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Financial Investment and Insurance –
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ACCURACY EVALUATION OF MODELING THE VOLATILITY OF VIX USING GARCH MODEL

Summary: Measuring the volatility of volatility is an important issue in case of constructing portfolio strategies including the volatility index as an individual financial instrument. The market-oriented attitude including implied volatility available in VVIX index is complex and most precise estimator of volatility of volatility index because it projects the market deeply than only by considering the historical observations. This convenience is available only on very few exchanges, which means that in many cases managing volatility of volatility must be based on conditional variance and other models. This attitude does not seem to be reliable. The paper examines both attitudes – model-based methodology including forecasting variability of VIX index and its multiple simulations, and market-oriented one including implied volatility of volatility index – the VVIX realizations.

Keywords: Volatility simulations and forecasts, GARCH modeling, implied volatility indices, volatility of volatility.

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The only thing that is constant – is change.

Heraclitus

1. Introduction

Volatility is still one of the most important and hard to interchangeably define and calculate parameters which are especially important on actual unstable financial markets. Both forecasting and simulating the volatility of financial instruments is very popular with investors, so natural consequence was to improve prepared indices developed strictly to make following their volatility faster and easier. The appearance of dedicated volatility indices has made that calculating volatility of given instruments by using complicated models seems to be unnecessary, because these indices usually include quite complex mathematical formulas and it is enough precise to forecast volatility of selected instruments. This kind of volatility indices are developed with taking under consideration the financial market dependencies and important parameters that do not appear in other methodologies. They are created strictly for given basic instruments and apparently better project the market. On the other hand, in case of measuring the volatility of volatility indices, there still exists the problem with choosing the best adjusted model and with minimizing aforementioned models' constraints caused by the dynamic and interchangeable capacity of volatility itself.

The purpose of this paper will be to prove what measuring the volatility of volatility by using model-based methods such as GARCH can be in some cases comparable with volatility determined by the financial market, which is represented by implied volatility included in VVIX and how much more effective are these realised values obtained by VVIX in comparison with the GARCH multiple simulations and forecasts of the VIX. The research hypothesis assumes that GARCH modeling gives not sufficient and not enough precise or even comparable results to the VVIX index and only the latter is effective and reliable in predicting volatility of VIX, which presents the need for creating and developing indices such as VVIX on the other exchanges.

This paper proceeds as follows. Section 2 describes some key facts about VIX and VVIX indices and basic information about how both of them are calculated. It also presents the most important elements of volatility models' theory, such as GARCH model, and volatility itself. Section 3 represents a description of required data. Section 4 presents the results of estimation and comparison of required volatility GARCH models parameters with other weaker estimates which were also considered. Section 5 and section 6 include obtained calculations necessary to prove its research hypothesis and presents basic comparison of both methods of predicting the volatility of VIX index, interpretation of obtained results and final conclusions.

2. The theoretical aspects of volatility

2.1. Volatility as a process on financial markets

Volatility has fundamental importance among financial markets' parameters. In long-term investments the aim of traders is not to forecast accurate values of instrument`s quotations, but it is necessary to predict precisely the level of volatility, its direction and clustering. The most questionable issue about volatility is that this kind of process is unobserved – both *ex ante* and *ex post*. Andersen and Bollerslev have also proved in their significant paper that the assessment of volatility forecasts strongly depends on established proxy [Fuertes, Izzeldin, Kalotychou 2009].

To control fluently the level of volatility, many mathematical formulas and models have been invented. These implements help to calculate volatility *ex ante* or *ex post*. Because the frequency of financial data is very high and is still rising, the higher is quickness of calculations the better. To relieve high-frequency traders from time-consuming computations, many dedicated financial instruments have been created strictly to present the forecasts and simulations of other instruments' – such as options, futures, etc. – volatility level. These implementations usually are available as volatility indices.

Indices that measure level of other instruments' volatility have wide range of basic assets – as mentioned before, it could be any commodity, currency or other financial instrument, including concept of measuring the volatility of volatility itself. Indices measuring expected volatility of volatility are convenient implement which enables traders to save the time while simultaneously monitor its basic volatility instrument.

