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MODELING STOCK MARKET VOLATILITY IN CROATIA: A REAPPRAISAL

Abstract

Purpose: In this paper, the volatility of the Croatian stock market index CROBEX is investigated using the GARCH(1,1) model.

Methodology: The novelty provided by this paper is the estimation of the GARCH(1,1) model by using three conditional error distributions (normal (Gaussian) distribution, Student's-distribution with fixed degrees of freedom and generalized error distribution (GED) with fixed parameters).

Results: The findings obtained in the research are in the line with previous research in this field (Erjavec & Cota, 2007; Sajter & Ćorić, 2009). The volatility of CROBEX returns is positively correlated with the volume of trade on the Zagreb Stock Exchange and movements on the main European and American stock markets. The movement of S&P 500 stock market index returns is transmitted from the previous day, providing signals for the direction of change of CROBEX index returns in the present.

Conclusion: Therefore, this paper provides evidence that investors in Croatia strongly rely on the past information received from the American S&P500 stock market index. Furthermore, there seems to exist the co-movement between CROBEX and main European indexes on the same trading day.

Keywords: Stock market volatility, GARCH (1,1), American and European stock markets, Croatia

1. *Introduction*

Stock market volatility refers to a measure of dispersion around the mean return of a security on the stock market. Volatility is often associated with the swings in the value of stock or index in either direction. More volatile assets are often considered much riskier than less volatile ones. Too much volatility on the market means uncertainty which is not good for the investor. In this paper, the volatility of the Croatian stock market index CROBEX will be investigated. The novel paper in the field of modelling stock price volatility in Croatia is attributed to Erjavec and Cota (2007). The authors constructed GARCH models for the period from 4 January 2000 to 31 December 2004, following the hypotheses that the volatility of CROBEX returns in the short run depends on the volume of traded stocks on the Zagreb Stock Exchange (ZSE) and the co-movement effects with the main European and American indexes. Since there was a strong ARCH effect detected in all proposed models, GARCH(1,1) specification was chosen to be applied in all models. The volume of trade proved to be a significant explanatory variable as well as two European indexes

(DAX and FTSE100) indicating the existence of contemporaneous co-movement effects between CROBEX and the aforementioned indexes over the same trading day. On the other hand, the predictive GARCH model, including only explanatory variables lagged by one day, pointed to the conclusion that the direction of movements on the American stock markets from the previous day transmitted signals in the direction of change of the CROBEX index in the present.

Sajter and Ćorić (2009) came to similar conclusions. Investors on the Croatian stock market dominantly rely on movements of American indexes, which was especially apparent at the beginning of the World Financial Crisis in October 2008. The co-movements between Croatian and American indexes were explained by the following three concepts: global factors, contagion and irrational escalation. By using a copula GARCH approach, Dajčman (2013) investigated the dependence between the returns on the Croatian and five European stock markets. The basic conclusion was that the dependence between the Croatian and European stock markets is dynamic and can be captured by dynamic normal or symmetrized Joe-Clayton copula GARCH models. Dedi and Škorjanec (2017) provided evidence of co-movement of equity returns, volatility persistence and spillovers in selected Central and Southeast European countries in the period from 2011 to 2017. These findings also highlighted the potential for closer and more intense collaboration between the selected markets. Arnerić and Škrabić Perić (2018) investigated cross-sectional dependence between CEE emerging markets. The results indicated a strong presence of the Monday effect in both mean and variance equations. On the other hand, the Tuesday effect was present only in the mean equation. Škrinjarić (2020) applied the GM-GARCH model to the Croatian stock market. The GM-based model was found to be superior compared to its counterpart.

