Forecasting Analysis of Stock Prices on European Markets Using the ARIMA-GARCH Model

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Abstract

The achievement of profits when trading on the stock markets is conditioned by a quality analytical forecast of the development of stock prices in the coming period.

This research attempts to compare the results of the ARIMA model and the ARIMA-GARCH model to forecast the development of stock prices on a sample of selected stocks from the Czech, German, Austrian, Polish and British markets. The 4 most liquid titles from each of the above-mentioned markets were selected for the sample of analyzed stocks. Available daily closing stock price data, mostly from the period 2000–2022, were used for the analysis.

Research has shown that for most of the analyzed titles, it is more appropriate to use the ARIMA-GARCH model, which better captures variability for this data than just the ARIMA model. The quality of the selected model is evaluated by autocorrelation, heteroskedasticity tests, and Theil´s inequality coefficient.[3]

Keywords	***DOI***	***JEL code***
ARIMA, GARCH, stock price prediction, time series	*https://doi.org/10.54694/stat.2023.4*	*C22, C52, C58, G17*

INTRODUCTION

A functioning stock capital market enables the appreciation of invested capital, thus creating investment opportunities and, at the same time, offering opportunities for obtaining temporarily free capital to finance prospective projects that can support the development of businesses, sectors, and the entire economy. The development of stock prices is therefore an important information for investors who have invested their capital in stocks, or for subjects who are only considering their investment in certain stocks. Investing in stocks is one of the most sought-after investment options, which is characterized by easy access to investment and the possibility of achieving high returns, however, with a certain considerable level of risk. However, every investor must realize that the key to successful investing in stocks is the ability

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to estimate the future development of stock prices, because based on this estimate it is necessary to take either a long position in anticipation of an increase in stock prices or a short position in anticipation of a fall in stock prices. The development of stock prices is very variable, in recent years quite volatile. Stock prices are affected by a large number of fundamental factors that are studied by fundamental analysts, but also by technical factors that are at the forefront of the interest of technical analysts. The influence of both one and the other group of factors on stock prices must be carefully analyzed to make a high-quality prediction of the further development of stock prices and to take an adequate investment position based on this prediction.

However, making a high-quality prediction of the development of stock prices is quite complicated, as financial time series of stock prices are usually characterized by non-stationarity, heteroskedasticity, and non-linear development. To successfully predict the development of stock prices, it is, therefore, necessary to choose a statistical model that can take into account and treat the specific characteristics of the financial time series of stock prices. If the application of such a model to the financial time series of stock prices would produce a high-quality prediction of the future development of stock prices, the investor could buy or sell at an appropriate moment, thereby achieving above-average profits while limiting risk in inefficient market conditions.

ARIMA models are statistical models that can be used to predict the future development of stock prices. There are three parts of ARIMA models: AR – autoregressive model, I – integrated part, MA – moving-average model. The paper is based on the Box-Jenkins methodology (Box and Jenkins, 1976), which according to Cipra (2013): "There is not yet a better routine tool for analyzing time-dependent observations." ARIMA modeling is frequently used for the forecasting of not only financial time series.

The financial time series often show signs of heteroskedasticity therefore the paper focuses on its testing and application of the ARIMA-GARCH modeling. This paper aims to check the applicability of the ARIMA model and its extension ARIMA-GARCH model in predicting the development of stock prices. A discussion about the volatility modeling with ARIMA and ARIMA-GARCH models is conducted. The quality of forecasts is measured based on the holdout sample with MAPE and Theil´s inequality coefficient.

The 4 most liquid stock titles from the Czech, British, German, Polish, and Austrian markets were chosen for the research. If the predictions of stock price development produced by ARIMA or ARIMA-GARCH models correspond to the actual stock price development, ARIMA or ARIMA-GARCH models can be considered effective tools that could help the investor in the European markets under investigation to "beat the market".

1 LITERATURE SURVEY

The Box-Jenkins methodology was described by (Box and Jenkins, 1976) and they show the ways how to find the best fit of a time-series model to past values of a time series.