Available measures of volatility vary from rather simple mathematical formulas such as standard deviation and variance to more or less sophisticated econometric models such as GARCH or VaR which is one of the most popular risk measures.

Standard deviation presents the amount of variation or dispersion from the mean value [Bland, Altman (eds.) 1996]. It is algebraically simpler than the average absolute deviation [Walker 1931]. VaR is a popular risk measure. It finds application in financial mathematics. Issue to which has been given a critical judgment of models such as GARCH or VaR is requirement that input data set must settle condition of Gaussian distribution, which strongly limit the application of this risk measure [Jakubowski 2006].

2.2. GARCH models

GARCH is an acronym of Generalized Autoregressive Conditional Heteroscedasticity and represents time series model designed to simulate and forecast volatility. It is an extension of Engle's ARCH model for variance heteroscedasticity [Engle 1982]. Conditional heteroscedasticity is a property of returns in volatility modeling process that determines the way in which these returns form themselves and which consists in appearance of phenomenon of volatility clustering. It means that when during given period of time volatility is high, in the other period of time it is relatively low. There is also a possibility that volatility does not assume constant value, but it varies during the time [Doman, Doman 2009].

GARCH modeling framework and its application is still widely popular with financial analysts to research the level of dynamics of return variation. Its biggest disadvantage is that the expected variance of returns appears as a polynomial of the historical values – past squared returns. On the other hand, the GARCH models can expand with more variables with high level of prediction power for forecasted returns [Fuertes, Izzeldin, Kalotychou 2009].

The biggest advantages of this class of models are construction simplicity, relative easiness of parameters estimation and the small number of them. Also interpretation of GARCH models is quite intuitive. These features caused the rising popularity of GARCH as a conditional variance model for predicting volatility of financial instruments. Formally GARCH models can be classified as a group of nonlinear models designed to examine time series which also allow for analysing profoundly dynamics of processes that exist in a given time series.

GARCH models are described by the following formulas:

$$y_t = \sigma_t \varepsilon_t, \tag{1}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \, y_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2. \tag{2}$$

The most popular and most often applied for different calculations model is GARCH with parameters both *p* and *q* equal to 1 – the GARCH(1,1) and it will be representation of the GARCH class models in the elements of theory below. Dependence describing conditional variance combines volatility with its past realisations and squares of returns. Parameter α_i determines the influence of volatility for information available in squares y_{t-i}^2, and β_j parameter describes dynamics of expectations which the financial market requires about future volatility forming issue in analogous way to the actual conditions. Volatility σ_t^2 from the theoretical point of view can depend even on the infinite number of squares of returns y_{t-i}^2 despite the intensification of this influence decreasing with the lag increase. Additionally, when the following assumption is fulfilled

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1, \tag{3}$$

the y_t process generated by the GARCH model is covariance-stationary. An important limit of this kind of model is necessary condition for the existence of a kurtosis which appears as follows:

$$(\alpha_1 + \beta_1)^2 + 2\alpha_1^2 < 1. \tag{4}$$

There is also an assumption that GARCH model has mean value equal to zero and variance equal to one.

The forecast at the moment *t* determined for one period forward can be achieved also in model GARCH(1,1) directly by using a formula in which there are present data on conditional variance h_t and the residue of the model e_t. Both of mentioned values can be received by adjusting model to the empirical values.

Using the following signs for equation (5):

h_t – estimated conditional variance at moment *t*,

ε_t – estimated residual of model at moment *t*,

$(\hat{\mu}, \widehat{\omega}, \hat{\alpha}, \hat{\beta})$ – vector of estimated model parameters,
$h_{f,t+k}$ – forecast of conditional variance at moment $t + k$,
the obtained equation appears as follows:

$$h_{f,t+1} = \widehat{\omega} + \alpha\widehat{\hat{\varepsilon}_t^2} + \dot{\hat{\beta}}\widehat{h_t}\,. \tag{5}$$

The GARCH class models are characterised by possibility of describing the effect of return to mean value. Determined at the moment t, the value of $\widehat{h_t}$ represents the level from which next forecasts will be returning to the long-term mean value. For the quickness with which the return to mean value will appear an expression $(\hat{\alpha} + \hat{\beta})$ is responsible. The closer this expression will sum up to 1, the more slowly the conditional variance forecasts for next days will return to long-term mean value – and this means the increase in length of influence of information on next elements of the forecast [Piontek 2002].

