INTRADAY VOLATILITY AND VAR: AN EVIDENCE FROM THE CONSTRUCTION SECTOR

Krzysztof DRACHAL
Kozminski University
Warsaw, Poland
e-mail: kdrachal@kozminski.edu.pl

Abstract. This article presents the outcomes from the estimation of the multiplicative component GARCH model for intraday data from the construction sector in Poland. This model is a recent modification of a well-known in finance GARCH model, which can deal with tick data. It is found that all the considered stocks from the construction sector follow very similar patterns as financial time-series. It is a non-trivial result, because when comparing with other estimations (in particular, those not differentiating between various economy sectors) different outcomes on volatility patterns can be found. Secondly, the volatility pattern numerical estimation for stocks from the construction sector is quite different from what is usually found in the literature not differentiating between sectors.

Key words: backtesting, construction sector in Poland, high-frequency data, mcsGARCH, volatility patterns, WIG-budownictwo, WIG-construction

1. Introduction

High-frequency data become the subject of an extensive investigations recently. There are many reasons for such a trend. However, there are two most significant aspects. First, the computational capabilities of computer devices increase in a very rapid dynamics. As a result, it become possible to efficiently work on enormous databases and to produce reasonable outcomes based on such analyses in quick time. For example Cartea and Jaimungal (2013) observed that much more than a half of trading in U.S. is based not on human actions, but on the algorithmic trading, in which the computer device is making the particular decisions.

Such an approach allows to use complex trading algorithms with a hope to beat traditional investors (Ait-Sahlaia and Jacod, 2014; Mariano and Tse, 2008; Dacorogna *et al.*, 2001).

Secondly, high-frequency data (i.e., tick data – the one of every separate transaction) provide some new insight into the market microstructure. Some specific patterns and phenomena can be observed, which cannot be seen by the analysis of, for example, daily data (O'Hara, 1997; Hautsch, 2012).

Many of these aspects were confirmed for the developed economies. On the other hand, obtaining high-frequency data is usually not so easy as daily data. Moreover, recently Diao and Tong (2015) noticed that a specific Chinese market regulation possibly results in the violation of an U-shaped pattern in the diurnal volatility of the 5 min. returns of CSI 300 index. It is in a clear contradiction with the performance of the majority of European and American stock markets.

Therefore, the aim of this research is to analyze high-frequency data from the Polish construction sector. It will be shown that certain patterns for the construction sector differs from the average one (i.e., that of the leading Polish stock companies).

Secondly, a newly proposed mcsGARCH model (Engle and Sokalska, 2012) is evaluated. This model was proposed as a simple and a suitable tool to deal with intraday data. The obtained results are backtested in the context of Value at Risk (VaR) forecasting, which might be of an interest to practitioners and construction sector investors.

2. Literature review

The most important characteristic of high-frequency data is the non-synchronous trading. In other words, the duration between trading activities is unequal. Usually, it is observed that much trading occurs in the beginning of the session and next, in the end of the session day. The middle of the day is characterized by a relatively small number of transactions (Cartea and Meyer-Brandis, 2010; Ghysels, 2000).

Yet, there is also an interesting relationship between returns and duration, as well as, between returns and trading volume. In 1987 Diamond and Verrecchia influentially postulated that there should be a negative correlation between price changes and duration. Their arguments were derived from the short-selling constraints. As a result, the full trading can be done on good news, but not in the same way on bad news. More recent analysis of this problem can be found in the paper by Grullon *et al.* (2015). Still, the initial hypothesis remains inconclusive in the view of many researches.

Another interesting observation was made by Ammann and Kessler (2009), who observed that the liquidity is generally higher during price falls on U.S. market. As a result, there could be a negative correlation between returns and trading volume. In case of the Polish stock markets certain aspects were analyzed, for example, by Strawiński and Ślepaczuk (2008).

Usually, such financial researches ignore the sector differentiation. However, the construction sector, for example, is characterized by specific features. For example, building cycles (Bahadir and Mykhaylova, 2014), durability, immobility, large quantities, etc. (Pearce, 2006; Finkel, 2015; Myers, 2013; Ofori, 1990).

On the other hand, nowadays, financial markets do not seem to consider these features as any drawback for trading on the same footing as any other equities (Burstein, 1999; Han *et al.*, 2010). As a result, the links of the construction sector and financial markets are very interesting (Bianconi and Yoshino, 2012; Ng, 2015; Chan *et al.*, 2016).

