УДК 336.761
JEL Classification C12, C60, G18, E43
DOI https://doi.org/10.33146/2307-9878-2024-3(105)-75-86

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Methodological Principles of Simulating Asymmetrical Volatility of Corporate Credit Market Dynamics

Abstract. *Forecasting and modelling of price dynamics of financial instruments and their volatility is an essential element of technical analysis of financial markets. The real sector is also interested in changes in volatility as it seeks to maintain stability in financial and commodity markets. The article aims to develop methodological approaches to modelling the dynamics and volatility of the Ukrainian corporate credit market using asymmetric GARCH approaches. It has been established that the risky nature of financial markets is a prerequisite for analyzing and modeling the volatility of their dynamics in order to correctly respond to possible spikes in volatility, as well as to predict their duration. The analysis was based on daily data on interest rates on the corporate credit market. A graph of the initial time series, autocorrelation functions was plotted, the series was checked for stationarity by the Dickey–Fuller test, which led to its differentiation and subsequent formation of the optimal ARIMA specification. When checking the residuals for autocorrelation and the ARCH effect, positive results were obtained, which led to the use of the GARCH model. Going through various GARCH specifications made it possible to choose GJR-GARCH for modeling, which takes into account the asymmetry of the impact of information shocks on the profitability management of active bank operations. The resulting model was tested by the Leung–Box test, the ARCH LM test, and the Pearson test for the optimality of the specification. The model was compared with actual time series data. All the results confirmed the correctness of the built models, which allows them to be used for analysis and forecasting for further periods.*

Keywords: *interest rate, ARIMA model, GARCH model, asymmetric distribution, information shocks, volatility.*

Suggested Citation
Mandych, O., Staverska, T., Makohon, V. (2024). Methodological Principles of Simulating Asymmetrical Volatility of Corporate Credit Market Dynamics. *Oblik i finansi,* 3(105), 75-86. https://doi.org/10.33146/2307-9878-2024-3(105)-75-86

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Методологічні засади моделювання асиметричної волатильності динаміки корпоративного кредитного ринку

Анотація. *Прогнозування та моделювання динаміки цін на фінансові інструменти та їх волатильності є важливим елементом технічного аналізу фінансових ринків. Реальний сектор також зацікавлений у змінах волатильності, оскільки він прагне підтримувати стабільність фінансових і товарних ринків. Метою статті є розробка методологічних підходів до моделювання динаміки та волатильності ринку корпоративного кредитування України з використанням асиметричних GARCH-підходів. Встановлено, що ризиковий характер фінансових ринків є передумовою для аналізу та моделювання волатильності їх динаміки з метою коректного реагування на можливі сплески волатильності, а також прогнозування їх тривалості. Аналіз проводився на основі щоденних даних про процентні ставки на ринку корпоративних кредитів. Було побудовано графік вихідного часового ряду, автокореляційні функції, перевірено ряд на стаціонарність за допомогою тесту Дікі-Фуллера, що призвело до його диференціювання та подальшого формування оптимальної ARIMA-специфікації. При перевірці залишків на автокореляцію та ARCH-ефект було отримано позитивні результати, що зумовило використання GARCH-моделі. Перебір різних специфікацій GARCH дозволив обрати для моделювання GJR-GARCH, яка враховує асиметрію впливу інформаційних шоків на управління прибутковістю активних операцій банку. Отриману модель було перевірено на оптимальність специфікації за допомогою тесту Леунга-Бокса, ARCH LM-тесту та тесту Пірсона. Модель було порівняно з фактичними даними часових рядів. Всі результати підтвердили коректність побудованих моделей, що дозволяє використовувати їх для аналізу та прогнозування на подальші періоди.*

Ключові слова: *процентна ставка, ARIMA модель, GARCH модель, асиметричний розподіл, інформаційні шоки, волатильність.*

PROBLEM STATEMENT

Forecasting and modelling the dynamics of financial instrument prices and their volatility is an important element of technical analysis of financial markets, including the credit market. Building volatility models and managing risks under uncertainty are traditional objects of scientific research, as evidenced by the growing number of studies in this area in recent years. Considerable attention is paid to finding patterns of financial market volatility, its clustering, and the reasons for the leptokurtic distribution of prices for financial instruments, their sharp peaks and "heavy" tails [40].

Against this background, the analysis of the leverage effect described by [8], which is based on the asymmetry of price and income changes, which causes a negative correlation between asset returns and their volatility, when the latter increases in response to "bad news" and decreases in the case of "good news", becomes important. Recent studies have shown that financial instrument prices have a "long memory", when current events have a lasting impact for a long time [29]

The researchers proved the prevalence of heteroscedasticity - the variable volatility of the residuals of financial asset price series, for which it is appropriate to apply the General Autoregressive Conditional Heteroscedasticity (GARCH) model. Since the works of R. Engle and T. Bollerslev, this method has been used to determine the presence of heteroscedasticity (ARCH effects) caused by the influence of information asymmetry in high-frequency distributions of financial indicators, in particular, loan interest rates [11, 27].

The heteroscedastic nature has been proven for most empirical time series of financial instruments valuation [41, 47]. At the same time, an increase in volatility entails an increase in investment risk and is the basis for financial crises. The results of GARCH modelling allow us to consider the laws of volatility changes in spot prices when evaluating derivatives, developing hedging strategies and managing investment portfolios. The real sector is also interested in changes in volatility as it seeks to maintain the stability of financial and commodity markets. Given this, it is particularly relevant to test GARCH modelling approaches in analysing the dynamics and volatility of the domestic corporate credit market.