The goal of this paper is to estimate stock market volatility in Croatia using the GARCH(1,1) model. The methodology of the paper is based on Erjavec and Cota (2007) by specifying the conditional mean equation and conditional mean variance. The novelty in the paper is the use of conditional error distributions. Commonly used conditional error distributions are normal (Gaussian) distribution, Student's -distribution with fixed degrees of freedom and generalized error distribution (GED) with fixed parameters. All three conditional error distributions were estimated in the paper. The models incorporate both factor and predictive elements taking into account lagged explanatory variables. A one-day lagged specification was applied in the predictive GARCH model referring to variables representing the returns of American stock market indexes (Dow Jones Industrial Average (DJI), NASDAQ Composite (IXIC) and S&P 500 (GSPC)). It is expected that the direction of the movements of the American stock market index returns from the previous day will be transmitted to the change of returns on the Croatian stock market index CROBEX in the present. On the other hand, according to previous research, contemporaneous co-movement effects between CROBEX and two main European stock market indexes (the DAX performance-index, GDAXI and FTSE 100, FTSE) over the same trading day is expected to exist. The paper is structured in five sections. After the introduction, the literature review section gives an overview of the empirical literature on stock market volatility on international stock markets. The main characteristics of data used in the analysis are explained in the data and methodology section, as well as the methodological framework for conducting the analysis. The main findings of the paper are presented and elaborated in the results and discussion section. The final chapter presents concluding remarks.

2. Literature review

In this section, a review of empirical literature about stock market volatility on international stock markets is presented and elaborated. Bonga (2019) explored the volatility of the Zimbabwe Stock Market using symmetric and asymmetric models testing the presence of ARCH effects. The GARCH (1,1) model has proved to be the most efficient model for modeling stock market volatility. The conclusion of the study is that the positive and negative shocks have a different impact on stock market returns, i.e. bad and good news increase volatility on the stock market in different magnitudes. Atoi (2014) tested the volatility of the Nigerian stock market using GARCH models. He especially highlighted the importance of various error distributions (Normal, Student's t- and Generalized Error Distribution) used in enhancing the efficiency of the models. The results indicate the presence of the leverage effect, meaning that volatility responds much more to bad news than to good news. Ching and Siok (2013) compared the performance of GARCH-type models (GARCH, TGARCH and EGARCH) to model the volatility of the stock market in Malaysia. The performances are evaluated using three statistical error measures (MSE, RMSE and MAPE). The symmetric GARCH model performed better than the asymmetric GARCH model. The exception was the crisis period for which the asymmetric GARCH model was preferred. On the other hand, the TGARCH model worked well in the post-crisis period.

Maqsood et al. (2017) used GARCH type models for the estimation of the volatility of daily returns on the Nairobi Securities Exchange (NSE). The volatility process was highly persistent, giving evidence for the existence of a risk premium for the NSE index supporting the positive correlation hypothesis between volatility and expected stock returns. The relationship between stock volatility and stock market returns was also investigated for South Africa's and China's stock markets (Cheteni, 2016). Empirical results showed the evidence of high volatility in both countries with persistent volatility that resembles the same movement in returns. The paper mainly utilizes the GARCH and ARCH models with the purpose of estimating the volatility of financial time-series and the existence of dependence in stock market returns. The conclusion was that markets in both countries exhibited the same features in terms of volatility clustering. Bhowmik and Wang (2020) provided a systematic literature review featuring GARCH-type models, stock market returns and volatility. There have been a significant number of papers on stock market volatility on developing stock markets within the past ten years. Stock markets today have a pivotal role in economic and financial activities. It is particularly important to effectively measure the volatility of stock market returns in order to prevent uncertainty and risk on the stock market.