The first description of the ARCH (autoregressive conditional heteroskedasticity) was introduced by Engle (1982), 21 years before receiving the Nobel Prize in Economics. In his article Engle also introduced the original Lagrange multiplier (LM) test for ARCH which is very simple to compute, and relatively easy to derive (Bollerslev et al., 1994).

Bollerslev et al. (1992) provided an extensive ARCH literature review that aimed to support further research in this area.

In the year 1986 independently Bollerslev (1986) and Taylor (1986) independently introduced GARCH (generalized ARCH), which proposed a natural generalization of the ARCH process introduced in the paper by Engle (1982).

Financial decisions are usually based on the tradeoff between risk and return. The paper by Engle (2001) presented an example of risk measurement which could be the input to a variety of economic decisions.

In his paper, Engle (2002) describes two frontiers in detail: the application of the ARCH models to the broad class of non-negative processes, and the use of Least Monte Carlo to examine the non-linear properties of any model that can be simulated. Using this methodology, he analyses more general types of the ARCH models, stochastic volatility models, and long-memory models breaking volatility models.

Poon and Granger (2003) mention 93 studies to date about volatility forecasting in financial markets. This study confirms that financial market volatility is forecastable but they also pose a question of how far ahead one could accurately forecast and to what extent can volatility changes be predicted. Among other conclusions, they state that GARCH (1,1) is the most popular structure for many financial time series

The article of Poon and Granger (2005) compared models with tests of volatility-forecasting methods on a wide range of financial asset returns and produced some practical suggestions for volatility forecasting. The authors induce that the financial market volatility is forecastable.

40 years after his first paper about ARCH Engle et al. (2012) declared that the ARCH/GARCH framework proved to be very successful in predicting volatility changes. They also stated that volatility clustering was most easily understood as news clustering. Trades convey the news to the market and the macroeconomy can moderate the importance of the news. These can all be thought of as important determinants of the volatility that is picked up by ARCH/GARCH. In the same paper, the authors conclude that the original modeling of conditional heteroskedasticity proposed by Engle (1982) has developed into a full-fledged econometric theory of the time behavior of the errors of a large class of univariate and multivariate models.

Hameed et al. (2006) focused on the Pakistani stock market, where they tried to model and forecast stock return volatility and test for weak efficiencies using the GARCH model and daily data for December 1998–March 2006.

One of the current applications of ARCH and GARCH models can be found in (Veselá, 2019) where she applies the ARCH and GARCH models to the prices of the PX index (Prague stock exchange index).

Challa et al. (2020) discuss the opinion of many researchers that GARCH and EGARCH models cannot provide the best results compared with ARIMA models. In their study, they conclude that ARIMA and ARIMA-GARCH models produce the same results over time, and volatility does not change.

2 METHODS AND METHODOLOGY

Methods applied in this paper combine typical steps for the ARIMA modeling – assumptions testing for stationarity and autocorrelation, ARIMA model application with a test of residual autocorrelation, and homoscedasticity. In the case of the homoscedasticity hypothesis rejection, the ARIMA-GARCH model is applied and forecast quality is evaluated.

2.1 Assumptions testing

The assumption of the use of ARIMA is stationarity. In the literature, it is mostly assumed that financial time series are at least weakly stationary, therefore it is possible to apply Box-Jenkinson procedures. In the case of non-stationarity, under certain conditions, it is possible to make the time series stationary, especially through differentiation.

The stationarity is verified by the ADF (Augmented Dickey-Fuller) unit root test and by the test of linear dependence, the Ljung-Box test. The lag length for the ADF is chosen on the base of AIC.

The Ljung-Box test needs to have set the lag m due to the fact, that different lags may affect the performance of the test statistic. Simulation studies suggest that the choice of $m \approx \ln(T)$ provides better power performance (Tsay, 2002).

2.2 ARIMA

The ARIMA models contain three parts – AR (autoregressive process), I (integrated process), and MA (moving average process). In particular, financial data such as return on investment show serial dependence, which can be modeled using an autoregressive process of order p – AR(p). The MA(q) process is the simplest model in this methodology and has the form of a linear combination of white noise processes, so the value of the time series depends only on the current and past values of this process.