2.3. The volatility indices – VIX and VVIX

Volatility indices are instruments designed to control the latest forecasts of other assets volatility without necessity of calculating it. These indices project the market by including more parameters of given instrument than only historical values as it is calculated in model-based methodologies. They are constantly available on stock exchanges and help traders with taking investment decisions whereas simultaneously help to save time for calculations.

One of the most popular measures of implied volatility of S&P500 index options is the VIX index. As VX it is also a trademarked ticker symbol for the index designed by Chicago Board Options Exchange, which is also called "fear index" or "fear gauge". The VIX describes uniform measure of market's expectations of these options market volatility for the period of 30 days forward.

In calculating the VIX index one of the most important elements is implied volatility that includes measurement errors. The implied volatility series may be potentially incorrect and this can possibly account for some of the conflicting results. Fleming in 1995 presented a version of implied volatility index (VIX), which passes over the misspecification issue [Becker, Clements, McClelland 2009].

Because there are no limits on instruments that can be basic assets for volatility indices and because of the growing demand for measuring volatility as quickly and efficiently as possible, Chicago Board Options Exchange designed index which measures the volatility of volatility. More precisely, CBOE designed VVIX – which is a VIX based on VIX itself. VVIX is an indicator which forecasts expected volatility of a 30-day forward price of the VIX index using the same calculation method as VIX uses to forecast option prices. This index also includes term structure in its calculations for different expiration dates and is based on a portfolio with liquid at- and out-of-the-money VIX options. This index is dedicated to those investors who are focused on VIX (their number still grows) and its destination is to guide and inform them about VIX expected variability [http://www.cboe.com/micro/VVIX/].

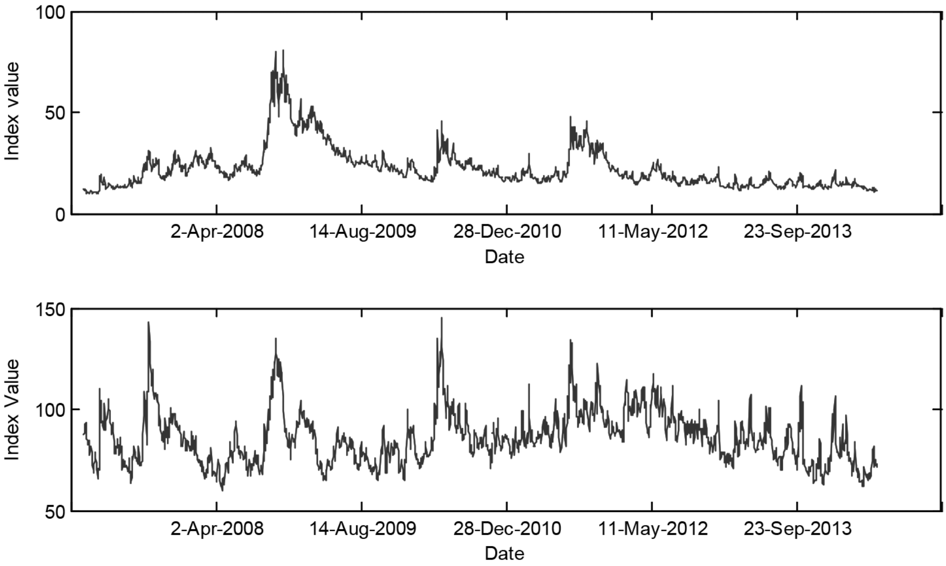

Figure 1. Daily VIX index (top panel) and daily VVIX index (bottom panel) for the same period

Source: own elaboration based on data retrieved from http://www.cboe.com/micro/VVIX.

