Econometric Modeling of Financial Time Series Volatility Using Software Packages

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Abstract. The article is devoted to the comparative analysis of software packages in financial time series modeling. The most common among economists packages R, Eviews and Gretl are considered. Volatility is often used as a rough approximation to measuring of overall risk financial instruments. Polish stock index WIG for the modeling of financial time series volatility was chosen. Econometric model of family GARCH describing the volatility of financial time series is built by means of these packages. Advantages and disadvantages of each software are considered.

Keywords. GARCH model, stock indices, volatility, modelling

Key Terms. Model, Research, Specification Process

1   Introduction

The great achievement of mankind is the development of science and technology. Computing operations require much less efforts of researcher thanks to modern computer technology. Today IT sector is developing rapidly. The results of its activities are the funds of multiplying income, reduce the cost of resources, facilitate professional activity.

Information technology facilitates the research process. Analysis of the vast amount of data is possible due to modern software packages. These software products enable to analyze and to model the time series dynamics, to search interdependencies of the time series.

The research of stock indices dynamics and stock prices is an important problem in the investment portfolio management. Stock market indices are the indicators of the global economy, group of countries or national economy, investment climate in the country, tools of analysis of securities market and its forecasting trends. In addition, stock index is also independent financial instrument to hedge the securities market. Typically, absolute index values are not so important for investors as its dynamics,

which you can use to determine the direction of the stock market dynamics. Analytical agencies and stock exchanges calculate Stock Indices.

The aim of the article is an analysis of software that is popular among economists and modeling of financial time series volatility using software packages R, Gretl, Eviews.

Software R is the most popular tool among economists, Eviews occupies the second position. The package Gretl is not so widespread and powerful. However Gretl has the ability to use scripts R, Octave, Python etc. Functions package Gretl is appended by users and it is gaining popularity gradually.

2   Analysis of Recent Research

Modeling and forecasting of time series volatility in financial markets is an urgent problem for investment advisors, economists and other professionals. Therefore, a large number of scientific papers are devoted to this sphere. Thus, Subbotin [1] investigates the main approaches to modeling the volatility of shares and exchange rates, and reviews the cascade of volatility models in multiple horizons.

Leucht, Kreiss, Neumann [2] suggest the specification test for consistent generalized autoregressive conditional heteroskedasticity model (GARCH (1,1)), based on the Cramer-Mises test statistics in their paper.

Barunik, Krehlik, Vacha [3] propose an improved approach to the volatility modeling and forecasting using high-frequency data. The model of forecasting based on Realized GARCH with multiple time-frequency data is used.

Harvey and Lange [4] propose an updated and expanded ARCH in Mean model. EGARCH-M model, which is displayed in the paper, is useful theoretically and practically. This model expansion allows distinguishing long and short effects of return to the volatility.

The global financial crisis of 2008-2009 has raised new questions about the relationship between investment funds and stock market returns. Therefore, Babalos, Caporale and Spagnolo [5] analyze US monthly data for the period 2000:1-2015:08. Authors estimate VAR-GARCH(1,1)-in-mean model with a BEKK and the switch as a dummy variable, which is necessary to display the global financial crisis. The relationship between the yield of the stock market and direct investment flows fund is investigated. It was found that such relationship is weakened during the crisis.

3   Research Method

One of the characteristics of financial markets is the uncertainty that changes over time. In this regard, there is such a thing as "volatility clustering". It means that the volatility varies periodically, i.e. stock index dynamics changes from slightly changing to more chaotic.

It's worth to note that many financial relationships are nonlinear internally. It dealt with peculiarities of financial data, such as the tendency of financial time series (e.g., income on assets) to have an unusual distribution of critical areas ("tails") and dis-

placements to the average (leptokurtosis). In addition, often financial time series change by clusters or pools (volatility clustering or volatility pooling), while larger deviation of time series prior to high deviation, low deviation of time series - minor deviations (regardless of sign). It is also possible the leverage effect, i.e. the tendency to volatility increasing not of the growth but the fall of certain financial and economic indicators (information asymmetry). Overall volatility modeling and forecasting in the stock market became a priority for both theoretical and applied research in recent years. Volatility, as measured by standard deviation or variance of return (such as securities) is often used as a rough approximation to measuring of overall risk financial instruments (securities).