This paper applies the Box-Jenkins methodology of ARIMA models that contains three steps:

1. Model identification,
2. Parameter estimation,
3. Model diagnostics.

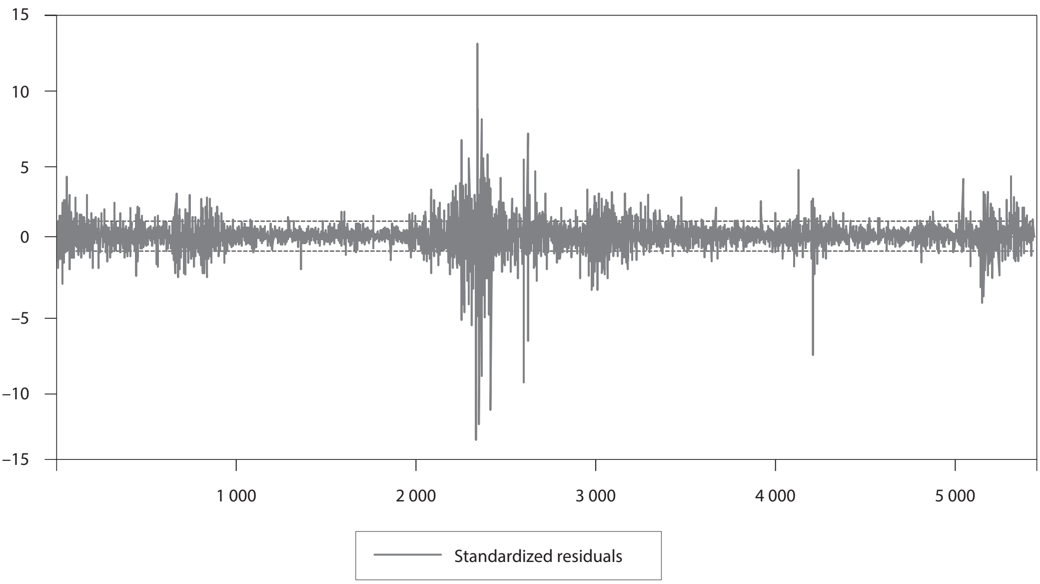
The model estimation is made with the automatic ARIMA modeling within the Eviews based on the AIC (Akaike information criterion). The model with statistically significant parameters that is reasonably simple and has a low value of AIC is chosen. For the parameter estimation, the maximum likelihood method was employed.

A fitted model must be examined carefully to check for possible model inadequacy. If the model is adequate, then the residual series should behave as white noise (Tsay, 2002: 39). The model diagnostic checks for the properties of residuals. In the case of a correct model, the residual should behave like white noise, it should not show serial correlation. In case of rejection of the hypothesis of the Ljung-Box test, the closest possible model to the former that does not lead to the rejection of this hypothesis was chosen.

Another white noise property is homoscedasticity. If the errors are heteroscedastic then the standard error estimates are not correct. In the area of financial time series, the constant variance of errors is very rare. One of the reasons is volatility clustering where large changes are usually followed by other large changes as well as small changes (Brooks, 2019).

The volatility clustering can be seen in Figure 1, where large returns follow large returns, and small returns follow small returns.

Figure 1 Standardized residuals (model ARIMA, LLOY.L)



Source: Own construction

The presence of heteroscedasticity of residuals is tested by the ARCH-LM test proposed by Engle (1982). The Engle test for ARCH effects in the residuals of an estimated model was computed to assure that this class of models is appropriate for the data. The number of lags to include was 5 according to common practice. After the rejection of the hypothesis of homoscedasticity, the ARIMA-GARCH model was applied.

2.3 ARIMA-GARCH

The volatility can be modeled using the autoregressive process (AR), where after considering the volatility, we get the ARCH (autoregressive conditional heteroskedasticity) model, which was first introduced by Engle (1982). ARCH(1) – 'autocorrelation in volatility' is modeled by allowing the conditional variance of the error term, σ_t^2, to depend on the immediately previous value of the squared error, e_{t-1}^2.

The conclusions of the applications of the ARCH model in the literature confirm the predominance of its generalized model – GARCH (generalized ARCH), which was proposed by Bollerslev (1986). Compared to ARCH models, GARCH is a very popular tool for modeling conditional heteroskedasticity, and its modifications are constantly appearing in the literature (Veselá, 2019). GARCH(1, 1) – conditional variance σ_t^2 can also be modeled by its own lagged values of lag = 1.