3. Datasets

The all datasets which were used in this paper were the time series of the VIX index on a more than 5 year long period from the beginning of 2009 to the middle of 2014 and time series of VVIX from 2 January 2013 to 30 June of 2014. First the data points of VIX index were converted into the returns from daily closed prices. The distribution of returns was likely to Gaussian what shows Figure 2.

The dataset which was necessary to estimate proper parameters of GARCH model to simulate and forecast model results was VIX closed prices on period from 9 February 2009 to 31 December 2012. The dataset that was necessary to compare with results of simulations and forecasts were VVIX close prices in period from 2 January 2013 to 30 June of 2014 converted into returns that represent the market-oriented volatility level of VIX. The latter period is also the one used as horizon of forecast and multiple Monte Carlo simulations.

The comparison of attitudes was necessary to deduct whether the information included in implied volatility measures (VVIX) is far more accurate than average of multiple GARCH model simulations or forecast, and whether in all presented attitudes exist any similar trends. The three approaches represent different calculating methodologies so the precise accuracy of forecasts quality is not possible mainly because of quite random character of simulations. Because of presumptions of their dependencies with the input dataset, it should be empirically examined.

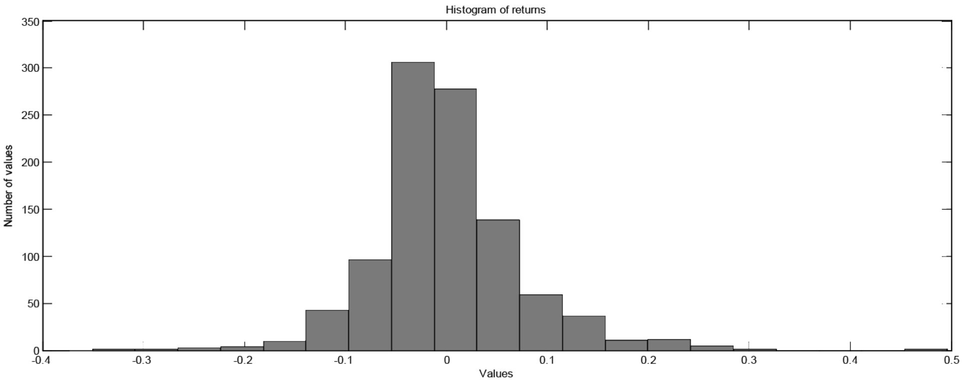

Figure 2. The histogram of VIX index returns showing likeness to Gaussian distribution

Source: own elaboration based on data retrieved from http://www.cboe.com/micro/VVIX.

All the datasets consisting the closing prices of the index were acquired from Chicago Board Options Exchange official website.

For all the calculations in this paper the Matlab software was used. Also the presented figures were received from Matlab. Most often used toolbox was Econometric Toolbox in integral connection with Database Toolbox.

4. Estimation of GARCH parameters

After preparation of time series of VIX from the beginning of 2009 to 30 June 2014 the Engle's ARCH effect test was made and time series was accepted (h = 1), and at the 0.01 significance level (p-value = 1.8707e-13) there exists in given time series mentioned ARCH effect and it is valid, so it can be used for estimation of appropriate GARCH model.

Therefore, the model parameters could be calculated for valid GARCH model. Parameters of ARCH, GARCH and constant elements were selected from specified and fitted to time series of VIX returns of ARCH(1), GARCH(1,1), GARCH(2,1) and GARCH(3,2). A likelihood ratio test was conducted to compare the restricted GARCH(1,1) model fit to the unrestricted models, in sequence ARCH(1), GARCH(2,1) and GARCH(3,2) model fit. The degree of freedom for this test was 1 which represented the number of restrictions. At the 0.05 significance level, the null GARCH(1,1) model was rejected (h = 1) in favor of the rest of the concerned models, for instance the unrestricted GARCH(2,1) alternative returned *p*-VALUE equal to 0.0431. The most accurate estimation was GARCH(1,1), hence it was involved for all calculations in this paper.