In finance, the most common approach towards volatility modeling is by using various GARCH-type models (Bollerslev, 1986; Drachal 2015; Heryan 2014; Xekalaki and Degiannakis, 2010). These models proved to be very useful not only in purely financial sectors, but also in industry, energy, etc. (Efimova and Serletis, 2014).

The simplest one, i.e., GARCH(1,1) can be described as follows. Let r_t be the modeled variable. It is assumed that there is given a mean equation

$$r_t = u_t + e_t$$

with u_t being some formula describing the process and e_t is the error term. It is also assumed that $e_t = z_t \sigma_t$ with z_t following the standard normal distribution (i.e., the one with mean 0 and variance 1) and σ_t^2 being the variance of e_t. Additionally, σ_t follows the variance equation

$$\sigma_t^2 = w + \alpha e_{t-1}^2 + \beta \sigma_{t-1}^2 .$$

However, in case of intraday data a GARCH model must be suitably modified in order to catch the effects of unequal duration, but there is no obvious recipe for this.

Many approaches were proposed to deal with this characteristic. For example, certain deseasonalizations, inclusion of periodicity, application of the flexible Fourier methods, etc. (Bollerslev and Ghysels, 1996; Andersen and Bollerslev, 1997; Engle, 2000). Recently, Sokalska (2012) and Engle (2012) proposed an elegant and simple solution by decomposing the volatility into daily, diurnal and stochastic intraday components.

In particular, let $r_{t,i}$ be the logarithmic return from the selected stock with t denoting the day and i denoting the regularly spaced time interval (for example, 5 min. interval). The mcsGARCH process can be described in the following way:

$$r_{t,i} = u_{t,i} + e_{t,i} ,$$
$$e_{t,i} = z_{t,i} (q_{t,i} \sigma_t s_i) \quad (1)$$

with $q_{t,i}$ being the stochastic intraday volatility, σ_t being a daily forecast volatility externally obtained, s_i being the diurnal volatility and $z_{t,i}$ being a certain variable following (usually) the standard normal distribution.

Moreover, in order to obtain AR(1)-MA(1) specification (which is usually desired in applications) it is assumed that

$$u_{t,i} = c + a r_{t,i-1} + b e_{t,i-1} \quad (2) .$$

In mcsGARCH the diurnal volatility is defined in the following way

$$s_i = (1/T) \sum_{t=1}^{T} (e_{t,i}^2 / \sigma_t^2)$$

with T being the number of days in the sample. The stochastic intraday volatility $q_{t,i}$ can be modeled as a GARCH(1,1) process, i.e.:

$$q_{t,i}^2 = w + \alpha \tilde{e}_{t,i}^2 + \beta q_{t,i-1}^2 \quad (3)$$

with

$$\tilde{e}_{t,i} = e_{t,i} / (\sigma_t s_i) = z_{t,i} q_{t,i} .$$

A daily forecast volatility, i.e., σ_t, can be exogenously derived, for example, from the standard GARCH(1,1) model for daily data. For the Polish stock market there are serious arguments (Drachal, 2016a) to use a slight modification, i.e., E-GARCH(1,1) for the daily data volatility estimation.

In particular, σ_t is estimated from the following AR(1)-MA(1)-E-GARCH(1,1) process for the daily data

$$r_t = const. + f r_{t-1} + g e_{t-1} + e_t ,$$

with $e_t = z_t \sigma_t$ and with the variance equation given by

$$\ln(\sigma_t^2) =$$
$$= w_1 + \alpha_1 z_{t-1} + \gamma (|z_{t-1}| - E|z_{t-1}|) + \beta_1 \sigma_{t-1}^2 .$$

Definitely σ_t should not be estimated on the basis of the whole available sample. For a time t only information preceding time t should be used. As a result, a rolling estimation should be performed. Because of the limitations of an ordinary computer device, the first 250 observations were taken as a training data set. Also, the model was updated (re-estimated) after every 250 new observations.

On average there are 250 session days in a year on the Warsaw Stock Exchange, so it roughly approximates 1 year period.

Although, the original formulations of GARCH-type models assume that z_t follows the standard normal distribution, there are important arguments to consider other distributions.

Stock returns usually do not have a normal distribution. Skewed Student t distribution is one of the possible variations, which can capture both asymmetry and fat tails in finance time-series (Jondeau *et al.*, 2007). These characterizes also the Polish stocks (Koronkiewicz and Jamróz, 2014).

