enterprises the relationship between the WIG index volatility and firms volatility was statistically significant and positive. All additional variables describing market volatility ($V_{m,t-1}$_WIG, $R_{m,t}$, $R_{m,t}^2$) turned out to be statistically insignificant in case of all estimated models.

Table 5. Results on commonality in volatility for construction sector in stable period

Company	Model specification	Estimate of $V_{m,t}$_WIG parameter	Significance of the influence of others market variables ($V_{m,t-1}$_WIG, $R_{m,t}$, $R_{m,t}^2$) on firm volatility
Mostostal Export (MSX)	ARMAX(1,1)-FIGARCH(1,0.54,1), t-Student distribution	2.069 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Prochem (PRM)	ARFIMAX(1,0.121,1)-GARCH(1, 1), t-Student distribution	0.390 [0.005]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Mostostal Zabrze Holding (MSZ)	ARFIMAX(1,0.049,1)-GARCH(1, 1), t-Student distribution	1.191 [0.013]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Budimex (BDX)	ARFIMAX(1,0.021,1)-GARCH(1, 1), skewed t-Student distribution	0.090 [0.006]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Elektrobudowa (ELB)	ARFIMAX(1,0.105,1)-GARCH(1, 1), t-Student distribution	0.677 [0.010]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Energoaparatura (ENP)	ARFIMAX(1,0.086,0)-ARCH(1), t-Student distribution	0.539 [0.022]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Energopol-Południe (EPL)	ARFIMAX(1,0.185,1)-GARCH(1, 1), t-Student distribution	0.075 [0.410]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model

Table 5. continued

Company	Model specification	Estimate of $V_{m,t}$_WIG parameter	Significance of the influence of others market variables ($V_{m,t-1}$_WIG, $R_{m,t}$, $R_{m,t}^2$) on firm volatility
Projprzem (PJP)	ARFIMAX(1,0.027,0)-ARCH(1), t-Student distribution	0.167 [0.003]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Elkop (EKP)	ARMAX(1,1)-GARCH(1, 1), t-Student distribution	0.023 [0.018]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Ulma Construccion Polska (ULM)	ARFIMAX(0,0.06,1)-FIGARCH(1,0.57,1), t-Student distribution	0.041 [0.355]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Energomontaż-Południe (EDP)	ARFIMAX(1,0.042,1)-GARCH(1,1), t-Student distribution	0.815 [0.045]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Mostostal Płock (MSP)	ARX(2)-GARCH(1,1), t-Student distribution	3.642 [0.000]	$R_{m,t}$: 0.081 [0.027] $R_{m,t}^2$: –0.069 [0.001]
Budopol-Wrocław (BDL)	ARFIMAX(0,0.06,1)-FIGARCH(1,0.79,1), t-Student distribution	0.024 [0.283]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Awbud (AWB)	ARFIMAX(0,0.06,1)-GARCH(1,1), t-Student distribution	0.921 [0.005]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Pemug (PMG)	ARX(2)-GARCH(1,1), t-Student distribution	0.748 [0.099]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Instal Kraków (INK)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	2.618 [0.000]	$R_{m,t}^2$: –0.076 [0.001]

Note: p-value in brackets.

In the turbulent period for five enterprises: Awbud, Projprzem, Prochem, Elkop, Ulma Construccion the relationship between the WIG index volatility and firm volatility was statistically insignificant. For the remaining 15 enterprises statistically significant influence of market volatility on firm volatility was confirmed, while the direction of this dependence was positive. Additionally, share price volatility of Mostostal Warszawa was significantly shaped by market volatility observed on the previous day. In case of the remaining enterprises additional variables did not significantly influence share price volatility. The conducted commonality in volatility analysis for the enterprises listed on the Warsaw Stock Exchange shows that in the stable period 82% of analyzed enterprises were sensitive to the WIG index volatility, the appropriate ratio in the turbulent period reached the value of 75%.