Table 1. Parameters of GARCH(1,1) conditional variance model

Parameter	Value	Standard Error	t Statistic
Constant	3.68303	0.928722	3.9657
GARCH{1}	0.807839	0.0333931	24.1918
ARCH{1}	0.108235	0.0172235	6.28418
Offset	–0.0572758	0.20645	–0.277431

Source: own elaboration.

The parameters of chosen GARCH(1,1) model are presented in Table 1. Algorithm selected for the computations was sequential quadratic programming. The conditional probability distribution which was selected was Gaussian distribution.

5. Results

After specifying a GARCH(1,1) model it was applied to simulate from the GARCH process using pre-sample data – which was prepared data from time points of VIX returns in period from the first daily close price in 2009 to the last one in 2012, so before the beginning of the observation and compared period (2013–2014). This is so because in conditional variance models, such as GARCH, the current value of innovation conditional variance depends on historical information which contains past conditional variances and past innovations.

The VIX index daily returns (Figure 3) exhibit volatility clustering. It could be observed that large changes in the returns used to cluster together, and small changes tend to cluster together. Therefore, the series exhibits conditional heteroscedasticity.

The calculations received for GARCH(1,1) were used to design both forecast for the comparison period and about 10,000 Monte Carlo simulations. These simulations have random character and could not be directly compared with other more precise methods, but large number of them was received and the average values of simulations were calculated to deduct whether any similarity in main trends appeared. Figure 4 presents 5 randomly chosen paths of conditional variances simulations from calculated and averaged 10,000.

In the simulation attitude there were received 10,000 different paths which possibly could appear and which fulfill the model requirements of model and estimated parameters and the other initial assumptions. They were also fitted to the VIX index returns dataset. Each of these 10,000 paths includes 978 observations from the model, which responds to the length of the period from 9 February 2013 to 30 June 2014.

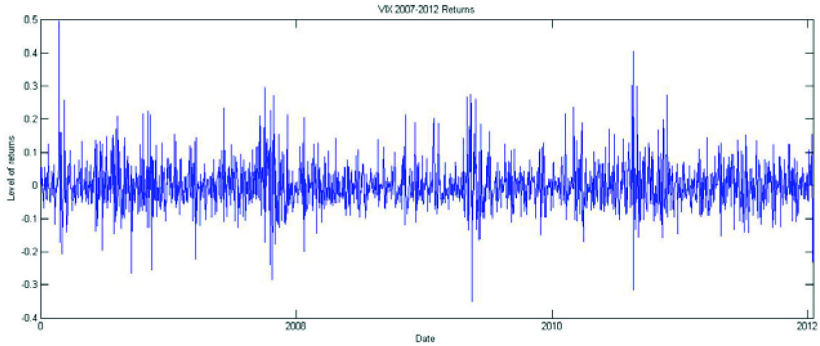

Figure 3. Observed returns of VIX index from 3 January 2007 to 31 December 2012

Source: own elaboration.

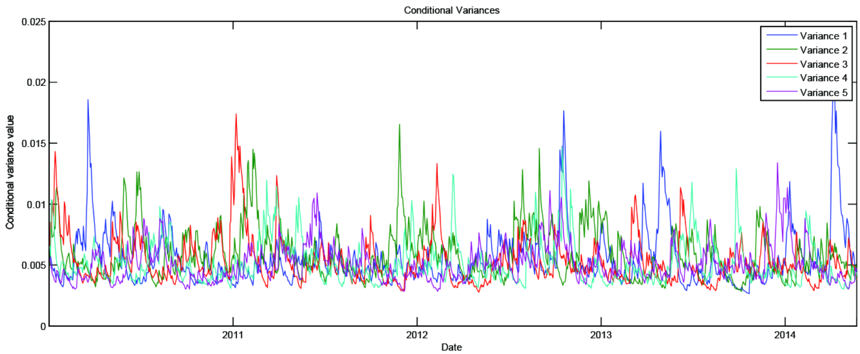

Figure 4. The 5 random paths from 10,000 of the VIX index conditional variances simulations

Source: own elaboration.