Ahmed and Suliman (2011) used GARCH models to model stock market volatility of the Khartoum Stock Exchange in Sudan. The results showed that the conditional variance process was highly persistent, providing evidence for the existence of a risk premium and supporting the hypothesis of a positive correlation between volatility and expected stock returns. Furthermore, asymmetric models provided a better fit than symmetric models. Goudarzi and Ramanarayanan (2010) examined the volatility of the Indian stock market using BSE500 index and ARCH models. It was found that the GARCH(1,1) model satisfactorily explains the volatility of the Indian stock market as well as stylized facts including volatility clustering, fat tails and mean reversion. Abdalla (2012) estimated and modeled the Saudi stock market index (TASI) by applying GARCH models, including both symmetric and asymmetric models and capturing stylized facts about index returns such as volatility clustering and leverage effects. The main findings of this paper are as follows: (1) TASI returns showed departure from normality and the existence of heteroscedasticity in the residuals series, and (2) conditional volatility of stock returns was quite persistent. Ugurlu et al. (2014) examined the use of GARCH-type models for modeling the volatility of stock market returns for the four European emerging countries and Turkey. The impact of past news on volatility was significant, while volatility shocks were quite persistent. According to Karunanithy and Ramachandran (2015), GARCH(1,1) and TGARCH(1,1) estimations were found to be most appropriate for modeling stock market volatility in India. The GARCH(1,1) model pointed out the existence of a positive and insignificant risk premium, while negative shocks had a significant effect on the conditional variance. Abdalla and Winker (2012) modeled stock market volatility of two African stock markets, i.e. the Khartoum Stock Exchange (KSE) and the Cairo and Alexandria Stock Exchange (CASE). The empirical results showed that the conditional variance is an explosive process for the KSE index return and quite persistent for the CSE index return. There was also evidence for the existence of a positive risk premium on both markets, supporting the hypothesis of a positive correlation between volatility and the expected stock returns. Murinde and Poshakwale (2001) investigated the main features of volatility on emerging stock markets in CEEC by applying ARIMA, the BDSL procedure and symmetric and asymmetric GARCH models. Volatility exhibited significant conditional heteroskedasticity and nonlinearity with persistent nature and could not explain expected returns for any of the six markets observed.

3. Data and methodology

The goal of this paper is to estimate and measure stock market volatility in Croatia using the GARCH(1,1) model. The focus is on the Croatian major stock market index – CROBEX. CROBEX is a price index for which the dividends are not included in the calculation. It consists of 15 to 25 shares.

In order to be included in the CROBEX index, a share should be actively traded on more than 75% of trading days. The weights of each share are based on the free-float market capitalization and the maximum weight is 10%. The revisions of CROBEX are conducted semi-annually and the last one was done in September 2020 (Zagreb Stock Exchange, 2020b). For the purpose of the analysis, CROBEX daily data for the period from 8 January 2010 to 9 October 2020 were collected (Zagreb Stock Exchange, 2020a). Data referring to the following world stock market indexes were collected in addition to CROBEX data: the DAX performance-index – GDAXI (Yahoo Finance, 2020a), FTSE 100 – FTSE (Yahoo Finance, 2020c), Dow Jones Industrial Average – DJI (Yahoo Finance, 2020b), NASDAQ Composite – IXIC (Yahoo Finance, 2020d) and S&P 500 – GSPC (Yahoo Finance, 2020e)).

It has to be emphasized that only the days for which data across all indexes were available will be used in the analysis. The data were adjusted for non-tradable days including holidays in the countries under study. It has to be mentioned that stock markets in Croatia and Germany have the same trading hours because they are located in the same time zone, while London Stock Exchange is lagging one hour behind. Stock markets in the United States of America, New York precisely, are lagging 6 hours behind in relation to the Zagreb Stock Exchange. Therefore, European indexes will be included in the mean equation and American indexes will be included in the conditional equation. Since financial time series are going to be observed, volatility clustering is likely to be present. Accordingly, a strong autocorrelation in squared returns is present, and therefore estimates calculated by the least square method are unbiased but inefficient (Erjavec and Cota, 2007). This problem can be overcome by applying generalized autoregressive conditional heteroskedasticity (GARCH) introduced by Bollerslev (1986). According to Bollerslev (1986), the GARCH (p, q) model is defined as follows:

$$\begin{gathered} y_t = x_t'b + \epsilon_t \\ \epsilon_t|\psi_{t-1} \sim \mathcal{N}(0, \sigma_t^2) \\ \sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2 \end{gathered} \quad (1)$$

where σ^2 is the order of generalized autoregressive conditional heteroskedasticity (GARCH) terms and ϵ^2 is the order of autoregressive conditional heteroskedasticity (ARCH) terms. For the purpose of the analysis, the most frequently applied GARCH model, i.e. the GARCH (1,1) model, will be applied (Campbell et al., 1997). In order to apply the GARCH (1,1) model, the conditional mean equation, the conditional variance equation and the conditional error distribution should be specified. The conditional mean equation, which is going to be applied is the following one:

$$\begin{aligned} rCROBEX_t = C_1 + C_2 \times rCROBEX\_VOL_t + \\ C_3 \times rDAX_t + C_4 \times rFTSE_t + \epsilon_t, \end{aligned} \quad (2)$$

where the conditional variance equation is:

$$\begin{aligned} \sigma_t^2 = C_5 + C_6 \times \epsilon_{t-1}^2 + C_7 \times \sigma_{t-1}^2 + C_8 \times rDJI_{t-1} + \\ C_9 \times rIXIC_{t-1} + C_{10} \times rGSPC_{t-1} \end{aligned} \quad (3)$$

Daily returns defined as daily percentage changes of the observed stock market indexes and CROBEX volume are used in equations 2 and 3. Equation 3 refers to a predictive model which takes into account lagged explanatory variables of American stock market indexes (Dow Jones Industrial Average (DJI), NASDAQ Composite (IXIC) and S&P 500 (GSPC)). The predictive model therefore possesses a dynamic structure. The research question which will be investigated is the existence of co-movement between CROBEX and European indexes for the same trading day and co-movement between CROBEX and American indexes lagging by one day. In order to avoid the multicollinearity problem and its negative consequences, the correlation matrix will be constructed and correlations between American and European indexes will be examined. Three conditional error distributions will be applied in the analysis. Commonly used conditional error distributions are normal (Gaussian) distribution, Student's-distribution with fixed degrees of freedom and Generalized Error Distribution (GED) with fixed parameters. Given a distributional assumption, ARCH models are typically estimated by the method of maximum likelihood. For the GARCH(1,1) model with conditionally normal errors the contribution to the log-likelihood for observation is:

$$l_t = -\tfrac{1}{2}\log(2\pi) - \tfrac{1}{2} log\sigma_t^2 - \tfrac{1}{2}(y_t - X_{t'}\theta)^2/\sigma_t^2 \quad (4)$$

For the Student's -distribution the log-likelihood contribution is of the form:

$$l_t = -\frac{1}{2}\log\left(\frac{\pi(v-2)\Gamma(v/2)^2}{\Gamma((v+1)/2)^2}\right) - \frac{1}{2}log\sigma_t^2 - \frac{(v+1)}{2}\log\left(1+\frac{(y_t - X_t{}'\theta)^2}{\sigma_t^2(v-2)}\right), \tag{5}$$

where v is the degree of freedom larger than 2 and t-distribution approaches the normal as v→∞, IHS Global (2020). Generalized Error Distribution can be expressed as:

$$l_t = -\frac{1}{2}\log\left(\frac{\Gamma(1/r)^3}{\Gamma(3/r)(r/2)^2}\right) - \frac{1}{2}log\sigma_t^2 - \left(\frac{\Gamma(3/r)(y_t - X_t{}'\theta)^2}{\sigma_t^2\Gamma(1/r)}\right)^{r/2}, \tag{6}$$

where r>0 is the tail parameter, GED is the normal distribution if r=2, and fat-tailed if r<2. If one has to choose between these three conditional error distributions, they could ask which one is optimal or best. To find that out, the following three conditions must be fulfilled. The first condition requires that there is no serial correlation in the residuals of error term. This condition will be tested by using the Ljung-Box Q test of standardized residuals squared. The test statistic of the Ljung-Box Q test of standardized residuals squared is:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k}, \tag{7}$$

where n is the sample size, $\hat{\rho}_k$ is a sample autocorrelation for lag k, while h is the number of lags. The second condition requires that the residuals are normally distributed. For that purpose a Jarque-Bera test statistics will be used (Equation 8):

