Research Paper

Volume : 2 | Issue : 9 | September 2013 • ISSN No 2277 - 8179

Investigating Long-Term Volatility of Warsaw Stock Exchange Based on Garch Family Models

Management

KEYWORDS : volatility patterns, GARCH family models, financial integration

Ramona Birău — University of Craiova, Faculty of Economics and Business Administration ROMANIA

Jatin Trivedi — International School of Business & Media Pune, INDIA.

ABSTRACT

This paper aims to investigate long-term volatility of Warsaw Stock Exchange based on GARCH family models, namely GARCH (1,1), EGARCH and GJR-GARCH models. Moreover, a sharp introspection regarding the particular behavior of emerging stock markets raised significant issues as a direct consequence of international portofolio diversification and financial globalization. Volatility is a highly heterogeneous concept which is extremely difficult to commensurate due to the influence of a very large range of both intrinsic and extrinsic factors. Empirical analysis provides additional insight regarding volatility patterns, similar reaction to external shocks, investor risk aversion, consequences of the inflow of new informations on the market, financial integration, risk management and negative impact of the global financial crisis.

INTRODUCTION

This article covers volatility, estimation and forecasting of WIG20 stock market. Estimation of volatility in stock markets becomes primary study for investors and decision makers. WIG20 represents the index performance of Warsaw stock exchange (WSE) which is weighted stock market index which includes twenty largest companies. It is index of Poland, an emerging stock market of central Europe. Advanced econometrics has given opportunity to identify risk factor, estimate volatility and estimation of stock market which provides opportunity for calculated investment risk. The most used model of estimation of volatility is Generalized Autoregressive Conditional Heteroskedisticity (GARCH) presented by Bollerslev and Taylor (1986). There are variety of studies for estimation and forecasting of stock markets using GARCH and GARCH class models.

REVIEW OF LITERATURE

In recent past, a wide variety of empirical studies have been performed on modelling and forecasting stock market volatility by applying GARCH family models. Nevertheless, most of these research articles were focused on developed stock markets behavior. In other words, emerging stock market behavior is still a relatively unexplored territory with great attraction potential for financial investors. A major contribution was provided by Engle (1982) who developed the AutoRegressive Conditional Heteroscedasticity (ARCH) in order to model volatility by relating the conditional variance of the disturbance term to the linear combination of the squared disturbances in the recent past. The basic idea is that financial asset return is serially uncorrelated but dependent, considering the fact that the dependence can be expressed using a cuadratic function. The ARCH methodology suggests that high returns tend to be followed by another high return, issue which coincides with the fundamental of volatility clustering. Generalized ARCH model (GARCH) developed by Engle (1982) which is extended by Bollerslev (1986) and Nelson (1991) is most used model for conditional heteroskedasticity. Rao, Kanagaraj and Tripathy (2008) have focused on modeling asymmetric volatility in Indian stock market using EGARCH and TGARCH models. Angabini, and Wasiuzzaman have carried out study on GARCH models and the financial crisis, the study prepared on Malaysian stock market and employed GARCH (1, 1) and EGARCH (1, 1). They have concluded that there was a significant increase in volatility and leverage effect with just a small drop in persistency due to the global financial crisis.

CASE STUDY

In this research paper was used the most general model GARCH (1, 1) Bollerslev and Taylor (1986) for estimation of volatility, but this model does not provide leverage effect or effect of news on volatility. Therefore we employ GARCH class models, EGARCH and GJR-GARCH. EGARCH or Exponential GARCH model presented by Nelson (1991) which easily represents leverage effect or asymmetric effect in time series of WIG20. GJR-GARCH model, Glosten, Jagannathan and Renkle (1993) is capable to identify effect of news on volatility. GARCH (1, 1) was introduced by Engle (1982) further it is extended by Bollerslev (1986) and again by Nelson (1991). This model allows conditional variance of all variables to be dependent upon previous legs and reflects on entire series. However the first leg of squared residual will be from mean equation and this presents idea about volatility from the previous time periods. General most used model for formulate GARCH (1, 1) as the following expression :

$$h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$$

Nelson (1991) has provides Exponential GARCH or EGARCH model which assures confidence for positivity of conditional variance. It covers the asymmetric impact. The specimen of EGARCH model can be explored as the following expression :

$$\text{Log } h_t = \omega + \beta_1 \log h_{t-1} + \alpha 1[\theta V_{t-1} + \gamma\{|V_{t-1}| - E|V_{t-1}|\}]$$