The measure of volatility is a variance of series. ARIMA model can not adequately take into account the inherent characteristics for financial time series. Therefore, there is a need to use other tools. One of them is ARCH-processes (Autoregressive Conditional Heteroskedasticity). The first such expansion of regression models was presented by Engle [6], after that numerous modifications of the basic design and examples of the new model for financial and macroeconomic time series were developed. First, ARCH-models studied inflation uncertainty. Later, they were used in the volatility analysis of prices and yields of speculative assets. On the basis of applying ARCH-models it was found that the dynamics of volatility for many financial variables subject to stable laws.

ARCH/GARCH models belong to the class of nonlinear models of conditional variance, which changes over time. This allows, in addition to the average value of the studied parameters, to model the dynamics of its variance simultaneously. Therefore, such model can correctly describe phenomena such as clustering of volatility, asymmetric information, etc.

Examples of financial time series with high frequency are stock prices and indices of commodity exchanges. In practical researches they are often analyzed in the form of geometric income, i.e. the logarithm of the rate of increase in the price of an asset (or rate of stock index growth) y_t :

$$ r_t = \log\left(\frac{y_t}{y_{t-1}}\right) = \log(y_t) - \log(y_{t-1}), \qquad (1) $$

where r_t — geometric income of the asset.

ARCH-extension model is the GARCH-model volatility, where the current volatility affects both preceding price changes and preceding volatility estimates (so-called "old news"). Memory of ARCH(q)-process is limited by q-periods. We need long lag q and a large number of parameters for using models. Generalized ARCH-process (Generalized ARCH or GARCH), proposed by Bollerslev [7], has infinite memory and allows more economical parameterization.

Overall, ARCH/GARCH methodology can be described as studied parameters dispersion modeling methodology. Since the variance is second-order moment, the dispersion model is nonlinear. Therefore, it can not be evaluated by the methods developed for linear models, particularly using ARIMA models. Autoregressive conditional

heteroskedasticity, i.e. the change of random variables (disturbances) variance in the time, formalized represented as:

$$a_{t+1} = y_{t+1} - \mu_y \left(y_1, y_2, y_3, ..., y_t \right),\qquad(2)$$

where a_{t+1} – perturbations (random variable) at time period (t+1),

y_{t+1} – value at time period (t+1),

$\mu_y \left(y_1, y_2, y_3, ..., y_t \right)$ – mean value estimated on the basis of data that preceded the moment (t+1).

Dispersion equation in GARCH models unlike ARCH models takes into account variables other than lagged random variables, and more variables lagged conditional variance. Actually overall ARCH/GARCH model can be presented as a series of filters.

Note that the smoothing procedure or seasonal deprivation for time series are optional and executed as needed. Overall, ARCH/GARCH model can be considered as "supplement" for a multi-linear regression and ARIMA models. Evaluation of ACRH/GARCH models can not be implemented by the method of least squares. Special procedures developed for evaluation of these models, including maximum likelihood method.

4   Results

According to the Bloomberg Businessweek, 97 percent of companies in Fortune 500 have used business analytics and some forms of Big Data analytics to conduct their business. Big Data analytics that processes data into information and particularly knowledge has emerged as a contemporary business trend in industry and academics [8]. Many consultants, scientists, and researchers pay attention to Big Data because it contains meaningful information. Various applications such as healthcare, security, medicine, politics, etc. can use the information to solve data-related problems in society.

One of the most dominant analytics tools in Big Data Analytics is the R Project, or R. R is a general statistical analysis platform that runs on the command line. It is world's most widely used, open-source statistical programming language designed for friendly use.

Other popular packages are Eviews and Gretl. Here is a comparative description of these software packages (Table 1).

Features in Gretl [9].

1. Easy intuitive interface.
2. A wide variety of estimators: least squares, maximum likelihood, GMM; single-equation and system methods.

3. Time series methods: ARIMA, a wide variety of univariate GARCH-type models, VARs and VECMs (including structural VARs), unit-root and cointegration tests, Kalman filter, etc.
4. Limited dependent variables: logit, probit, tobit, sample selection, interval regression, models for count and duration data, etc.
5. Panel-data estimators, including instrumental variables, probit and GMM-based dynamic panel models.
6. Output models as LaTeX files, in tabular or equation format.
7. Integrated powerful scripting language (known as hansl), with a wide range of programming tools and matrix operations.
8. GUI controller for fine-tuning Gnuplot graphs.
9. An expanding range of contributed function packages, written in hansl.
10. Facilities for easy exchange of data and results with GNU R, GNU Octave, Python, Ox and Stata.