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right), \tag{8}$$

where n, S and K are the number of observations (degrees of freedom), skewness and kurtosis. The third condition that must be fulfilled is that there is an ARCH effect present for which the ARCH heteroskedasticity test of residuals should be used. The null hypothesis of this test states there is no ARCH effect, while an alternative hypothesis claims the opposite. To test the null hypothesis of this test that there is no ARCH effect up to order q, we run the regression:

$$e_t^2 = \beta_0 + \left(\sum_{s=1}^{q}\beta_s\, e_{t-s}^2\right) + v_t, \tag{9}$$

where e is a residual, IHS Global (2020). The main results of the analysis will be displayed and discussion of findings elaborated in the next section.

4. Results and discussion

The basic descriptive statistics for the observed variables are presented in Table 1. The results are based on daily data for the period from 8 January 2010 to 9 October 2020. Not all days in the observed period are taken into account, only days for which the data were available across all observed stock market indexes were used in the analysis.

Table 1 Descriptive statistics for the observed variables, n=2,489 trading days

Statistics	rCROBEX	rCROBEX_VOL	rDAX	rFTSE	rDJI	rIXIC	rGSPC
Average	-0.01%	20.75%	0.04%	0.01%	0.05%	0.07%	0.05%
Std. dev.	0.79%	101.45%	1.35%	1.09%	1.13%	1.26%	1.14%
Coeff. var.	-11,543%	489%	3,364%	11,700%	2,441%	1,735%	2,221%
Median	0.00%	-1.48%	0.08%	0.05%	0.07%	0.11%	0.07%
Minimum	-10.18%	-92.68%	-12.24%	-10.87%	-12.93%	-12.32%	-11.98%
Maximum	8.94%	2,211.31%	10.98%	9.05%	11.37%	9.35%	9.38%

Source: Authors

If the CROBEX volume return variable is put aside, the descriptive statistics results for the observed stock market indexes are quite consistent across all indexes. However, if median values are compared between the stock market indexes, it seems that the CROBEX index had a negative return rate on most observed days.

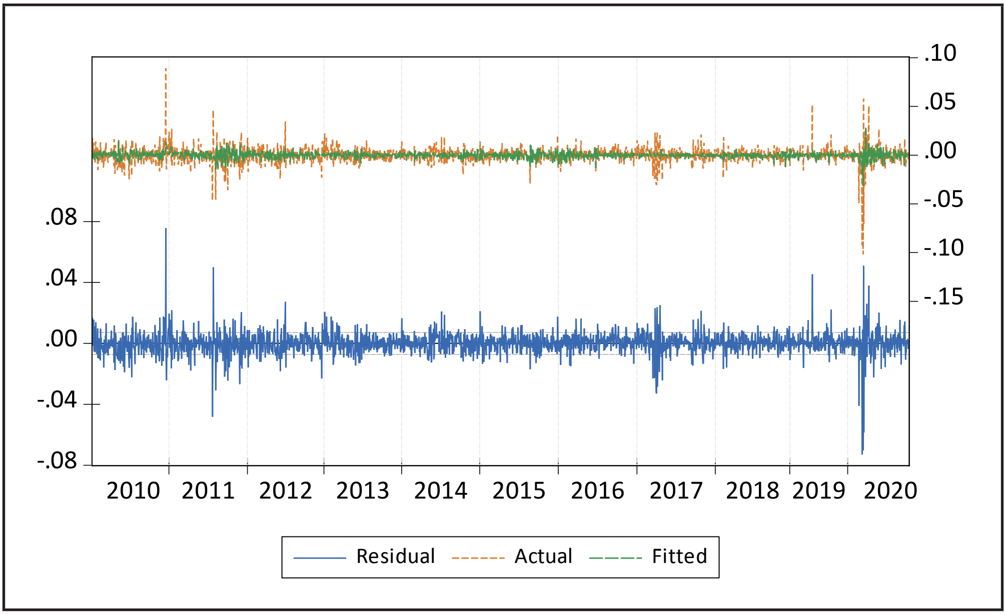
Table 2 Correlation matrix of the observed variables, n=2,489 trading days