This model can describe the behavior of volatility (not only) in financial data, where there is a larger fluctuation of data in more observations in a row.

Poon and Granger (2003) claim that: "Empirical findings suggest that GARCH is a more parsimonious model than ARCH and GARCH(1,1) is the most popular structure for many financial time series." This paper, therefore, uses the GARCH(1,1) model.

There are two conditions for estimates:

1. Non-negative GARCH coefficients.
1. Sum of GARCH coefficients (except constant) < 1 for the process to be stationary.

2.4 Model quality assessment

For the model quality assessment, the last 250 observations are not used for the parameter estimation and are used for the model quality assessment (holdout sample). The dynamic and static forecasts are calculated, where the dynamic forecast is a multi-step forecast starting from the first period in the forecast sample and the static forecast is a sequence of one-step-ahead forecasts, rolling the sample forward one observation after each forecast.

The two criteria are applied – the MAPE (mean absolute percentage error) and Theil's inequality coefficient U (Brooks, 2019). Theil's inequality coefficient (U) measures the prediction accuracy of a model. Theil's U is calculated in the Eviews and it always lies between zero and one, where zero indicates a perfect fit. The forecasts from the benchmark model (the random walk) is calculated and they are compared to the forecasts from the chosen model. A U-statistic equal to one implies that the model under consideration and the benchmark model are equally (in)accurate, while a value of less than one implies that the model is superior to the benchmark, and vice versa.

2.5 Data

The four most liquid stock titles from the Czech, British, German, Polish, and Austrian markets were chosen for the research in the period 1/2000–4/2022. The data of most of the titles are since 1/2000, 9 of them are traded for a shorter period, and the shortest is VIG.PR (since 2008). For each series, there are 3 566 to 5 711 observations. The closing prices were obtained from Finance Yahoo (2022). The logarithmic returns were used according to other studies. The calculations were made in the Eviews, ver. 12.

3 RESULTS

Twenty time series were tested for stationarity by the ADF test and autocorrelation by the Ljung-Box test. After confirming the suitability, the ARIMA model was applied and results together with the test of the ARCH effect are shown. After the rejection of the residual homoscedasticity hypothesis, the ARIMA-GARCH model was employed and the residual homoscedasticity hypothesis was tested. Then the quality of forecasts of the holdout sample was assessed.

3.1 ADF (augmented Dickey-Fuller) unit root test

The augmented Dickey-Fuller (ADF) test hypothesis says that the series contains the unit root, against the hypothesis that the series is stationary.

Table 1 ADF unit root test results

Series	p-value at level		p-value at 1st difference	
	Constant	Constant & Trend	Constant	Constant & Trend
CEZ.PR	0.6251	0.8674	0.0001*	0.0000*
ERBAG.PR	0.1329	0.3376	0.0001*	0.0000*
KOMB.PR	0.1630	0.3677	0.0000*	0.0000*
VIG.PR**	0.0272**	0.0640	0.0000*	0.0000*
BOIL.L	0.1532	0.0006**	0.0000*	0.0000*
LLOY.L	0.6284	0.7916	0.0000*	0.0000*
OEX.L	0.5890	0.4426	0.0000*	0.0000*
VOD.L**	0.0015**	0.0154**	0.0000*	0.0000*
CBK.DE	0.2206	0.5876	0.0000*	0.0000*
DBK.DE	0.5572	0.2284	0.0000*	0.0000*
DTE.DE**	0.0000**	0.0000**	0.0000*	0.0000*
LHA.DE	0.1105	0.3117	0.0001*	0.0001*
GNB.WA**	0.0001**	0.0006**	0.0000*	0.0000*
LBW.WA	0.0959	0.2238	0.0000*	0.0000*
PGN.WA	0.1044	0.0470**	0.0001*	0.0000*
PKO.WA**	0.0170**	0.0731	0.0000*	0.0000*
OMV.VI	0.2808	0.2929	0.0000*	0.0000*
RBI.VI	0.5464	0.4752	0.0000*	0.0000*
UQA.VI	0.5424	0.7446	0.0000*	0.0000*
VOE.VI	0.2131	0.4839	0.0000*	0.0000*

Notes: ** 5 series stationary (no unit root) on 5% level of sig. * after the 1st differencing all series stationary.
Source: Own construction

The most of time series is not stationary at level but after differencing this assumption of the ARIMA models is met.