Table 1. Comparative description of data analysis software packages

Features	Eviews	Gretl	R
Data extensions	*.wf1	*.gdt, *.gdtb	*.R
User interface	Mostly point-and-click	Scripting/point and click	Programming
Data manipulation	Strong	Strong	Very strong
Data analysis	Powerful	Powerful	Powerful/versatile
Graphics	Good	Good	Excellent
Cost	Expensive, but has free student lite version	Open source	Open source
Output extensions	*.wf1	CSV, gdt, gdtb, GNU R, Octave, Stata, JMulTi, PcGive	*R, *.txt(log files, any word processor can read)

Features in Eviews [10].

1. Integrated support for handling dates and time series dat.
2. Support for high-frequency (intraday) data, allowing for hours, minutes, and seconds frequencies. In addition, there are a number of less commonly encountered regular frequencies, including Multi-year, Bimonthly, Fortnight, Ten-Day, and Daily with an arbitrary range of days of the week.
3. Long-run variance and covariance calculation: symmetric or one-sided long-run covariances using nonparametric kernel (Newey-West 1987, Andrews 1991), parametric VARHAC (Den Haan and Levin 1997), and prewhitened kernel (Andrews and Monahan 1992) methods. In addition, EViews supports Andrews (1991) and Newey-West (1994) automatic bandwidth selection methods for kernel estimators,

and information criteria based lag length selection methods for VARHAC and prewhitening estimation.

4. Linear quantile regression and least absolute deviations (LAD), including both Huber's Sandwich and bootstrapping covariance calculations.
5. Stepwise regression with seven different selection procedures.
6. Threshold regression including TAR and SETAR.
7. Heckman Selection models.
8. Object-oriented command language provides access to menu items.
9. Batch execution of commands in program files.
10. String and string vector objects for string processing. Extensive library of string and string list functions.

Features in R [11].

1. R is free, open-source software distributed and maintained by R-project, R source code is available under the Free Software Foundation's GNU General Public License.
2. R supports most of the data analysis techniques such as virtual data manipulation, statistical model, and charts.
3. R support beautiful and unique data visualizations to present multidimensional data in multi-panel charts, 3-D graphs.
4. A global R community of 2 million users, developers, and contributors support contribute and maintain R language. Revolution Analytics community was acquired by Microsoft.
5. Provides better results faster than legacy statistical software's counterpart does.
6. R has data structures (vectors, matrices, arrays, data frames) that users can operate on through functions for performing statistical analyzes and creating graphs.
7. Object-oriented programming: C, Java, Perl, Python, parallel programming, etc.
8. Applications: Chemometrics, Clinical trial, Econometrics, Medical images, etc.
9. Data Mining and Machine Learning: Arules, Cubist, knnTree, randomFores, etc.
10. Statistical methodology: Bayesian inference, Spatial data, Time Series, etc.

In summary, the paper defined Big Data, compared and contrasted the statistical features of R to its programming features and its relevance. It provided the primary programming features available in R and described how the analytics software tool R was suited for Big Data today [11].

Polish stock index WIG for the modeling of financial time series volatility was chosen. The data obtained from the Google Finance site [12]. The results of volatility modeling for the stock index WIG in software packages R, Eviews, Gretl are compared.

First of all we analyze time series data for normality of distribution, define the asymmetry and kurtosis. The package R uses a series of commands and obtain the following numerical characteristics:

```
> skewness(wr)
[1] -0.4892253
```

```
> kurtosis(wr)
[1] 3.844628
> mean(wr)
[1] 0.03569432
```

Asymmetry is -0.4892253, which means that the distribution of data is skewed slightly to the left. We have 3.844628 for excess, that is greater than 3, and therefore, the distribution is leptokurtic. Fig. 1 shows the density of index WIG yield (2004-2016 daily), which is asymmetric and leptokurtic.
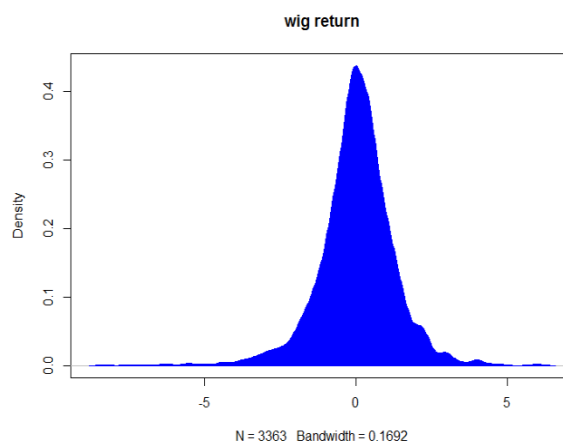

Fig. 1. Distribution density of index WIG yield in R

In Eviews software package it is much easier to conduct a preliminary analysis of time series, for pressing a sequence of buttons View-Descriptive Statistics… - Histogram and Stats we obtain simultaneous display table of distribution and numerical characteristics (Fig. 2).