Variables	rCROBEX	rCROBEX_VOL	rDAX	rFTSE	rDJI	rIXIC	rGSPC
rCROBEX	1.000000						
rCROBEX_ VOL	0.109813	1.000000					
rDAX	0.379942	-0.037510	1.000000				
rFTSE	0.381407	-0.043422	0.855102	1.000000			
rDJI	0.358617	0.016946	0.641000	0.643651	1.000000		
rIXIC	0.314334	0.009650	0.600113	0.582975	0.901236	1.000000	
rGSPC	0.345075	0.010624	0.639863	0.641615	0.975479	0.956175	1.000000

Source: Authors

The correlations between the observed variables are displayed in Table 2. The correlation between the CROBEX return variable and the CROBEX volume return variable is positive but quite week. The individual correlations of the CROBEX return variable with other stock market index return variables are positive and of about the same strength. The CROBEX return variable has the lowest correlation with the IXIC return variable (the coefficient of correlation 0.3143), whereas the highest correlation is with the FTSE return variable (the coefficient of correlation 0.3814). Still, the difference between the lowest and the highest coefficient of correlation is very small. If the correlation coefficients between other stock market indexes are observed, it can be noticed that all three individual correlation coefficients between the DJI, the IXIC and the GSPC return variables are above the value of 0.90, implying a strong correlation between American indexes.

Figure 1 Residuals of the conditional mean equation, n=2,489 trading days



Source: Authors

As described in Equation 2, the conditional mean equation was estimated by applying the ordinary least squares method and the residuals of that model are shown in Figure 1. It seems that the periods of low volatility are followed by the periods of low volatility and the periods of high volatility are followed by such periods. Accordingly, it seems that the residual of error term is conditionally heteroscedastic, which approves the use of GARCH model. The results of the Ljung-Box Q test of standardized residuals squared for the GARCH(1,1) models are shown in Table 3.

Table 3 Ljung-Box Q statistics of standardized residuals squared for GARCH(1,1) models

Lag	Model 1	Model 2	Model 3
1	0.4275	0.3894	0.4017
2	0.5287	0.5540	0.5403
3	2.8628	1.9648	2.4435
4	2.8641	1.9743	2.4477
5	3.1273	2.2936	2.7401
6	3.9678	3.1064	3.5775
7	3.9701	3.1080	3.5791
8	3.9715	3.1828	3.5927
9	3.9850	3.2200	3.6119
10	59.905*	44.042*	52.595*
15	61.770*	45.840*	54.395*
20	63.148*	46.912*	55.598*
25	65.389*	48.851*	57.706*
30	66.262*	49.479*	58.445*
35	66.589*	49.947*	58.840*

Note: *statistically significant at a significance level of 0.05.
Source: Authors

The null hypothesis of this test contains the assumption that there is no serial correlation present in the GARCH model. The test results are the same across all three estimated models. Up to and including lag 9, the null hypothesis of the Ljung-Box Q test cannot be rejected at the 0.05 significance level, which leads to the conclusion that there is no serial correlation present in the GARCH(1,1) models. However, higher lags point to the opposite conclusion.