Table 6. Results on commonality in volatility for construction sector in turbulent period

Company	Model specification	Estimate of $V_{m,t}$_WIG parameter	Significance of the influence of others market variables ($V_{m,t-1}$_WIG, $R_{m,t}$, $R_{m,t}^2$) on firm volatility
Mostostal Export (MSX)	ARFIMAX(1,0.07,1)-GARCH(1,1), t-Student distribution	0.949 [0.007]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Mostostal Warszawa (MSW)	ARX(2)-GARCH(1,1), t-Student distribution	0.171 [0.006]	$V_{m,t-1}$_WIG: 0.176 [0.040]
Prochem (PRM)	ARMAX(1,1)-FIGARCH(1,0.68,1), t-Student distribution	0.138 [0.483]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Budimex (BDX)	ARFIMAX(1,0.103,1)-GARCH(1,1), t-Student distribution	0.206 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Mostostal Zabrze Holding (MSZ)	ARFIMAX(1,0.076,0) -GARCH(1,1), t-Student distribution	0.867 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Elektrobudowa (ELB)	ARFIMAX(1,0.121,1)-GARCH(1,1), t-Student distribution	0.122 [0.082]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Ulma Construccion Polska (ULM)	ARFIMAX(1,0.041,1)-GARCH(1,1), t-Student distribution	0.227 [0.454]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Energoaparatura (ENP)	ARFIMAX(1,0.111,0)-GARCH(1,1), t-Student distribution	0.508 [0.005]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Polimex-Mostostal (PXM)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	1.639 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Mostostal Płock (MSP)	ARMAX(1,1)-ARCH(1), t-Student distribution	0.401 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Energopol-Południe (EPL)	ARFIMAX(1,0.045,1)-GARCH(1,1), t-Student distribution	0.521 [0.012]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Instal Kraków (INK)	ARFIMAX(0,0.12,1)-FIGARCH(1,0.75,1), t-Student distribution	0.541 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Projprzem (PJP)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.065 [0.562]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Elkop (EKP)	ARFIMAX(1,0.999,0)-ARCH(1), t-Student distribution	0.054 [0.189]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model

Table 6. continued

Company	Model specification	Estimate of $V_{m,t}$_WIG parameter	Significance of the influence of others market variables ($V_{m,t-1}$_WIG, $R_{m,t}$, $R_{m,t}^2$) on firm volatility
PBG (PBG)	ARFIMAX(1,0.236,1)-GARCH(1,1), t-Student distribution	1.041 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Herkules (HRS)	ARFIMAX(1,0.063,1)-GARCH(1,1), t-Student distribution	1.016 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Erbud (ERB)	ARFIMAX(1,0.04,1)-GARCH(1,1), t-Student distribution	0.269 [0.020]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Energomontaż-Południe (EDP)	ARFIMAX(1,0.14,1)-GARCH(1,1), t-Student distribution	0.457 [0.009]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Budopol-Wrocław (BDL)	ARFIMAX(1,0.087,1)-GARCH(1,1), t-Student distribution	0.972 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Awbud (AWB)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	–0.018 [0.735]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model

Note: p-value in brackets.

Estimation of volatility models for the IT sector enterprises in both analyzed periods was conducted in the same manner as in case of the construction sector enterprises (Tables 7–8).

The estimated models indicate a statistically insignificant relationship between market volatility and share price volatility of IT sector companies only in case of Macrologic and Talex. Moreover, included in the modelling process the additional variables describing market volatility, did not have a statistically significant impact on shares volatility of the analyzed enterprises.

In the turbulent period for the seven analyzed enterprises from the IT sector: Comarch, Talex, Simple, Wasko, PC Guard, Unima 2000, Infovide-Matrix the relationship between the WIG index volatility and share price volatility was statistically insignificant at 10% significance level. In addition, for three enterprises: Comarch, Procad and NTT System market volatility from the previous day significantly affected share price volatility of these enterprises.

On the basis of empirical studies results for IT sector one may draw the conclusion that ARFIMAX-FIGARCH specification has been chosen more frequently for the post-crisis period compared to pre-crisis period. Therefore, long memory property is not an inherent feature of firm volatility process and the structural change connected with the subprime crisis may influence to the assessment of the long memory property in the volatility[5]. The conducted commonality in volatility analysis for the IT sector enterprises listed

Table 7. Results on commonality in volatility for IT sector in stable period

Company	Model specification	Estimate of $V_{m,t}$_WIG parameter	Significance of the influence of others market variables ($V_{m,t-1}$_WIG, $R_{m,t}$, $R_{m,t}^2$) on firm volatility
Calatrava Capital (CTC)	ARFIMAX(1,0.104,1)-GARCH(1,1), t-Student distribution	1.186 [0.002]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
ZUK Elzab (ELZ)	ARFIMAX(1,0.044,1)-GARCH(1,1), t-Student distribution	0.362 [0.030]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Asseco Poland (ACP)	ARFIMAX(1,0.108,1)-GARCH(1,1), t-Student distribution	0.536 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Comarch (CMR)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.349 [0.003]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Macrologic (MCL)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.392 [0.133]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Talex (TLX)	ARMAX(1,1)-GARCH(1,1) with t-Student distribution	0.362 [0.155]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Simple (SME)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	1.414 [0.061]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
CD Project Red (CDR)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.949 [0.001]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Sygnity (SGN)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.349 [0.086]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Wasko (WAS)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.719 [0.056]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model

Note: p-value in brackets.