In the software package Gretl we need to make a few clicks to display the graph and numerical characteristics of series or write a script. The results of these actions are presented in Figure 3. Herewith Skewness = -0.48944, Kurtosis = 3.8487.

In all software package kurtosis and skewness do not differ significantly, but average values are equal.

The next step is to analyze the yield graph to identify the phenomenon of clustering and analysis of autocorrelation and partial autocorrelation for time series. The package R should use the command: tsdisplay(wig$wig_return) to display graphics and return of time series.

Fig. 4 shows the results of this command. Graph of yield has signs of clustering. There is also residual autocorrelation. Graphs of autocorrelation function (ACF) and partial autocorrelation residues (PACF) show strong visible emissions for the first order lagged values indicating the feasibility of using GARCH(1,1).
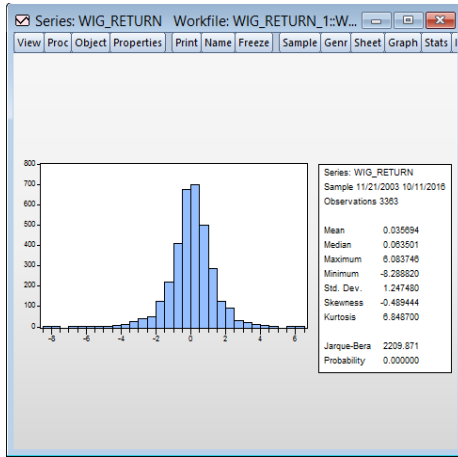
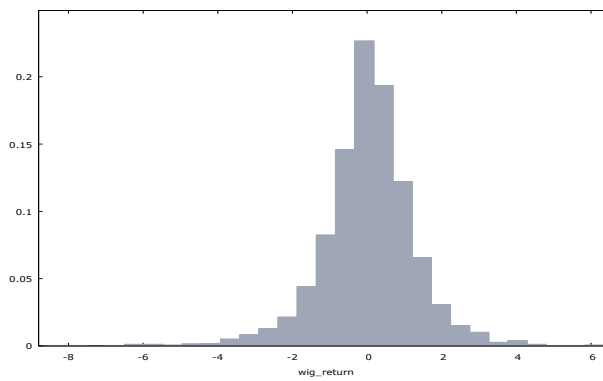**Fig. 2.** Distribution density of index WIG yield in Eviews

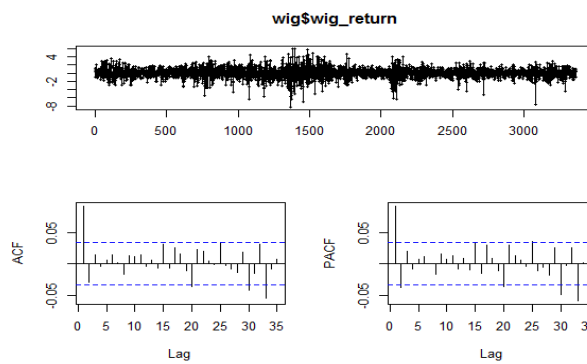**Fig. 3.** Distribution density of index WIG yield in Gretl

Fig. 4. The graphs of WIG return, autocorrelation function and partial autocorrelation residues function in R

According to the software packages Eviews and Gretl we can do this in a few clicks. It is noticeable that received graphic display is identical (Fig. 5, 6).