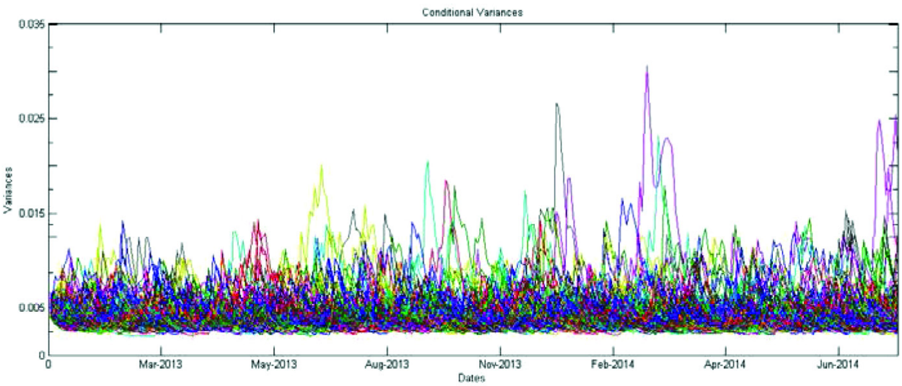

Figure 5. 10,000 simulations of conditional variances for adjusted GARCH(1,1) model

Source: own elaboration.

The sample unconditional variances come from the Monte Carlo simulation which approximates the theoretical values of GARCH based on unconditional variance. The simulation was made for earlier mentioned simulated period of time – 376 days length – and for 10,000 sample paths. The results were averaged and treated as a global representation of the methodology. Obviously the method is unreliable, but when the quickness of calculations is required more than the accuracy of forecasts, the average of 10,000 simulations will be compared with realized observations, to see whether any trends are similar.

Results for averaged values of 10,000 simulation paths of conditional variances are presented in Table 2. The simulations were diversified and randomly tracked, but the bigger number of paths makes the smaller differences from forecasted values. For appropriate large number of simulation paths, the average simulation asymptotically tends to theoretical unconditional variance.

The fitted model GARCH(1,1) was used to generate forecasts over a 376-period horizon. The observed return series were used as pre-sample data. Forecast infers the corresponding pre-sample conditional variances. The asymptote of the variance forecast tends in comparison to the theoretical unconditional variance of the GARCH(1,1) model which amounts to 0.0044.

Forecasts were made for the 376 observations horizon, from the beginning of 2013 to July 2014. They were made using pre-sample innovations, but the opposite approach (without using these innovations) also was adopted to compare with first one – as it could be observed, approach without using pre-sample innovations gives the unconditional innovation variance which amounts to 0.0044. Forecasts made with pre-sample innovations converge asymptotically to the unconditional innovation variance. Their values vary from 0.0019 at the beginning to 0.0044 at the end.

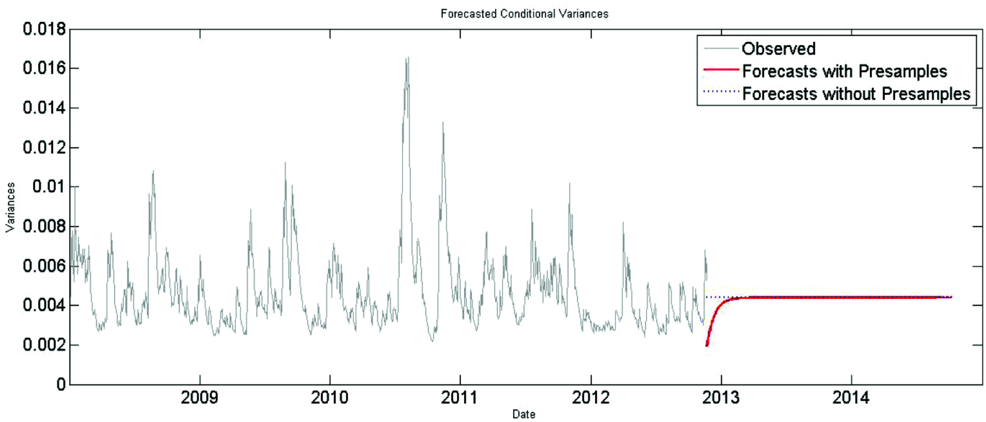

Figure 6. Forecasted conditional variances with presample data

Source: own elaboration.