Therefore, it was assumed that z_t and $z_{t,i}$ herein follow such a distribution. Its exact parameters were estimated numerically.

3. Empirical results

The tick data were obtained from BOŚ (2015). Initially, 27 stocks were analyzed. The selection was based on WIG-construction stock index, which represents the companies from the construction sector listed on the Warsaw Stock Exchange. The index is computed since the end of 1998, and its value is published 3 times per day. However, stock from the construction sector are traded much more often. As a result, it is reasonable to analyze each stock separately in order to catch the high-frequency characteristics. There is also no futures derivative, which could serve as an equity representative.

Definitely, there are more stocks from the construction sector listed on the Warsaw Stock Exchange. However, it is reasonable to narrow the considerations to the ones from WIG-construction index, i.e., the ones constituting the index at the end of 2015 (GPW, 2015).

All calculations were done in R (R Core Team, 2015) with a help of highfrequency (Boudt *et al.*, 2014) and rugarch (Ghalanos, 2014) packages.

Table 1 presents the number of tick data for each stock, as well as, the date of the first observation for each sample. It can be definitely concluded that samples of DEKPOL and PEKABEX contain too few observations to continue with the GARCH methodology (Zivot, 2009).

On the other hand, the majority of the samples consists of enough observations and, moreover, even from quite wide time horizon. This is a desired feature in case of making further conclusions from the analysis.

Table 2 presents the estimated Pearson correlation coefficients between log returns and duration and trading volume for each stock, as well as, the corresponding p-values. It can be seen that at 5% statistical significance level, there is a significant and negative correlation between log returns and duration for every analyzed stock except just one, for which it is still negative, but not statistically significant.

Table 1. Data Description

stock names	no obs.	date of the first obs.
AWBUD	7170	2011-03-04
BUDIMEX	195930	2000-11-17
CNT	6780	2013-03-22
DEKPOL	376	2015-02-11
ELBUDOWA	53333	2000-11-17
ELEKTROTI	29936	2007-05-22
ENAP	84352	2004-07-13
ERBUD	27756	2007-06-19
HERKULES	26321	2011-12-16
INSTALKRK	65440	2005-10-18
INTERBUD	18925	2010-11-25
MIRBUD	87266	2008-12-29
MOSTALPLC	58115	2001-04-18
MOSTALWAR	120355	2000-11-17
MOSTALZAB	341766	2000-11-17
PANOVA	14980	2007-08-27
PEKABEX	915	2015-07-08
PROCHEM	38016	2001-10-29
PROJPRZEM	58064	2001-04-19
RESBUD	71083	2007-09-27
TESGAS	18524	2009-09-16
TORPOL	9610	2014-09-05
TRAKCJA	196524	2008-04-01
ULMA	21239	2006-12-14
UNIBEP	21081	2008-05-12
VISTAL	11669	2014-01-08
ZUE	7211	2010-11-03

This is an interesting result in the context of the mentioned Diamond and Verrecchia (1987) hypothesis. Moreover, such a result was not found, if just the biggest stocks were analyzed for the Polish market (Drachal, 2016b). It justifies the hypothesis that the construction sector stocks behave a bit differently than ordinary stocks.

It is also an interesting observation from Table 2 that the observed positive correlation between log returns and trading volume is simultaneously characterized by very large p-values, indicating statistical insignificance in such cases.

Yet, such a positive correlation was observed only for 3 stocks. For the rest a negative correlation was found, and after all, it can be seen that for 70% of them there is a negative statistically significant (at 5% significance level) correlation between log returns and trading volume.