However, according to the fig. 6 it is hard to understand when autocorrelation residues present, and we can be argued that there is autocorrelation residues to 36 order (lag) given the probability value (Prob.). Therefore, for the analysis of residual autocorrelation and time series clustering the best software packages are R and Gretl.
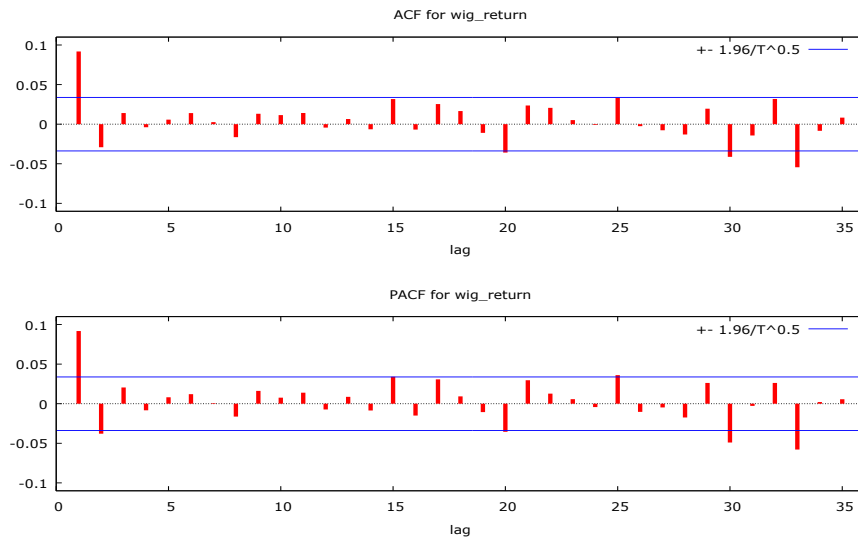

Fig. 5. The graphs of autocorrelation function and partial autocorrelation residues function of WIG returns in Gretl

We turn to the construction of model and its specification. To select the best models in R, its testing and forecasting should prescribe following code:

```
spec <- ugarchspec()
fit = ugarchfit(data = wr, spec = spec, out.sample =
3000)
show(fit)
forc = ugarchforecast(fit, n.ahead=100, n.roll = 100)
forc
plot(forc, which = "all")
```

As a result of the code, we received the best model GARCH(1,1) and model for average ARMA(1,1). Optimal parameters of the model GARCH(1,1) are presented in the Table 2, information criteria of the model are given in the Table 3.

Table 2. GARCH(1,1) optimal parameters

	Estimate	Std. Error	t value	Pr(>|t|)
Mu	0.154131	0.052193	2.953101	0.003146
ar1	-0.683459	0.153773	-4.444588	0.000009
ma1	0.780920	0.129864	6.013347	0.000000
omega	0.000085	0.007050	0.012009	0.990418
alpha1	0.049252	0.015846	3.108058	0.001883
beta1	0.949748	0.017353	54.729664	0.000000

According to the t-statistics, which probability value indicates the significance of the model parameters, we obtained omega only as insignificant factor. Wherein the information criteria are not high, therefore the model is well constructed.

Table 3. Information criteria of the model

Akaike	2.9394
Bayes	3.0038
Shibata	2.9389
Hannan-Quinn	2.9650

So, we specify GARCH(1,1) in Gretl and Eviews similarly. In the package gig.gfn one has the opportunity to evaluate various options of GARCH family models and to add ARMA model for average. In the process of the model constructing, it was found that adding lag for AR automatically added lag for MA, due to the fact that the adding of AR(1) only the model will be not identified. The results are shown in Fig. 6.
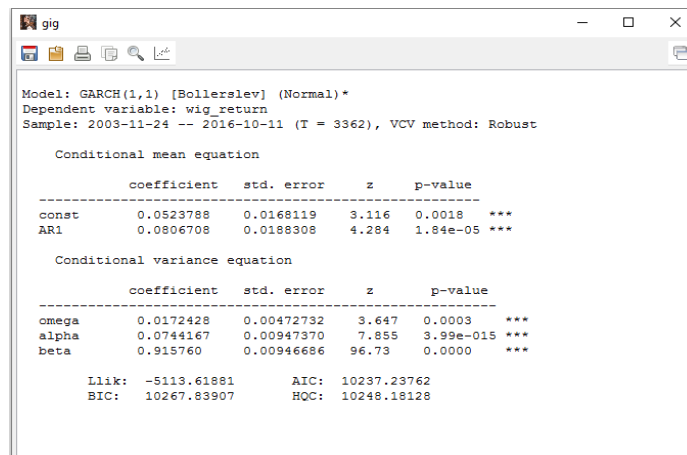
```
gig                                                    —   □   ×

Model: GARCH(1,1) [Bollerslev] (Normal)*
Dependent variable: wig_return
Sample: 2003-11-24 -- 2016-10-11 (T = 3362), VCV method: Robust

   Conditional mean equation

           coefficient  std. error    z      p-value
   ------------------------------------------------------
   const    0.0523788   0.0168119    3.116   0.0018   ***
   AR1      0.0806708   0.0188308    4.284   1.84e-05 ***

   Conditional variance equation

           coefficient  std. error    z      p-value
   ------------------------------------------------------
   omega    0.0172428   0.00472732   3.647   0.0003   ***
   alpha    0.0744167   0.00947370   7.855   3.99e-015 ***
   beta     0.915760    0.00946686   96.73   0.0000   ***

       Llik:  -5113.61881     AIC:  10237.23762
       BIC:   10267.83907     HQC:  10248.18128
```