3.2 Ljung-Box test

For all series, the lag of 9 was chosen because the number of observations in the studied time series T is between 3 566 and 5 711 therefore m as ln(T) is between 8.2 and 8.7. Results are not shown and for all series, the hypothesis of no linear dependence in the data is rejected so the use of ARIMA is appropriate.

3.3 ARIMA results

The parameter estimation is made with the automatic ARIMA modeling based on the AIC (Akaike information criterion). All series residuals show no autocorrelation (according to the Ljung-Box test, not shown).

Table 2 ARIMA results

Series	Model	Max. p-value of max AR/MA coefficient(s)	Series	Model	Max. p-value of max AR/MA coefficient(s)
CEZ.PR	(2,0)	0.0000	DTE.DE	(3,3)	0.0000
ERBAG.PR	(2,3)	0.0000	LHA.DE	(2,2)	0.0105
KOMB.PR	(4,4)	0.0000	GNB.WA	(4,3)	0.0021
VIG.PR	(3,1)	0.0053	LBW.WA	(2,4)	0.0000
BOIL.L	(4,2)	0.0000	PGN.WA	(2,4)	0.0001
LLOY.L	(4,4)	0.0000	PKO.WA	(2,2)	0.0000
OEX.L	(0,2)	0.0000	OMV.VI	(0,1)	0.0000
VOD.L	(3,3)	0.0077	RBI.VI	(2,2)	0.0000
CBK.DE	(3,4)	0.0000	UQA.VI	(1,3)	0.0000
DBK.DE	(3,0)	0.0000	VOE.VI	(2,2)	0.0000

Source: Own construction

For all models, the model estimation is statistically significant on the 5% level of significance. The next important step is to test the homoscedasticity assumption for residuals by the ARCH-LM test.

3.4 Test for ARCH effects – ARIMA model

Two heteroscedasticity tests for ARCH effects – ARCH-LM test of the residuals of the ARIMA model are calculated.

Table 3 Test for ARCH effects – ARIMA model

Series	Prob. F	Prob. Chi-square	Series	Prob. F	Prob. Chi-square
CEZ.PR	0.0000	0.0000	DTE.DE	0.0000	0.0000
ERBAG.PR	1.0000*	1.0000*	LHA.DE	0.0000	0.0000
KOMB.PR	0.0000	0.0000	GNB.WA	0.2248*	0.2246*
VIG.PR	0.0000	0.0000	LBW.WA	0.0000	0.0000
BOIL.L	0.0000	0.0000	PGN.WA	0.0000	0.0000
LLOY.L	0.0000	0.0000	PKO.WA	0.0000	0.0000
OEX.L	0.0000	0.0000	OMV.VI	0.0000	0.0000
VOD.L	0.0000	0.0000	RBI.VI	0.0000	0.0000
CBK.DE	0.0000	0.0000	UQA.VI	0.0000	0.0000
DBK.DE	0.0000	0.0000	VOE.VI	0.0000	0.0000

Note: * hypothesis of the homoscedasticity assumption not rejected.
Source: Own construction

Almost all tests reject the hypothesis of the homoscedasticity assumption (except ERBAG.PR and GNB.WA). ARIMA model residuals of 18 time series show the heteroscedasticity, the GARCH model needs to be applied for these series.

3.5 ARIMA-GARCH results

The model with statistically significant parameters is used. All series residuals show no autocorrelation (Ljung-Box test, not shown). All GARCH coefficients meet the conditions of nonnegativity and sum up to 1.