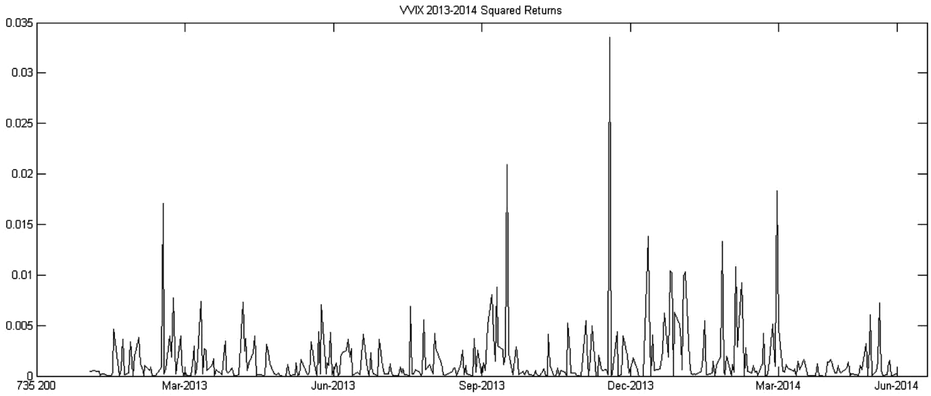

Figure 7. Realized market-oriented variances of VIX calculated as the VVIX observed squares of returns

Source: own elaboration.

Volatility as an unobserved parameter must be calculated from other observed parameters. In this article the realized observations of the VIX index volatility are – as aforementioned – represented by implied volatility of VIX included in market-oriented VVIX index observed time series. Its prices were previously turned into rates of return, absolute values were calculated and next they were squared. Prepared in that way VVIX observations could be compared with previously calculated GARCH(1,1) average simulations and forecasts.

As it can be observed in Table 2, average values of VIX forecasts and simulations are very similar – the difference appears at 5th decimal places. Their difference from market-oriented values occurs with the exactness to 3 decimal places, which is satisfying precision in comparison of volatility measures in different methodologies considering the unobservable character of this parameter. It could be useful in predicting main trends and long-horizon changes and other important tendencies, but it is not enough precise to deduct more particular values for each shorter periods. Median presents that similar forecasts and simulations oscillate around 0.0044 versus two attitudes of rates of return that oscillate around 0.0005. This fact shows that most values of VVIX squared returns oscillate around smaller values (a half of dataset includes values smaller than 0.0005 in comparison with the 0.0044 in model-based forecasts and simulations). Positive skewnesses in simulation attitude and return attitude indicate that the right side of the tail of probability density function is longer or fatter than the opposite side. The situation is different (opposite) only in the forecast attitude. In all four attitudes the distributions are leptokurtic, which means that values of characteristics are more densely concentrated than in the normal distribution. The forecasts attitude is apparently more efficient than the one with simulation. The ranges between maximum and minimum values are apparently larger in the case of VVIX index squares of returns, which starts with minimum value equal to zero, because of established approach in which volatility measure is a modified rate of return.

Table 2. Comparison of statistics of model-based (forecasts and simulations) and implied volatility (squared returns of the VVIX) attitudes in conditional variance model

Parameter	Forecasts	10,000 simulation paths	Rate of return – simple	Rate of return – logarithmic
Average	0.004321543	0.004395798	0.002884585	0.002791522
Median	0.0044	0.004331111	0.000547195	0.000549949
Skewness	–5.197236064	0.894084842	5.535364109	4.656489579
Kurtosis	29.41336709	0.653622813	40.23480143	26.73033905
Min value	0.0019	0.003895556	0	0
Max value	0.0044	0.005473333	0.072799755	0.057059196

Source: own elaboration.