Fig. 6. Model GARCH(1,1) AR(1)

All parameters of the model are significant, but the value of information criteria are high compared with those calculated in R. Gig.gfn package does not allow to check ARCH-effects or autocorrelation stability parameters of the model.

The package Gretl doesn't make possible to check the model ARCH-effects or autocorrelation stability parameters. You can build a forecast and graphics in this package.

If you use standard functional (basic), which is immediately available after installing the software package Gretl, it provides an estimate normal GARCH model, which results are shown in Fig. 7.
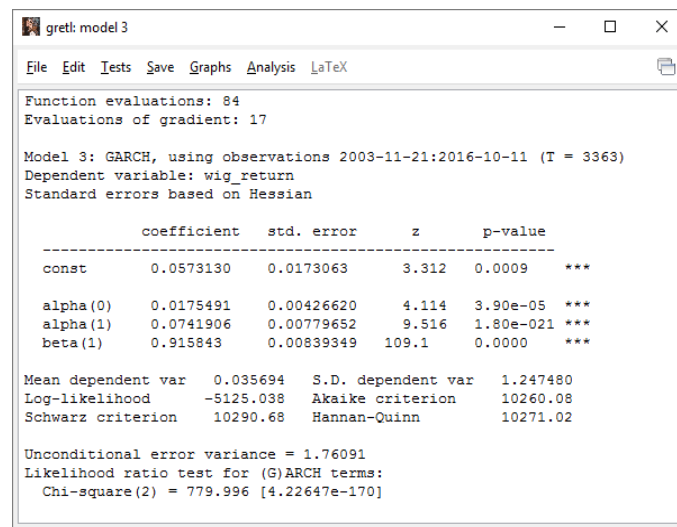


```
gretl: model 3                                              —    □    ×

File  Edit  Tests  Save  Graphs  Analysis  LaTeX

Function evaluations: 84
Evaluations of gradient: 17

Model 3: GARCH, using observations 2003-11-21:2016-10-11 (T = 3363)
Dependent variable: wig_return
Standard errors based on Hessian

                coefficient    std. error       z       p-value
     --------------------------------------------------------------
     const       0.0573130     0.0173063       3.312    0.0009    ***

     alpha(0)    0.0175491     0.00426620      4.114    3.90e-05  ***
     alpha(1)    0.0741906     0.00779652      9.516    1.80e-021 ***
     beta(1)     0.915843      0.00839349    109.1      0.0000    ***

Mean dependent var    0.035694    S.D. dependent var    1.247480
Log-likelihood       -5125.038    Akaike criterion      10260.08
Schwarz criterion    10290.68     Hannan-Quinn          10271.02

Unconditional error variance = 1.76091
Likelihood ratio test for (G)ARCH terms:
  Chi-square(2) = 779.996 [4.22647e-170]
```

Fig. 7. GARCH(1,1) in Gretl

Compared with functional package gig.gfn, the basic functional of Gretl allows you to conduct more tests of the results. However, just three tests of the list are available in the tests menu.

Perform forecasting for two GARCH models were built in Gretl. Under the first model, which is shown in Fig. 8, forecast of 100 observations (days) has received.
From Fig. 8 it can be seen that the dynamics of the conditional variance will increase. This shows the impact of negative news in the market and the presence of asymmetry, so you should apply the model of GARCH family, which takes into account the asymmetries in the market, namely EGARCH model.

Fig. 9 shows the projected range of volatility fluctuation. According to the forecast the WIG return volatility will increase gradually over the forecast period and will increase by almost half.