Table 4 ARIMA-GARCH results

Series	Model	Max. p-value of ARMA coefficient(s)	Max. p-value of ARCH GARCH coefficients
CEZ.PR	(2,0)	0.0034	0.0000
KOMB.PR	(3,0)	0.0287	0.0000
VIG.PR	(1,0)	0.0033	0.0000
BOIL.L	(1,1)	0.0000	0.0000
LLOY.L	(4,4)	0.0033	0.0000
OEX.L	(1,2)	0.0481	0.0000
VOD.L	(2,2)	0.0014	0.0000
CBK.DE	(1,0)	0.0000	0.0000
DBK.DE	(3,0)	0.0429	0.0000
DTE.DE	(2,2)	0.0000	0.0000
LHA.DE	(0,0)	NA	0.0000
LBW.WA	(2,4)	0.0378	0.0000
PGN.WA	(1,2)	0.0047	0.0000
PKO.WA	(1,2)	0.0047	0.0000
OMV.VI	(0,1)	0.0007	0.0000
RBI.VI	(2,2)	0.0000	0.0000
UQA.VI	(1,3)	0.0125	0.0000
VOE.VI	(2,2)	0.0260	0.0000

Source: Own construction

The parameters of the ARIMA model and GARCH model are statistically significant at the 5% level of significance for all time series, except for the LHA series where the data can be modeled only by the GARCH model.

3.6 Test for ARCH effects – ARIMA-GARCH model

To test the ARCH effects 2 tests are calculated for the ARIMA-GARCH model residuals.

Both tests do not reject the residuals' homoscedasticity hypothesis. It can be argued that in all models the variability is captured using the ARIMA-GARCH model.

For the illustration of the domination of the ARIMA-GARCH concerning homoscedasticity, the two charts of a chosen time series of CEZ are drawn.

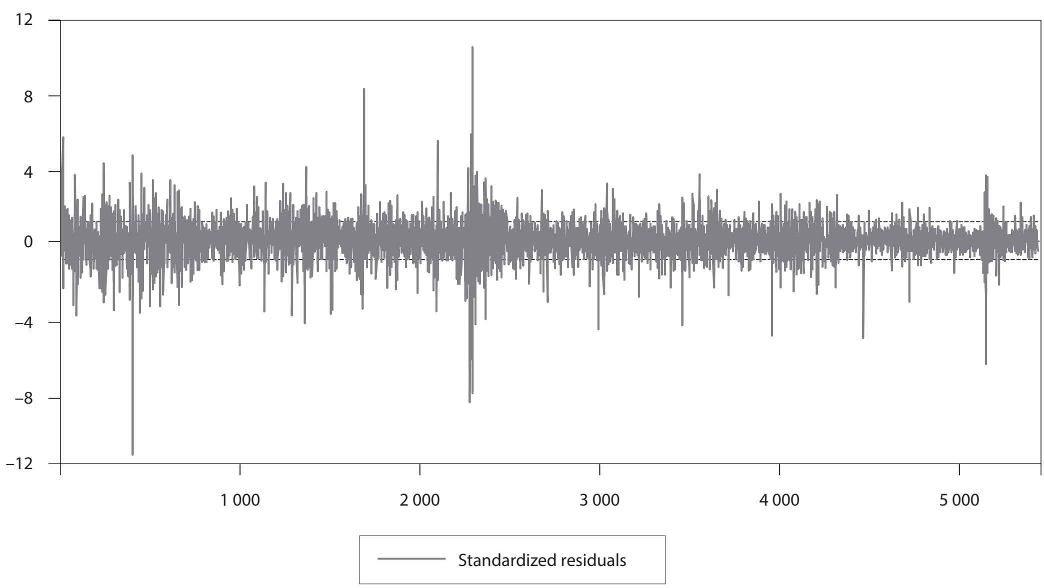
The volatility clustering after the ARIMA-GARCH model application has disappeared and residuals show a white noise behavior.