Table 3. Comparison of errors between model-based (forecasts and simulations) and implied volatility (squared returns of the VVIX) attitudes in conditional variance model

Error	Forecasts	Simulations
Mean error	–0.001530021	–0.001604276
Mean absolute error	0.004380762	0.004468328
Mean squared error	4.43308E-05	4.53196E-05
Root of mean squared error	0.006658141	0.006731986

Source: own elaboration.

Additional parameters, which are quality evaluating errors of forecasts, that prove aforementioned statements which are presented in Table 3, are as follows – negative ME which is in comparison with MAE higher means that forecasts are systematically overestimated. Comparable but bigger MSE than MAE values mean that there are only single observations loaded with large error.

6. Conclusions

The model-based results – both forecasts and simulations – of conditional variances could be used in measuring the long-horizon level of volatility of VIX, the equivalent of VVIX. The simulations of 10,000 paths are quite satisfying methodology of predicting future volatility trends, but the precision in short terms is very poor because of its random character. They asymptotically tend to unconditional variance's value. The forecasts are more stable in time. The bigger number of path, the higher similarity to forecast appears. It shows that single Monte Carlo simulations are useless, but analyzing multiple average simulations is apparently more rational.

Considering that variance is unobservable and that comparison is based on different kinds of volatility-measuring attitudes, even if strongly diversified from the VVIX squares of returns realizations, forecasts have a potential to be more efficient forecast of volatility of volatility in modified form. Search for model-oriented modifications of GARCH that depend on other market parameters is required. GARCH results are not sufficient to predict future values of volatility on accurate date. For this application, designing the implied volatility indices is strongly recommended.

The financial literature also claims that the estimates made using pre-sample data describe great majority of appropriate and valid information which is provided by VIX and hence there is very little additional incremental information, even in high-frequency index returns [Blair, Poon, Taylor 2001] and in comparison with returns VIX broadly tracks most of the available changes in the level of variability of the rates of return [Becker, Clements, McClelland 2009], what means that model-based predictions and simulations of the VIX index could be helpful in constructing quite efficient strategies in portfolios of both its basic instruments and the VIX index as a separate financial instrument.

The purpose of the paper was achieved, and shows that the portions of information provided by both methods – forecasts and simulations – are quite similar and predicted trends of variability changes are not sufficient estimator of volatility of VIX in comparison with market-oriented VVIX. Analyzing long-horizon volatility trends of VIX using model-based methods could be treated as an additional instrument especially at the moment when saving the time is more important than precision.

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OCENA DOKŁADNOŚCI MODELOWANIA ZMIENNOŚCI INDEKSU VIX Z ZASTOSOWANIEM MODELU GARCH

Streszczenie: Proces mierzenia zmienności zmienności jest istotnym elementem wpływającym na konstruowanie strategii zarządzania portfelem. Problematyka związana z indeksem zmienności może być w szerszym aspekcie traktowana jako odrębny instrument finansowy. Postawa zorientowana rynkowo wraz ze zmiennością implikowaną dostępną w indeksie VVIX może być uznana za estymator zmienności zmienności o dokładności wyższej niż pozostałe tego typu narzędzia, oparte na obserwacjach historycznych. Wadą tego typu rozwiązania jest jego stosunkowo mała dostępność, co w rezultacie prowadzi do wykorzystania algorytmów opartych na innych modelach, np. na analizie wariancji warunkowej. W pracy zawarto analizę oraz porównanie dwóch procedur obliczeniowych. Pierwsza jest oparta na modelu zawierającym prognozowanie zmienności indeksu VIX i jego wielokrotnej symulacji, a druga jest zorientowana rynkowo, w niej zawiera się zmienność implikowana indeksu zmienności w postaci zrealizowanych obserwacji indeksu VVIX.

Słowa kluczowe: symulacje i prognozowanie zmienności, modelowanie GARCH, indeksy zmienności implikowanej, zmienność zmienności.