Table 2. Pearson Correlation Coefficients for Tick Data

stock names	a	b	c	d
AWBUD	-0.03	0.02	0.00	0.69
BUDIMEX	-0.01	0.00	0.00	0.51
CNT	-0.16	0.00	-0.03	0.04
DEKPOL	-0.08	0.12	-0.03	0.55
ELBUDOWA	-0.02	0.00	-0.01	0.02
ELEKTROTI	-0.02	0.00	0.01	0.25
ENAP	-0.02	0.00	-0.03	0.00
ERBUD	-0.06	0.00	-0.01	0.03
HERKULES	-0.03	0.00	-0.01	0.04
INSTALKRK	-0.04	0.00	-0.01	0.16
INTERBUD	-0.08	0.00	-0.04	0.00
MIRBUD	-0.08	0.00	-0.05	0.00
MOSTALPLC	-0.05	0.00	-0.01	0.00
MOSTALWAR	-0.04	0.00	-0.01	0.00
MOSTALZAB	-0.02	0.00	-0.02	0.00
PANOVA	-0.09	0.00	-0.02	0.02
PEKABEX	-0.18	0.00	-0.03	0.32
PROCHEM	-0.07	0.00	-0.02	0.00
PROJPRZEM	-0.05	0.00	-0.02	0.00
RESBUD	-0.07	0.00	-0.03	0.00
TESGAS	-0.04	0.00	-0.02	0.01
TORPOL	-0.05	0.00	-0.04	0.00
TRAKCJA	-0.01	0.00	-0.02	0.00
ULMA	-0.03	0.00	-0.02	0.00
UNIBEP	-0.06	0.00	-0.01	0.11
VISTAL	-0.06	0.00	-0.04	0.00
ZUE	-0.05	0.00	-0.01	0.23

a – log returns / duration; b – p-value ; c – log returns / trading volume ; d - p-value

This is also much more evident behavior pattern than if just the biggest companies from every sector would be analyzed (Drachal, 2016b).

Table 3 presents the descriptive statistics for 5 min. aggregated log returns.

It can be seen from Table 3 that the average returns are 0 and the standard deviation is very small and similar for every stock. Almost 60% of stocks are negatively skewed. Only one stock has skewness 0.

Every stock is characterized by high kurtosis. This means that log returns are not normally distributed. This justifies the aforementioned application of the skewed Student t distribution in the model.

Table 3. Descriptive Statistics of 5 min. Aggregated log Returns

stock names	a	b	c	d
AWBUD	0.00	0.03	-0.33	7.18
BUDIMEX	0.00	0.01	0.20	23.54
CNT	0.00	0.02	-0.09	3.78
DEKPOL	0.00	0.03	-0.26	8.19
ELBUDOWA	0.00	0.01	-0.22	17.68
ELEKTROTI	0.00	0.01	-0.25	10.69
ENAP	0.00	0.01	-0.14	10.49
ERBUD	0.00	0.01	-0.59	21.44
HERKULES	0.00	0.02	58.00	5863.87
INSTALKRK	0.00	0.01	-0.03	13.77
INTERBUD	0.00	0.02	0.02	6.21
MIRBUD	0.00	0.01	0.26	20.86
MOSTALPLC	0.00	0.01	0.02	11.73
MOSTALWAR	0.00	0.01	-0.14	11.60
MOSTALZAB	0.00	0.01	-0.04	8.69
PANOVA	0.00	0.02	-0.03	9.31
PEKABEX	0.00	0.01	0.37	6.71
PROCHEM	0.00	0.01	-0.02	10.20
PROJPRZEM	0.00	0.01	-0.07	12.36
RESBUD	0.00	0.02	-0.17	10.50
TESGAS	0.00	0.01	-0.08	6.32
TORPOL	0.00	0.01	0.23	7.74
TRAKCJA	0.00	0.01	0.04	8.06
ULMA	0.00	0.01	-0.08	6.49
UNIBEP	0.00	0.01	2.28	94.41
VISTAL	0.00	0.01	0.04	8.28
ZUE	0.00	0.02	0.00	5.05
a – mean; b – standard deviation; c – skewness; d - kurtosis				

In particular, the model given by Eq. (1) was estimated, where $r_{t,i}$ represents the log returns from tick data aggregated to 5 min. intervals for each stock separately.

Table 4 presents the result of ARCH LM test. In every case, except just one case, the null hypothesis of the lack of ARCH effects should be rejected. As a consequence, for every stock, except HERKULES, mscGARCH model is justified to be constructed. Unfortunately, in case of AWBUD, ELBUDOWA, TORPOL, UNIBEP and VISTAL serious numerical problems occurred. Together with previously mentioned remark of too little observations in a few cases, finally mscGARCH model was estimated for 19 stocks. The results are presented in Tables 5 and 6 (after References).