Table 5 Test for ARCH effects – ARIMA-GARCH model

Series	Prob. F	Prob. Chi-square	Series	Prob. F	Prob. Chi-square
CEZ.PR	0.9322	0.9321	DTE.DE	0.9631	0.9630
KOMB.PR	0.1834	0.1833	LHA.DE	0.7726	0.7723
VIG.PR	0.1317	0.1317	LBW.WA	0.3251	0.3250
BOIL.L	0.6106	0.6103	PGN.WA	0.6587	0.6586
LLOY.L	0.1018	0.1018	PKO.WA	0.2377	0.2376
OEX.L	0.9998	0.9998	OMV.VI	0.0584	0.0585
VOD.L	0.5685	0.5682	RBI.VI	0.6410	0.6460
CBK.DE	0.1406	0.1405	UQA.VI	0.6960	0.6958
DBK.DE	0.1269	0.1269	VOE.VI	0.1708	0.1708

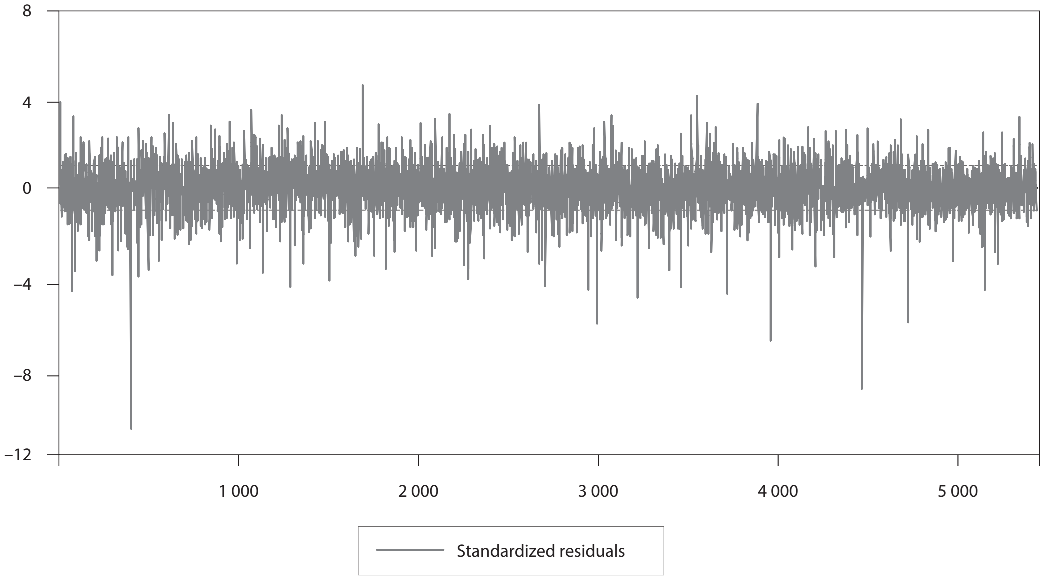
Source: Own construction

Figure 2 Standardized residuals (model ARIMA, CEZ.PR)



Source: Own construction

Figure 3 Standardized residuals (model ARIMA-GARCH, CEZ.PR)



Source: Own construction

3.7. Model quality assessment

Comparison of the dynamic and static forecast for holdout sample of the best model (ARIMA or ARIMA-GARCH).

Table 6 Dynamic and static forecast, Theil's U and MAPE

	Dynamic forecast		Static forecast	
	Theil's U	MAPE	Theil's U	MAPE
CEZ.PR	0.9616	178.3696	0.9295	175.6769
ERBAG.PR*	0.9758	184.4739	0.9460	177.7338
KOMB.PR	0.9832	186.8737	0.9463	180.6889
VIG.PR	0.9865	192.3616	0.9456	186.2756
BOIL.L	0.9804	196.5349	0.8812	186.8690
LLOY.L	0.9916	194.2859	0.9474	183.5451
OEX.L	0.9810	194.8318	0.9276	188.6082
VOD.L	0.9880	192.8578	0.9417	180.0431
CBK.DE	0.9891	196.9308	0.9451	185.6313
DBK.DE	0.9956	195.6509	0.9662	185.4271
DTE.DE	0.9930	194.9442	0.9781	188.5170
LHA.DE	0.9946	194.0667	0.9946	194.0667
GNB.WA*	0.9759	176.3603	0.9176	167.2431

Table 6				(continuation)
	Dynamic forecast		Static forecast	
	Theil's U	MAPE	Theil's U	MAPE
LBW.WA	0.9969	193.6844	0.9519	182.2170
PGN.WA	0.9879	188.7835	0.9242	173.6151
PKO.WA	0.9840	192.5113	0.9317	178.8812
OMV.VI	0.9724	183.1172	0.9498	178.2660
RBI.VI	0.9865	186.2470	0.9851	186.1770
UQA.VI	0.9804	188.6330	0.9584	185.5723
VOE.VI	0.9633	181.0152	0.9472	181.0183

Note: *ARIMA model.
Source: Own construction

The MAPE for the dynamic and static forecasts exceeds 100% for both forecasts for all time series. The model forecasts are unable to account for much of the variability of the out-of-sample part of the data. This is expected because forecasting changes in financial data is difficult.