[5] It is worth underlining that for both the construction and IT sectors there were no reasons for changing the basic specification of firm volatility models to Exponential GARCH model, which enables capturing the asymmetric effect of negative and positive shocks for conditional variance (results of Sign Bias tests). But for deepening the studies over the linkage between market volatility and firm volatility on the Polish Capital Market we will use the asymmetric multivariate GARCH structure in near future.

on the Warsaw Stock Exchange shows that in the stable period 80% of analyzed enterprises were sensitive to the WIG index volatility, while in the turbulent period the fraction of these enterprises dropped to 65%.

Table 8. Results on commonality in volatility for IT sector in turbulent period

Company	Model specification	Estimate of $V_{m,t}$_WIG parameter	Significance of the influence of others market variables ($V_{m,t-1}$_WIG, $R_{m,t}$, $R_{m,t}^2$) on firm volatility
Sygnity (SGN)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.633 [0.005]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Calatrava Capital (CTC)	ARFIMAX(1,0.049,1)-GARCH(1,1), t-Student distribution	1.401 [0.013]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
ZUK Elzab (ELZ)	ARMAX(1,1)-FIGARCH(1,0.39,1), t-Student distribution	1.494 [0.036]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Asseco Poland (ACP)	ARFIMAX(1,0.64,1)-GARCH(1,1),skewed t-Student distribution	1.381 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Comarch (CMR)	ARFIMAX(1,0.07,1)-FIGARCH(1,0.31,1), t-Student distribution	0.085 [0.410]	$R_{m,t}^2$: 0.011 [0.005]
Macrologic (MCL)	ARFIMAX(1,0.08,1)-FIGARCH(1,0.7,1), t-Student distribution	0.020 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Talex (TLX)	ARFIMAX(2,0.044,0)-GARCH(1,1), t-Student distribution	–0.008 [0.942]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Simple (SME)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.365 [0.203]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Wasko (WAS)	ARMAX(1,1)-GARCH(1,1), skewed t-Student distribution	0.073 [0.326]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
CD Project Red (CDR)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	2.180 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Betacom (BCM)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.706 [0.000]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
ATM (ATM)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.554 [0.049]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Comp (CMP)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.188 [0.080]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model

Table 8. continued

Company	Model specification	Estimate of $V_{m,t}$_WIG parameter	Significance of the influence of others market variables ($V_{m,t-1}$_WIG, $R_{m,t}$, $R_{m,t}^2$) on firm volatility
PC Guard (PCG)	ARFIMAX(1,0.002,1)-GARCH(1,1), t-Student distribution	0.003 [0.731]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model, problem with parameters' stability
Qumak-Sekom (QSM)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.271 [0.021]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Unima 2000 SystemyTele-informatycz-ne (U2K)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	–0.009 [0.661]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
LSI Software (LSI)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.807 [0.016]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Infovide-Matrix (IMX)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.043 [0.568]	All additional market variables have statistically insignificant impact on the firm volatility – elimination from the model
Procad (PRD)	ARMAX(1,1)-FIGARCH(1,0.29,1), t-Student distribution	0.896 [0.004]	$V_{m,t-1}$_WIG : 0.644 [0.005]
NTT System (NTT)	ARMAX(1,1)-GARCH(1,1), t-Student distribution	0.733 [0.000]	$V_{m,t-1}$_WIG : 0.539 [0.000]

Note: p-value in brackets.