Table 4 ARCH heteroskedasticity test results of residuals for GARCH(1,1) models

Statistics	Model 1	Model 2	Model 3
Obs*R-squared	0.4268	0.3888	0.4011

Note: *statistically significant at a significance level of 0.05.
Source: Authors

The ARCH heteroskedasticity test results are given in Table 4. In the ARCH test, the squared residuals are regressed on lagged squared residuals and a constant. The null hypothesis of the test contains the assumption that the ARCH effect is not present. For all three GARCH(1,1) models the ARCH heteroskedasticity test results have shown that the null hypotheses cannot be rejected at the 0.05 significance level. In that way, the conclusion is that the ARCH effect is not present in either of the three GARCH(1,1) models.

Table 5 Jarque-Bera test results of residuals for the GARCH(1,1) models

Statistics	Model 1	Model 2	Model 3
Jarque-Bera	12307.87*	19194.30*	15101.92*

Note: *statistically significant at a significance level of 0.05.
Source: Authors

Jarque-Bera test results of residuals for GARCH(1,1) models are shown in Table 5. The null hypothesis of the Jarque-Bera test contains the assumption that the residuals are normally distributed. However, the null hypothesis can be rejected for all three GARCH(1,1) models at the 0.05 significance level. The residuals did not seem to be normally distributed. No decisive conclusion can be drawn as to which GARCH model is the best so all three models will be estimated.

In order to estimate GARCH(1,1) models, normal (Gaussian) distribution, Student's -distribution with fixed degrees of freedom and Generalized Error Distribution (GED) with fixed parameters as conditional error distributions are used. Therefore, all three GARCH(1,1) models were estimated and named Model 1, Model 2 and Model 3 consequently. In the first GARCH(1,1) model, normal (Gaussian) distribution was used (Model 1) as conditional error distribution, in the second GARCH(1,1) model, Student's -distribution with fixed 10 degrees of freedom was used (Model 2), and in the third GARCH(1,1) model, Generalized Error Distribution (GED) with fixed parameters at value 1.5 was used as conditional error distribution (Model 3). The estimated GARCH(1,1) models are shown in Table 6.

Table 6 Estimated GARCH(1,1) models using equations (2) and (3)

	Estimates	Model 1	Model 2	Model 3
Mean equation	C_1	-8.28E-05 (-0.66)	-6.50E-05 (-0.58)	-5.94E-05 (-0.53)
	C_2	0.0005*** (8.12)	0.0003*** (3.42)	0.0004*** (5.31)
	C_3	0.1033*** (6.65)	0.0913*** (6.22)	0.0937*** (6.27)
	C_4	0.0692*** (3.39)	0.0571*** (2.97)	0.0606*** (3.10)
Variance equation	C_5	3.03E-06*** (10.28)	2.09E-06*** (6.44)	2.55E-06*** (7.29)
	C_6	0.0976*** (10.25)	0.0834*** (7.36)	0.0892*** (7.62)
	C_7	0.8442*** (64.61)	0.8526*** (51.49)	0.8484*** (48.88)
	C_8	-0.0011*** (-8.72)	-0.0003 (-1.35)	-0.0007*** (-4.19)
	C_9	-0.0007*** (-6.81)	-0.0002 (-0.99)	-0.0004*** (-2.96)
	C_{10}	0.0016*** (8.83)	0.0003 (0.84)	0.0010*** (3.55)

Notes: z-statistics in parentheses. ***statistically significant at a significance level of 0.01, **statistically significant at a significance level of 0.05, *statistically significant at a significance level of 0.1.
Source: Authors

The volume of trade proved to be a positive and significant explanatory variable. The estimates of this variable were stable in all three GARCH(1,1) models. The values of the C_2 regression coefficient were relatively low in the range of 0.0003 to 0.0005. There was a positive and significant effect of DAX and FTSE returns on CROBEX returns. The ARCH and GARCH terms (regression coefficients C_6 and C_7) were significant in all GARCH(1,1) models. They are both internal shocks of the dependent variable volatility or family shocks influencing CROBEX return. The values of regression coefficients for all three American stock market index returns proved to be significant in normal (Gaussian) and Generalized Error Distribution (Models 1 and 3). However, a positive value of the regression coefficient was achieved only for S&P500 stock market index return. In order to confirm the obtained findings, the robustness check was made by estimating the GARCH(1,1) models by setting a one day lag for all explanatory variables (Table 7).