The previous model takes long form, adds an additional term for leverage effect which we call asymmetric effect. EGARCH guarantees positive variance because of ht= exp (R.H.S.) > 0 always and θVt-1 covers asymmetric effect. However, EGARCH also limited to tell about effects of good news and bad news. Glosten, Jagannathan and Renkle (1993) have developed GJR-GARCH model which estimates effects of good news and bad news from JURI markets stock indices. GJR-GARCH can be explored as the following expression :

$$h_t = \omega + \alpha_1 u_{t-1} 2 + \beta_1 h_{t-1} + \theta I_{t-1} u_{t-1}^2$$

Here if $\theta > 0$, we say that there is a leverage effect. If ($u_{t-1} > 0$), that has an effect of $\alpha 1\ u_{t-1}^2$ on the variance and represents effect of good news on volatility, while bad news effects ($u_{t-1} < 0$) has an effect of $(\alpha_1+\theta)\ u_{t-1}^2$ on the variance.

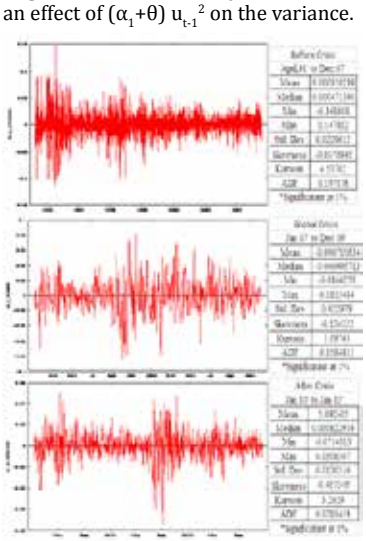

Figure 1 Descriptive statistics & ADF test results using WIG

20 log-return series from April 1991 to January 2013
Source: Author's computation

We are working with large data series, April 91' to Jan 13' which is divided into three parts, before-crisis (April 91'- Dec 07') global-crisis period (Jan 07'- Dec 09') and after-crisis period (Jan 10'- Jan 13'). Descriptive statistics suggests that overall series has negative skewness and creates long-left tail which is also suggested by high-kurtosis. Mean returns suggests that before and after crisis returns are positive, it means that investors has returns from investment whereas crisis period has negative Mean, which is for negativity from investment. Focused observation on Fig1 represents change in min-maximum -0.14 to 0.14 before-before crisis which covers span of more than 15 years where as same crisis-period indicates same in duration of 2 years 2007-2008 – ie 0.084 to 0.081, it indicates abnormal and unconditional movements of index. We can see that after crisis-period also indicates volatility sketches during September 2011 (see fig1).