Table 4. ARCH LM Test for Aggregated 5 min. log Returns

stock names	statistic	p-value
AWBUD	524.90	0.00
BUDIMEX	6489.55	0.00
CNT	492.60	0.00
DEKPOL	110.79	0.00
ELBUDOWA	2487.78	0.00
ELEKTROTI	1578.23	0.00
ENAP	4937.48	0.00
ERBUD	573.21	0.00
HERKULES	0.05	1.00
INSTALKRK	4396.19	0.00
INTERBUD	568.50	0.00
MIRBUD	8746.34	0.00
MOSTALPLC	4991.88	0.00
MOSTALWAR	6997.79	0.00
MOSTALZAB	10632.25	0.00
PANOVA	1259.15	0.00
PEKABEX	98.79	0.00
PROCHEM	2999.53	0.00
PROJPRZEM	5104.44	0.00
RESBUD	4760.38	0.00
TESGAS	712.22	0.00
TORPOL	307.86	0.00
TRAKCJA	6292.38	0.00
ULMA	789.86	0.00
UNIBEP	86.83	0.00
VISTAL	844.14	0.00
ZUE	413.85	0.00

From Table 5 it can be seen that the estimated parameters for Eq. (2) of mscGARCH model are very similar for every stock. The parameter a is always positive, and the parameter b is always negative, whereas c is close to 0. This indicates the similar behavior pattern.

In case of Eq. (3) the situation is more complicated. Of course, in every case $\alpha > 0$ and $\beta > 0$, which is required by the theory of the GARCH methodology. However, there is a strong persistence indicated by the fact that $\alpha + \beta \approx 1$. This is also quite a common feature in applications (Xekalaki and Degiannakis, 2010).

Table 5. ARCH LM Test for Aggregated 5 min. log Returns

stock names	Eq. (2)			Eq. (3)			skewed Student t distribution parameters	
	c	a	b	w	α	β	skew.	shape
BUDIMEX	0.00	0.22	-0.29	0.03	0.38	0.62	1.00	2.29
CNT	0.00	0.04	-0.14	0.22	0.52	0.48	0.96	2.40
ELEKTROTI	0.00	0.15	-0.20	0.02	0.27	0.73	0.99	2.36
ENAP	0.00	0.22	-0.34	0.00	0.10	0.90	0.99	2.76
ERBUD	0.00	0.16	-0.25	0.00	0.19	0.81	1.00	2.56
INSTALKRK	0.00	0.19	-0.27	0.12	0.44	0.56	1.00	2.25
INTERBUD	0.00	0.04	-0.20	0.04	0.30	0.69	1.01	2.84
MIRBUD	0.00	0.11	-0.25	0.19	0.48	0.51	1.01	2.41
MOSTALPLC	0.00	0.12	-0.20	0.03	0.28	0.72	0.99	2.39
MOSTALWAR	0.00	0.17	-0.24	0.05	0.32	0.67	1.00	2.33
MOSTALZAB	0.00	0.14	-0.20	0.04	0.25	0.75	1.00	2.37
PANOVA	0.00	0.10	-0.18	0.10	0.56	0.44	1.00	2.29
PROCHEM	0.00	0.05	-0.18	0.03	0.28	0.72	0.99	2.58
PROJPRZEM	0.00	0.12	-0.21	0.08	0.36	0.64	1.00	2.36
RESBUD	0.00	0.03	-0.14	0.00	0.15	0.85	1.01	2.77
TESGAS	0.00	0.20	-0.28	0.07	0.31	0.69	0.99	2.41
TRAKCJA	0.00	0.00	-0.01	0.00	0.94	0.05	1.00	2.07
ULMA	0.00	0.10	-0.18	0.01	0.22	0.78	0.99	2.39
ZUE	0.00	0.04	-0.25	0.11	0.40	0.60	0.99	2.90

Table 6. P-values for Coefficients from Table 5 and p-value of ARCH LM Test for Standardized Residuals

stock names	c	a	b	w	α	β	skew.	shape	ARCH
BUDIMEX	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CNT	0.39	0.77	0.29	0.12	0.00	0.00	0.00	0.00	0.00
ELEKTROTI	0.39	0.08	0.02	0.00	0.00	0.00	0.00	0.00	0.01
ENAP	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ERBUD	0.33	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
INSTALKRK	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
INTERBUD	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.25
MIRBUD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MOSTALPLC	0.01	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00
MOSTALWAR	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MOSTALZAB	0.94	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PANOVA	0.86	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PROCHEM	0.73	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PROJPRZEM	0.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RESBUD	0.11	0.41	0.00	0.92	0.00	0.00	0.00	0.00	0.79
TESGAS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TRAKCJA	0.90	0.83	0.43	1.00	0.00	0.00	0.00	0.00	0.00
ULMA	0.83	0.20	0.02	0.00	0.00	0.00	0.00	0.00	0.08
ZUE	0.39	0.51	0.00	0.01	0.00	0.00	0.00	0.00	0.00

However, usually α is relatively small and β is relatively large. In the obtained estimation α is quite large in many cases. This is a very peculiar result. For example, if the UHF-GARCH (Engle, 2000) model is applied to 20 biggest stocks from the Warsaw Stock Exchange, then α is always below 0.07 (Drachal, 2016b). Diao and Tong (2015) obtained similar outcomes for the Chinese stock index and Sokalska (2012) for the Polish stock index.