We proceed to the construction of GARCH(1,1), ARMA(1,1) models in the software package Eviews 9.5 Student's version Lite. Simulation results are presented in Fig. 10.
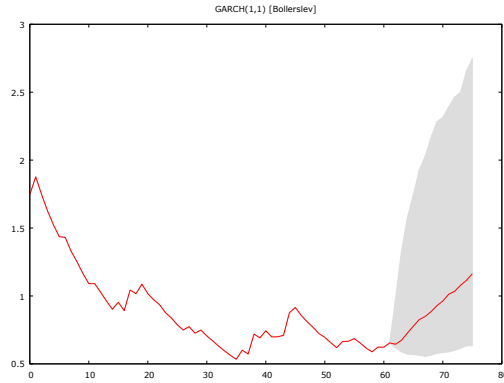
Fig. 8. Forecasting of conditional variance for WIG return volatility in gig.gfn
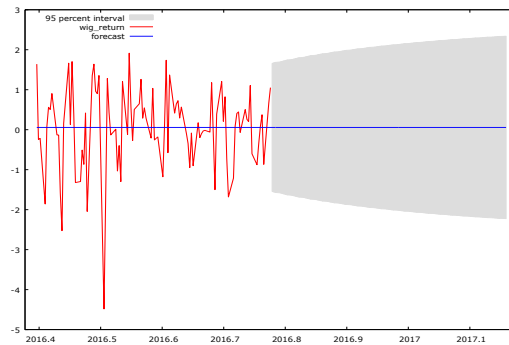

Fig. 9. Forecasting of WIG return volatility (the basic functional of Gretl)

The sum of the regression coefficients expresses the impact of variables variance prior period to the current value of the variance. This value is close to 1, which is a sign of the growing inertia effect of shocks on variance of financial assets returns. According to Durbin-Watson statistics the residual autocorrelation is absent, most coefficients of the model are significant. For Inverted ARMA Roots the parameters ARMA(1,1) are stable because they are smaller than 1.

Fig. 11 displays the results of checking ARCH-effects. In this model ARCH-effects are absent that is positive for the constructed model. The package allows the testing of the model in squares residual autocorrelation test using Q-statistics. The lack of residual autocorrelation to 36-th lag allows to include regression for the average as ARMA(1,1).
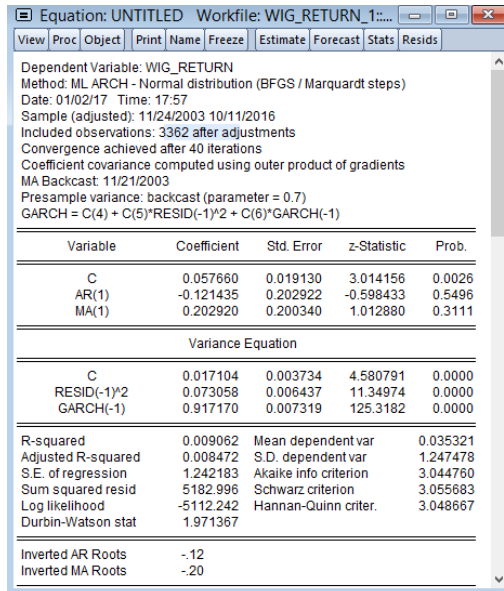
Fig. 10. Statistics of GARCH(1,1) model with ARMA(1,1) in Eviews
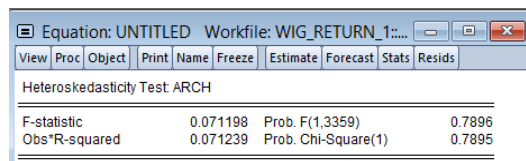

Fig. 11. The test for the presence of ARCH-effects in Eviews

Note that the GARCH(1,1) model building in Eviews and Gretl software packages is complicated process because of the inclusion of ARMA(1,1) model for average. However, the results of obtained model in Eviews and its statistics are more visible. The advantage of the software package R is that writing a few lines of code, you can get statistic models, options, and all necessary tests to check for correct specification. The key tests for GARCH models in software packages Eviews and Gretl are limited compared with the R. In order to detect, for example, the presence of the effect of leverage you should further evaluate other family of GARCH model and analyze the resulting statistics and conduct tests again.

Let us compare the results of forecasts obtained by Gretl, R and Eviews software products. We received the forecast of conditional variance for WIG return volatility, and the forecast of WIG return volatility (Fig. 8, 9) in gig.gfn additionally installed package and Gretl basic functional.