TABLE – 1 GARCH FAMILY MODEL ESTIMATIONS

Indices	Variable	GARCH (1, 1)	EGARCH	GJR-GARCH
Before crisis	Mean Eqn.	0.000834283 (0.0009)	0.000776322 (0.0004)	0.000718928 (0.0050)
	Omega	6.95019e-06 (0.0002)	0.343873 (5.32e-011)	7.21407e-06 (0.0001)
	Alpha	0.114228 (8.70e-015)	0.233211 (6.09e-023)	0.116892 (8.91e-016)
	Gamma	-	0.00496538 (0.0012)	0.0314429 (0.0042)
	Beta	0.872877 (0.0000)	0.979412 (0.0000)	0.869445 (0.0000)
Global crisis	Mean Eqn.	0.000532225 (0.0494)	0.000955014 (0.0026)	0.000906269 (0.0062)
	Omega	5.52014e-06 (0.2746)*	0.252041 (0.0258)	6.45193e-06 (0.0212)
	Alpha	0.0589944 (0.0042)	0.127663 (0.0033)	0.0474919 (0.0317)
	Gamma	-	0.0810695 (0.0073)	0.374726 (0.0553)
	Beta	0.93022 (0.0000)	0.980392 (0.0000)	0.933716 (0.0000)
After crisis	Mean Eqn.	0.000473675 (0.0052)	9.58738e-05 (0.0027)	0.000174743 (0.0039)
	Omega	2.50201e-06 (0.0539)	0.241238 (0.0014)	3.13177e-06 (0.0127)
	Alpha	0.0653931 (2.78e-05)	0.0933565 (0.0030)	0.0253107 (0.0709)
	Gamma	-	0.0996377 (3.17e-06)	1.00494 (0.2446)*
	Beta	0.918347 (0.0000)	0.981219 (0.0000)	0.924525 (0.0000)

Source: Author's computation

Augment Dickey-Fuller (ADF) test was employed which represents no unit root problems under hypothesis Ho=p0, & p1, it allows WIG20 index allows ARCH effect and thus we can proceed GARCH modeling. ADF test represents significant results at level of 1% which is presented in fig1. With exception to modeling GJR-GARCH in after crisis estimation, rest data are perfectly fitted in GARCH class models (see table1).

Now we execute data in our models for estimating and forecasting volatility in our sample WIG20 series. All the models follow student-t distribution. The following equation is outcome of GARCH (1, 1) where conditional variance should not exceed 1, positively and thus $\alpha_1 + \beta_1 < 1$ proved successfully

GARCH (1, 1) model formulation :
Before global financial crisis
$0.114228\ (\alpha_1 u_{t-1}^2) + 0.872877\ (h_{t-1}) = 0.987105 < 1$

During global financial crisis
$0.0589944\ (\alpha_1 u_{t-1}^2) + 0.93022\ (h_{t-1}) = 0.9890144 < 1$

After global financial crisis
$0.0653931\ (\alpha_1 u_{t-1}^2) + 0.918347\ (h_{t-1}) = 0.9837401 < 1$

Consequently volatility is highest in financial crisis period; it is increased by 0.0019 during financial crisis. We can notice that it is reducing slowly after crisis period. It represents good characteristics of investments in stock market of Polonia. Table1 indicates that WIG20 is not exempted from global crisis and unconditional shocks. The above model GARCH (1, 1) does not represents leverage effect and effect of news on market, thus the following GARCH class models explores it.

EGARCH – model formulation :
Before global financial crisis
$\text{Log } h_t = 0.000776322\ (\omega) + 0.979412\ (\beta_1) \log h_{t-1} + 0.233211\ (\alpha_1) [\theta V_{t-1} + 0.00496538\ (\gamma)\{|V_{t-1}| - E|V_{t-1}|\}]$

During global financial crisis
$\text{Log } h_t = 0.000955014\ (\omega) + 0.980392\ (\beta_1) \log ht\text{-}1 + 0.127663\ (\alpha_1) [\theta V_{t-1} + 0.0810695\ (\gamma)\{|V_{t-1}| - E|V_{t-1}|\}]$

After global financial crisis
$\text{Log } h_t = 9.58738e\text{-}05\ (\omega) + 0.981219\ (\beta_1) \log ht\text{-}1 + 0.241238\ (\alpha_1) [\theta V_{t-1} + 0.0996377\ (\gamma)\{|V_{t-1}| - E|V_{t-1}|\}]$

Exponential GARCH or EGARCH model represents asymmetric effects in WIG20 index. It indicates presence of leverage effects in before, during and after crisis period. Here we observed that (α_1) reduced to 0.127663 in crisis period from before crisis 0.233211, it suggests us that there are less chances of positive markets and negative market shocks have higher impact than positive market shocks during this period. Nevertheless, the improvement we can notice in after crisis, which indicates good parameters for WIG20. We have tested sample series with GJR-GARCH to finding out the effect of news on volatility. It also represents asymmetric effects. The GJR-GARCH formulates as under. We failed to explore effect of news after financial crisis period as p-value is too high for that period. The following modeling represents forecasting effect of news on stock market volatility.