Table 6 presents p-values for the coefficients from Table 5 and p-values of ARCH LM tests for standardized residuals of the estimated mscGARCH models. For the right variance equation specification there should remain no ARCH effects in residuals. In 3 cases there are still (at 5% significance level) significant ARCH effects even after mscGARCH application. In such a situation it might be tried to increase the number of lags in Eq. (3).

If a p-value for the coefficient indicates its statistical insignificance, it simply means that this coefficient can be assumed as equal to 0. Therefore, insignificance of many c coefficients is not problematic. Similar conclusion is valid for the coefficient w. On the other hand, in every case there is a strong evidence for statistical significance of both α and β parameters in the variance equation, i.e., Eq. (3), as well as, parameters of the skewed Student t distribution. In many cases also parameters a and b from the mean equation, i.e., Eq. (2), are statistically significant. Nevertheless, the aim was to predict the volatility, given by Eq. (3), which seems to be done with a success. Even more formally, this can be backtested with a help of Kupiec's test (Kupiec, 1995). Indeed, the last 64 aggregated observations in each time-series were tested at 5% significance level. In other words, it was checked how many times in this period the really observed variance exceeded the one predicted by the mscGARCH model. Of course, it was not the mscGARCH model reported in Table 5 based on all observations taken, but the one obtained by the rolling estimation, i.e., the one constructed on the basis of observations before the foretasted period.

As the computations are very time-costing the refitting was done every 30 observations, resulting in only 2 refittings. Probably, more often refitting would increase the accuracy of predictions, but even at the given parameters the computations took few hours for the whole sample. According to the Kupiec's test there should be no more than 3 exceedings in the backtested period. The results are presented in Table 7. From Table 7 it can be seen that in 42% of analyzed cases the backtesting confirmed that mscGARCH model cannot be rejected at 5% significance level as a model well predicting the intraday volatility.

Table 7. Results of Intraday VaR Backtesting

stock names	actual	p-value
BUDIMEX	6	0.15
CNT	7	0.06
ELEKTROTI	4	0.66
ENAP	8	0.02
ERBUD	8	0.02
INSTALKRK	8	0.02
INTERBUD	1	0.14
MIRBUD	7	0.06
MOSTALPLC	13	0.00
MOSTALWAR	8	0.02
MOSTALZAB	13	0.00
PANOVA	12	0.00
PROCHEM	11	0.00
PROJPRZEM	6	0.15
RESBUD	6	0.15
TESGAS	8	0.02
TRAKCJA	14	0.00
ULMA	11	0.00
ZUE	6	0.15

4. Final remarks

The multiplicative mcsGARCH model was quite successfully applied to modeling the volatility of stocks from the construction sector. The analysis was made on the basis of the selected stocks from the Warsaw Stock Exchange. The results are interesting. First of all, the Polish stock exchange is the leading one in the CEE region. Secondly, mcsGARCH model has not been extensively applied yet.

The results of the presented research showed a few interesting outcomes. First, the behavior of the construction sector in Poland is very consistent in-sample, which is in opposite with, for example, biggest companies not differentiated by sectors. Secondly, the effects of shocks on the present volatility in the construction sector were found to be much higher than on average stocks. In 60% of the selected stocks the numerical estimation and the diagnostic of the mscGARCH model succeeded. This is quite a satisfactory outcome, having in mind that the computations must deal with large data sets. Moreover, VaR backtesting succeeded in 42% of models. This means that mscGARCH can be of some interest to practitioners in the construction sector finance. However, the presented outcomes also suggest that such a modeling should be taken with a suitable caution.

The construction sector constitutes less that 1% of the market value on the Warsaw Stock Exchange (GPW, 2015), which might serve as some clue to the obtained outcomes. The obtained results confirm that the notion of a financial risk should be considered in the context of an economic sector (Chen *et al.*, 2015; Iglesias, 2015; Masik and Rzyski, 2014).