Theil's inequality coefficient (Theil's U) is below 1 for both forecasts for all time series. The forecasts of the ARIMA-GARCH model outperform the forecasts of the benchmark.

CONCLUSION

This article focused on comparing the capture of variability by the often-used ARIMA model with the ARIMA-GARCH heteroskedasticity model. Volatility clustering was detected in the selected financial time series, therefore, after applying homoscedasticity tests, it proved to be a better ARIMA-GARCH model. The homoscedasticity test leads to no rejection of the equal variances hypothesis after the ARIMA-GARCH model application.

It follows from the performed calculations that the ARIMA model cannot be applied to the financial series of stock prices for the vast majority of stocks from the monitored sample. On the contrary, the ARIMA-GARCH model could be applied to all analyzed stocks from the Czech, British, German, Polish, and Austrian markets. However, the ARIMA-GARCH model was not so successful in predicting the development of stock prices on the monitored markets. In our opinion, the low success of the ARIMA-GARCH model is due to the high volatility of stock prices, but also of financial markets, which is characteristic of both the first decades of the new century. This increased volatility of financial markets was fueled by the ongoing and increasing internationalization and globalization of the world's financial markets, and further essentially continuously fueled by a whole series of factors and events taking place in the new millennium in rapid successions, such as the bursting of the Technology Bubble, the attack on the WTC, accounting scandals, the bursting of real estate bubbles that resulted in a financial crisis, global world imbalances, the COVID-19 pandemic, ongoing war conflicts, etc.

The financial markets of the new millennium are very volatile, turbulent, and changeable, which does not contribute to the successful use of statistical models that are exclusively based on historical data. New major, often global, events that cannot be predicted deviate stock prices from common, normal values. It seems that in such an economic environment, the ARIMA and ARIMA-GARCH statistical models cannot be used as useful tools for predicting the development of stock prices, and therefore as a tool for taking an appropriate investment position leading to excessive profits.

We believe that in further research, it would be appropriate to investigate the usability of asymmetric GARCH and EGARCH models in predicting the development of stock prices. At the same time, we believe that it would be beneficial from the point of view of comparing the results to apply the ARIMA and ARIMA-GARCH models used by us to older historical series of stock prices from the 80s-90s of the last century when stock markets were not yet recognized as having excessive volatility like today. and then compare the success of the mentioned models in periods of less and greater volatility.

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ANNEX – STOCKS

	Symbol	Name
Czech	ERBAG.PR	Erste Group Bank AG
	KOMB.PR	Komercní banka, a.s.
	CEZ.PR	CEZ, a. s.
	VIG.PR	Vienna Insurance Group AG
British	BOIL.L	Baron Oil Plc
	OEX.L	Oilex Ltd
	LLOY.L	Lloyds Banking Group plc
	VOD.L	Vodafone Group Public Limited Company
German	LHA.DE	Deutsche Lufthansa AG
	DBK.DE	Deutsche Bank Aktiengesellschaft
	CBK.DE	Commerzbank AG
	DTE.DE	Deutsche Telekom AG
Polish	GNB.WA	Getin Noble Bank S.A.
	PKO.WA	Powszechna Kasa Oszczednosci Bank Polski Spólka Akcyjna
	PGN.WA	Polskie Górnictwo Naftowe i Gazownictwo S.A.
	LBW.WA	Lubawa S.A.
Austrian	RBI.VI	Raiffeisen Bank International AG
	OMV.VI	OMV Aktiengesellschaft
	VOE.VI	Voestalpine AG
	UQA.VI	UNIQA Insurance Group AG

Source: Finance Yahoo (2022)