The package R received several graphic maps expectations. In Figure 12 we present the results of forecasting time series of absolute dispersion, forecasting real time series data with conventional variance, forecasting unconditional variance and forecasting Rolling Sigma from time series.
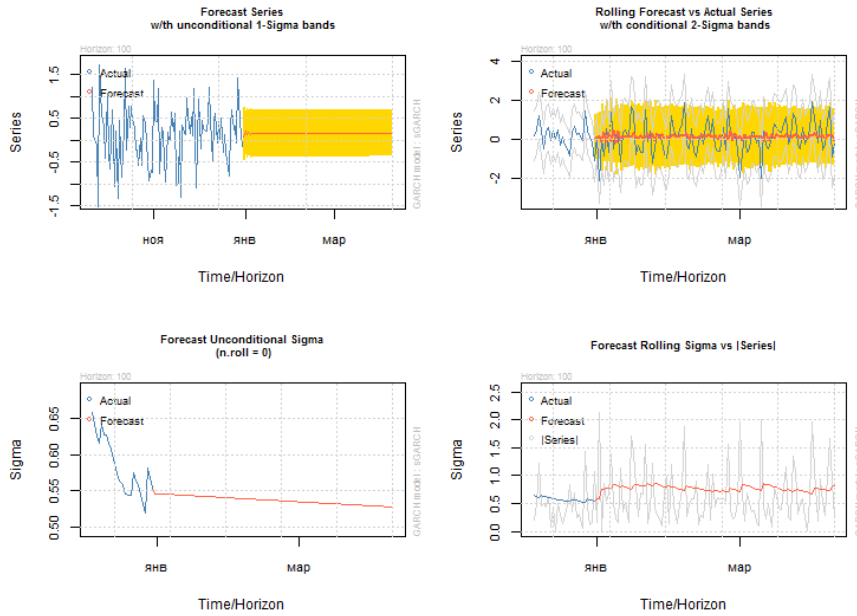
Fig. 12. Forecasting of WIG return volatility in R

Note that the dynamics of unconditional variance has a downward trend. This volatility of the time series will fluctuate at the same level of low growth.

In Eviews static and dynamic forecasts of volatility and variance of time series with numerical forecast forward 43 observations (Fig. 13, 14) can be built.

Note that the forecasts in Eviews are difficult to interpret. However, the volatility of dynamic forecast tends to increase. As for static forecast, the volatility of the time series will fluctuate around the same level.
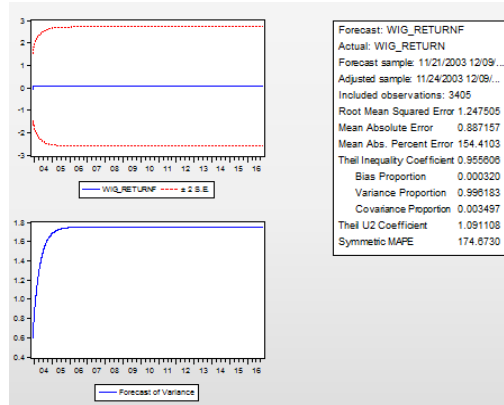

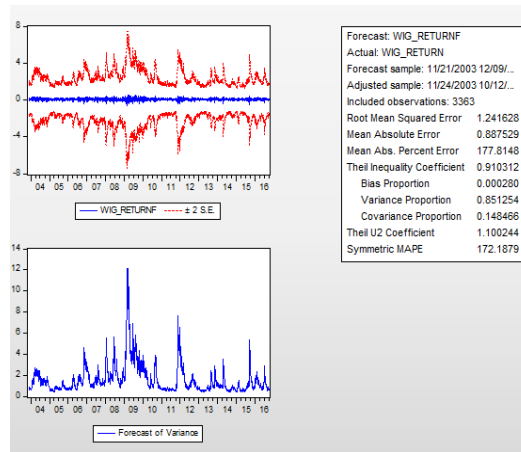**Fig. 13.** Dynamic forecasting of WIG return volatility and variance in Eviews

Fig. 14. Static forecasting of WIG return volatility and variance in Eviews

5   Conclusions

It can be concluded that Gretl, Eviews and R can model and forecast the volatility of financial time series, such as stock indexes. However, using an additional package gig.gfn it is worth to specify several models e.g. EGARCH or TGARCH models.

The kind of econometric analysis intended to use need to be considered while the choosing an appropriate package. R should be used for more advanced work, for example, to simulate economic models. Gretl and R have the significant advantage as they are generally available. Gretl basic package is complete and covers most applications time series and panel data. Add-ons that extend the functional include seasonal smoothing.

In our opinion, R together with R-studio is the best software package for modeling the volatility of financial time series. For educational purposes Eviews or Gretl should be used. Gretl is more flexible and free, extremely easy to use, unlike other software, therefore it is better to be used in educational institutions.

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