It should also be remembered that the construction sector in Poland started to develop very dynamically around 2005, which was the result of the increasing in the demand on new dwellings, as well as, the high supply of attractive house loans (Kulesza and Belej, 2015a; 2015b). Before 2012 much of the demand in the construction sector was stimulated by The 2012 UEFA European Championship hosted by Poland and Ukraine. Nevertheless, this also resulted in material price increase and bankruptcy of some construction firms. On the other hand, much infrastructure was also build in Poland during the recent 10 years, which stimulated the demand in the sector. Since 2010 the credit policies were also a bit tightened.

REFERENCES

Ait-Sahalia Y., Jacod J. (2014), *High-Frequency Financial Econometrics*, Princeton University Press, Princeton, NJ.

Ammann M., Kessler S. M. (2009), *Intraday Characteristics of Stock Price Crashes*, Applied Financial Economics **19(15)**:1239-1255.

Andersen T. G., Bollerslev T. (1997), *Intraday Periodicity and Volatility Persistence in Financial Markets*, Journal of Empirical Finance **4(2)**:115-158.

Bahadir B., Mykhaylova O. (2014), *Housing Market Dynamics with Delays in the Construction Sector*, Journal of Housing Economics **26**:94-108.

Bianconi M., Yoshino J. A. (2012), *Firm Market Performance and Volatility in a National Real Estate Sector*, International Review of Economics & Finance **22(1)**:230-253.

Bollerslev T. (1986), *Generalized Autoregressive Conditional Heteroskedasticity*, Journal of Econometrics **31(3)**:307-327.

Bollerslev T., Ghysels E. (1996), *Periodic Autoregressive Conditional Heteroscedasticity*, Journal of Business & Economic Statistics **14(2)**:139-151.

BOŚ (2015), *Daily Files (Intradays) – Metastock*, http://bossa.pl/notowania/pliki/intraday/metastock

Boudt K., Cornelissen J., Payseur S., Nguyen G., Schermer M. (2014), H*ighfrequency: Tools for Highfrequency Data Analysis (R Package Version 0.4)*, http://CRAN.R-project.org/package=highfrequency

Burstein G. (1999), *Macro Trading and Investment Strategies. Macroeconomic Arbitrage in Global Markets*, Wiley, New York, NY.

Cartea A., Jaimungal S. (2013), *Modelling Asset Prices for Algorithmic and High-Frequency Trading*, Applied Mathematical Finance **20(6)**:512-547.

Cartea A., Meyer-Brandis T. (2010), *How Duration Between Trades of Underlying Securities Affects Option Prices*, Review of Finance **14(4)**:749-785.

Chan S., Han G., Zhang W. (2016), *How Strong are the Linkages Between Real Estate and Other Sectors in China?*, Research in International Business and Finance **36**:52-72.

Chen M., Tang Z., Bai Y., Zhang X. (2015), *Relational Pattern of Urbanization and Economic Development: Parameter Re-evaluation of the Chenery Model*, Journal of Geographical Sciences **25(8)**: 991-1002.

Dacorogna M. M., Gençay R., Müller U. A., Olsen R. B., Pictet O. V. (2001), *An Introduction to High-Frequency Finance*, Academic Press, Cambridge, MA.

Diamond D. W., Verrecchia R. E. (1987), *Constraints on Short-selling and Asset Price Adjustment to Private Information*, Journal of Financial Economics **18(2)**:277-311.

Diao X., Tong B. (2015), *Forecasting Intraday Volatility and VaR Using Multiplicative Component GARCH Model*, Applied Economics Letters **22(18)**:1457-1464.

Drachal K. (2015), *Review of GARCH Model Applicability in View of Some Recent Research*, Journal of Academic Research in Economics **7(2)**:191-200.

Drachal K. (2016a), *Recent Analysis of the Leverage Effect for the Main Index on the Warsaw Stock Exchange*, In preparation.

Drachal K. (2016b), *Volatility Patterns of the Largest Polish Companies: Some Evidence from High-frequency Data*, In preparation.

Efimova O., Serletis A. (2014), *Energy Markets Volatility Modelling Using GARCH*, Energy Economics **43**:264-273.

Engle R. F. (2000), *The Econometrics of Ultra-High Frequency Data*, Econometrica **68(1)**:1-22.