GJR-GARCH– model formulation :
Before global financial crisis
$h_t = 0.000718928(\omega) + 0.116892(\alpha_1)u_{t-1}^2 + 0.869445\ (\beta_1)\ h_{t-1} + 0.0314429\ (\theta) I_{t-1}\ u_{t-1}^2$

During global financial crisis
$h_t = 0.000906269(\omega) + 0.0474919(\alpha_1)u_{t-1}^2 + 0.933716\ (\beta_1)h_{t-1} + 0.374726\ (\theta) I_{t-1}\ u_{t-1}^2$

We can understand very easily that series strongly supports asymmetric effects for Poland sample market. The above model suggests that good news or positive news has an impact of 0.116892 magnitudes in before-crisis markets which reduced to 0.04749 magnitudes during crisis period. It indicates that good news have very lower impact on market compare to bad news, increases volatility in WIG20 stock market. We can measure impact of bad news, 0.116292+0.0314429=0.1477349 magnitudes before crisis. Investors requires to pay attention here that before crisis there is very less difference in effects of good news and effects of bad news. It indicates calculated investment risk. Global crisis impacted WIG20 market and we can see increase in effect of bad news dramatically, considering the fact that 0.0474919+0.374726=0.4222179 magnitudes. It is very easy to understand impact of recent financial crisis on sample market.

CONCLUSIONS
The empirical results of present statistics and forecasting indicates that sample market of WIG20 is an investment opportunity for investors and represents conditional volatility during con-

Volume : 2 | Issue : 9 | September 2013 • ISSN No 2277 - 8179

ditional situations. Nevertheless we have noticed unconditional volatility within sample period. Descriptive statistics represents high skewness and effect of leptokurtosis. GARCH (1, 1) has noticed increase of volatility in sample market based on symmetric modeling, EGARCH and GJR-GARCH has estimated leverage effects which suggest that market reacts highly negative than positive during unconditional circumstances. GJR-GARCH modeling is perfectly fitted for the period of before-crisis and global-crisis and failed to forecast effects for after-crisis period. Nevertheless, Warsow stock market is perceived as atractive option for financial investment particularly as an emerging market.

REFERENCE

[1] Angabini, A. and S. Wasiuzzaman, (2011) GARCH Models and the financial crisis – a study of the Malaysian stock market". I. journal | [2] Birău, R., - Cointegration and Dynamic Linkage Between Warsaw Stock Exchange and Developed Stock Markets, 20th International Economic Conference - IECS 2013 „Post Crisis Economy: Challenges And Opportunities" Sibiu, Romania, May 17 - 18, 2013 | [3] Bollerslev, T., (1986), "Generalized autoregressive conditional heteroskedasticity", Journal Economic., 31: pp. 307-327. | [4] Dickey, D.A., W.A. Fuller, (1979), "Distribution of the estimators for autoregressive time series with a unit root", J. Am. Stat. Assoc., 74: 427-431 | [5] Engle, R. (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of UK Inflation", Econometrica, Vol. 50, 987-1008. | [6] Engle, R. F. and Rangel, J. G. (2004), "The Spline GARCH Model for Unconditional Volatility and Its Global Macro-Economic Causes", Review of Financial Studies, Vol. 21, No. 3, 1187-1222 | [7]Ramana Rao, S. V. A. Kanagaraj and Naliniprava Tripathy (2008), Does Individual Stock Futures Affect Stock Market Volatility in India?, Journal of the Indian Institute of Economics, Vol. 50, No.1, 125-135. | |