Table 7 Estimated GARCH(1,1) models, all explanatory variables lagged 1 day

	Estimates	Model 1	Model 2	Model 3
Mean equation	C_1	-2.35E-05 (-0.18)	-1.12E-06 (-0.001)	-1.23E-05 (-0.11)
	C_2	0.0005*** (7.22)	0.0002*** (2.59)	0.0003*** (3.99)
	C_3	0.0191 (0.97)	0.0196 (1.18)	0.0165 (0.96)
	C_4	0.0311 (1.27)	0.0268 (1.30)	0.0320 (1.49)
Variance equation	C_5	3.91E-06*** (13.42)	2.20E-06*** (6.82)	3.02E-06*** (8.56)
	C_6	0.1051*** (10.98)	0.0858*** (7.45)	0.0946*** (7.84)
	C_7	0.8275*** (64.50)	0.8524*** (52.58)	0.8385*** (48.52)
	C_8	-0.0014*** (-12.23)	-0.0003 (-1.37)	-0.0009*** (-5.26)
	C_9	-0.0009*** (-10.22)	-0.0003* (-1.84)	-0.0006*** (-4.42)
	C_{10}	0.0021*** (11.43)	0.0004 (1.19)	0.0013*** (4.60)

Notes: z-statistics in parentheses. ***statistically significant at a significance level of 0.01, **statistically significant at a significance level of 0.05, *statistically significant at a significance level of 0.1.
Source: Authors

The results are similar to those obtained from the Table 6: (1) the volume of trade on the ZSE proved to be positively related to the daily stock market returns, (2) there was a positive and significant effect of ARCH and GARCH terms in GARCH(1,1) models, and (3) there was a positive and significant value of regression coefficients related to American stock market returns with only S&P500 having the positive value of a regression coefficient. The difference in the results given in Table 6 are insignificant regression coefficients related to European stock market returns, meaning that changes on the European stock markets in the previous day do not send signals to the CROBEX returns on the actual trading day.

The main findings of this paper confirm previous research in this field. The C_2 regression coefficient was relatively low in the range of 0.0003 to 0.0005, which is in line with Erjavec and Cota (2007:4). There was a positive and significant effect of DAX and FTSE returns on CROBEX returns, which is also in line with the previous results indicating the existence of co-movement of the CROBEX index and two main European indexes on the same trading day. Furthermore, the results obtained in this research point out co-movement or interconnection between the value of CROBEX returns and S&P500 returns lagging one day; a similar result was obtained by Sajter and Ćorić (2009).

5. Conclusions

The goal of this paper was to estimate stock market volatility in Croatia using GARCH(1,1) models. For the purpose of analysis, all three conditional error distributions (normal (Gaussian), Student's -distribution with fixed degrees of freedom and Generalized Error Distribution (GED) with fixed parameters) were estimated. The results have shown that volatility of CROBEX stock market returns is positively correlated with the volume of trade on the ZSE and movement of returns on main European and American stock markets, which is in line with previous research in this field. It seems that movements of S&P500 index returns are transmitted from the previous day, providing signals in the direction of change of the CROBEX index in the present. The limitations of the paper are related to the fact that only the days for which the data across all indexes were available were included in the analysis. Furthermore, the data were adjusted for non-tradable days, including holidays in observing countries. Further research in this field should be made by analyzing stock market volatility in other Central and Eastern European countries. This paper proves another strong evidence of interconnection between international stock markets; investors in Croatia strongly rely on information received from American stock markets, namely the S&P500 stock market index.

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