Engle R. F., Sokalska M. E. (2012), *Forecasting Intraday Volatility in the US Equity Market. Multiplicative Component GARCH*, Journal of Financial Econometrics **10(1)**:54-83.

Finkel G. (2015), *The Economics of the Construction Industry*, Routledge, New York, NY.

Ghalanos A. (2014), *Package Rugarch*, http://CRAN.R-project.org/package=rugarch

Ghysels E. (2000), *Some Econometric Recipes for High-Frequency Data Cooking*, Journal of Business & Economic Statistics **18(2)**:154-163.

GPW (2015), *WIG-CONSTRUCTION*, http://www.gpw.pl/indeksy_gieldowe_en?isin=PL9999999896&ph_tresc_glowna_start=show

Grullon G., Michenaud S., Weston J. P. (2015), *The Real Effects of Short-Selling Constraints*, Review of Financial Studies **28(6)**:1737-1767.

Han S. H., Kim D.Y., Jang H. S., Choi S. (2010), *Strategies for Contractors to Sustain Growth in the Global Construction Market*, Habitat International **34(1)**:1-10.

Hautsch N. (2012), *Econometrics of Financial High-Frequency Data*, Springer, Berlin.

Heryán T. (2014), *Errors in Short Run Forecasts Next-day Volatility of Equity Risk Premium in the UK and U.S. Market: Empirical Research Before and After the Global Financial Crisis*, Procedia Economics and Finance **14**:243-252.

Iglesias E. M. (2015), *Value at Risk and Expected Shortfall of Firms in the Main European Union Stock Market Indexes: A Detailed Analysis by Economic Sectors and Geographical Situation*, Economic Modelling **50**:1-8.

Jondeau E., Poon S.-H., Rockinger M. (2007), *Financial Modeling Under Non-Gaussian Distributions*, Springer, Berlin.

Koronkiewicz G., Jamróz P. (2014), *Comparison of the Tails of Market Return Distributions*, Optimum. Studia Ekonomiczne **5(71)**:103-113.

Kulesza S., Belej M. (2015a), *Descriptive Analysis on Nonstationarity of the Time Series on Real Estate Market*, Journal of International Studies **8(2)**:34-42.

Kulesza S., Belej M. (2015b), *Local Real Estate Markets in Poland as a Network of Damped Harmonic Oscillators*, Acta Physica Polonica A **127(3-A)**:99-102.

Kupiec P. H. (1995), *Techniques for Verifying the Accuracy of Risk Measurement Models*, The Journal of Derivatives **3(2)**:73-84.

Mariano R. S., Tse Y.-K. (Editors) (2008), *Econometric Forecasting and High-frequency Data Analysis*, World Scientific, Singapore.

Masik G., Rzyski S. (2014), *Resilience of Pomorskie Region to Economic Crisis*, Bulletin of Geography. Socio-economic Series **25**: 129-141.

Myers D. (2013), *Construction Economics. A New Approach*, Routledge, London.

Ng E. C. Y. (2015), *Housing Market Dynamics in China: Findings from an Estimated DSGE Model*, Journal of Housing Economics **29**:26-40.

Ofori G. (1990), *The Construction Industry. Aspects of Its Economics and Management*, Singapore University Press, Singapore.

O'Hara M. (1997), *Market Microstructure Theory*, Wiley, New York, NY.

Pearce D. (2006), *Is the Construction Sector Sustainable?: Definitions and Reflections*, Building Research & Information **34(3)**:201-207.

R Core Team (2014), *R: A Language and Environment for Statistical Computing*, http://www.R-project.org

Sokalska M. E. (2012), *Comparison of Intraday Volatility Forecasting Models for Polish Equities*, Quantitative Methods in Economics **13(2)**:107-114.

Strawiński P., Ślepaczuk R. (2008), *Analysis of High Frequency Data on the Warsaw Stock Exchange in the Context of Efficient Market Hypothesis*, Journal of Applied Economic Sciences **3(5)**:306-319.

Xekalaki E., Degiannakis S. (2010), *ARCH Models for Financial Applications*, Wiley, New York, NY.

Zivot E. (2009), *Practical Issues in the Analysis of Univariate GARCH Models*, in: Andersen T. G., Davis R. A., Kreis J.-P., Mikosch T. (Editors), *Handbook of Financial Time Series*, Springer, Berlin, pp. 113-155.

Received: 22 May 2016 • **Revised**: 25 May 2016 • **Accepted**: 26 May 2016