In order to verify the hypothesis assuming that within a given sector the percentage of enterprises in the stable and turbulent period, for which a significant positive dependence between their share price volatility and stock market volatility is the same, we used a statistical test (Krysicki et al. 2012):

$$H_0 : p_1 = p_2$$
$$H_1 : p_1 \neq p_2.$$

The test statistics under the null hypothesis has a standardized normal distribution:

$$U = \left(2\arcsin\sqrt{\frac{k_1}{n_1}} - 2\arcsin\sqrt{\frac{k_2}{n_2}} \right) \cdot \sqrt{\frac{n_1 \cdot n_2}{n_1 + n_2}} \propto N(0,1), \quad (12)$$

where: p_1 – fraction of the firms in the given sector for which the commonality in volatility effect was confirmed in stable period, p_2 – fraction of the firms in the given sector for which the commonality in volatility effect was confirmed in turbulent period, $\frac{k_1}{n_1}$ and $\frac{k_2}{n_2}$ – sample proportions corresponding to p_1 and p_2.

Table 9. Statistics for similarity of commonality in volatility effect in stable and turbulent period

U statistic	Construction sector	IT sector
(1.95 – 5% critical value)	0.546	0.875

At 5% significance level there is no reasons for rejecting the hypothesis that commonality in volatility didn't differ significantly in the turbulent period compared to the stable period in construction sector as well as in IT sector on the Polish Capital Market (Table 9).

The conducted research show that the fractions of enterprises, in the stable and turbulent period, for which the occurrence of significant relationships between their share price volatility and the WIG index volatility was proved, did not significantly differ one from the other. This may confirm that analyzed sectors were characterized by resistance to external shocks absorbed by Polish stock market through the investor behaviour channel.

Conclusions

The analysis of relationships between market volatility and volatility of enterprises from the construction and IT sectors has shown that there is not an increase in the fractions of firms, for which their share volatility in a significant and positive way was connected with stock market volatility in the period corresponding to the subprime crisis and the debt crisis in the Euro zone. Moreover, one can observe a different relation of these sectors to external shocks coming to Polish market, namely in the IT sector the fraction of enterprises sensible to the WIG index volatility decreased, while in the construction sector it increased. However, the changes were not statistically significant. The financial situation of the enterprises from these sectors was conditioned not only by unforeseen factors connected with reaction of investors to the information about crisis, but first of all economic factors and skills of managers in the scope of adjusting enterprise strategies to the changeable conditions of external environment, making the use of the opportunities and threats filter in building and maintaining enterprise competitive position. On the basis of conducted empirical studies (Otola, 2013) concerning financial condition of enterprises from the construction and IT sectors we can draw the following conclusions. Majority of the analyzed enterprises from the construction sector did not possess financial liquidity which is the determinant of the ability to pay back their liabilities. Moreover, in case of over 65% of the examined enterprises their rates of debt exceeded 70%. In addition, majority of the discussed enterprises achieved low sales profitability already at the level of gross profit from sales or operational profit. There were such enterprises among all the examined ones which were characterized by high negative sales profitability. The situation was different in the IT sector. This sector enterprises were characterized by average debt level and maintained financial liquidity on the proper level (in accordance with the assumed norms of indexes), and a part of them possessed surplus of turnover assets with reference to the current liabilities, which indicates the excess of liquidity. Sales profitability indexes in the stable period were on a higher level than in the turbulent period, in which they can be considered as low and unsatisfactory for investors, nonetheless they were better than the ones from the construction sector.

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Analiza relacji między zmiennością rynku a zmiennością firm na polskim rynku kapitałowym

Z a r y s t r e ś c i. W artykule analizowano kształtowanie się zależności między zmiennością rynku a zmiennością cen akcji w spółkach z wybranych sektorów Giełdy Papierów Wartościowych w Warszawie przed i po kryzysie subprime. Badania empiryczne dotyczą wybranych przedsiębiorstw z sektorów budownictwo i IT w latach 2004–2011. Miary zmienności zostały obliczone na podstawie najniższego i najwyższego kursu dziennego spółek należących do indeksu WIG. Dla każdej firmy został oszacowany, zarówno dla okresu stabilnego, jak i niestabilnego, model ARFIMAX-FIGARCH z dodatkowymi zmiennymi egzogenicznymi, odzwierciedlającymi zmienność rynku. Przeprowadzone badania empiryczne nie wykazały, że negatywne szoki płynące z rynku amerykańskiego przez kanał zachowań inwestorów przyczyniły się do wzrostu frakcji firm z sektorów budownictwa i IT notowanych na GPW, których zmienność jest kształtowana przez zmienność rynku.

S ł o w a k l u c z o w e: ARFIMAX-FIGARCH, kryzys subprime, zmienność firm, zmienność rynku, Giełda Papierów Wartościowych w Warszawie.