LITERATURE REVIEW

An analysis has shown that the conclusions of one of the founders of the analysis of conditional volatility of financial indicators, R. Engle, were mainly based on the use of symmetric ARCH/GARCH [27]; however, in most subsequent studies, he and other scholars mainly use models with asymmetric distribution. For example, based on the properties of the asymmetry of the moving average described by W. Wecker in 1981, S. Elwood used threshold autoregressive models to prove the asymmetric impact of shocks (innovations) on GDP and industrial output [27, 57]. G. Koutmos, as well as R. Kumar and R. Dhankar, found that the conditional volatility of financial returns is also asymmetric [34, 36]. S. Diongue and D. Guegan used seasonal APARCH to analyse the seasonal asymmetry of time series of financial indicators [21]. L. Kilian and R. Vigfusson used VaR models to estimate asymmetric responses and proved that the dynamics of output fluctuations is affected by multifaceted deviations with different amplitudes [32].

To date, many asymmetric GARCHs have been tested: exponential GARCH, GJR model, threshold GARCH, and asymmetric power GARCH (APGARCH or PGARCH) [20, 28, 44, 59]. Its modifications are also common: quadratic (QGARCH), conditional autoregressive range model (CARR), dynamic asymmetric (DAGARCH), integrated (IGARCH), component (CGARCH), fractional integrated (FIGARCH), volatility switching model (VS-ARCH).

The prerequisites for using the asymmetric GARCH are its high statistical reliability. For example, D. Miron and C. Tudor (2010), analysing the US and Romanian stock indices, found higher forecasting accuracy of the EGARCH model compared to the PGARCH [41]. C. Su analysis of Chinese stock indices using EGARCH with the Student's distribution demonstrates better results than the classical GARCH [52]. An analysis of stock market volatility in ten countries by A. Yalama and G. Sevil using seven GARCH models showed a decrease in forecasting accuracy in the order from EGARCH to PARCH, TARCH, IGARCH, GARCH, GARCH GARCH-M [58].

B. Awartani and V. Corradi determined the advantage of asymmetric GARCHs by studying six horizons of forecasting volatility of the S&P-500 index [5]. Z. Kovacic proved that the GJR and TGARCH models have a higher forecasting ability for the Macedonian stock index compared to symmetric GARCHs [35]. At the same time, when studying the volatility of the Nigerian naira, H. Dallah found that TGARCH provides more accurate results compared to other models in the case of the US dollar and the Japanese yen, while the classical GARCH better models the rates against the British pound [17].

T. Watanabe and K. Harada identified two components of volatility in the CGARCH model - a long-term component, with shocks that are very persistent, and a short-term component, with less persistent innovations. An analysis of the impact of the Central Bank of Japan's interventions on the volatility of the yen/dollar pair showed that it is possible to decompose inflation uncertainty into temporary and permanent ones using CGARCH and to assess the impact of retrospective data on long-term uncertainty [56]. In turn, A. Kontonikas found the opposite effect of inflation targeting in the UK on the stability of the pound, using CGARCH to estimate the seasonally adjusted log difference between the monthly and quarterly inflation indices in 1972-2002 [33].

In the following years, a group of researchers led by S. Kang, using the dynamics of three daily spot oil prices, established the persistence or long memory of their volatility [31]. It was determined that CGARCH and FIGARC were better at modelling persistence than GARCH and IGARCH. For the dynamics of four sectors of fourteen stock exchanges, T. Ann proved the superiority of the CGARCH model over GARCH. It was determined that the trend of 1990-2004 has a high level of stability, and therefore GARCH provides better short-term forecasts from one to five days, although the CGARCH model proved to be more accurate for longer horizons [3].

At the same time, the works of Ukrainian researchers are mainly devoted to the application of asymmetric GARCH to assess the financial stability of financial institutions [15, 38], as well as to the formation of prices in the commodity and labour markets [39], and require an in-depth analysis of the formation of asymmetric volatility in the prices of financial assets, including credit resources in the corporate sector of the economy.

RESEARCH PURPOSE

The article aims to develop methodological approaches to modelling the dynamics and volatility of the Ukrainian corporate credit market using asymmetric GARCH approaches.

RESEARCH METHODOLOGY

The source of the data was the dynamics of interest rates on loans granted to business entities (legal entities) from 3 January 2020 to 23 February 2022 by Ukrainian banking (depository) corporations, as published on the website of the National Bank of Ukraine.

The study is based on the Box-Jenkins methodology for predicting the dynamics of financial market modelling using ARIMA-GARCH models [13]. This methodological approach involves the repetition of four steps: model identification, parameter estimation, testing and verification of the model's predictive ability. ARMA is a tool for analysing and modelling time series based on the dynamics of the autoregressive component (AR) and moving average (MA). The autoregressive AR(p) component estimates the degree of influence of previous levels of the time series on its current values, the number of which is characterised by the parameter p. The moving average MA(q) characterises the impact of previous forecast errors (deviations) on the expected value of the series. The ARMA(p,q) process is described by Eq:

$$Y_t = c + (\sum_{i=1}^{p} \phi_i L^i) Y_t + (1 + \sum_{j=1}^{q} \theta_j L^j)\varepsilon_t. \qquad (1)$$

Where: c – point of intersection with OY; L – lag operator ($L_p Y_t = Y_{t-p}$), φ_i, – autoregressive coefficients; θ_q – moving average coefficients; Yt, – value of the time series at time t; ε_t is white noise.

Compared to the ARMA model, ARIMA also includes the I(d) component, which allows transforming a non-stationary time series into a stationary one by integrating it d times until stationary values of the d-order differences are obtained. In most cases, it is sufficient to take the first differences in the presence of a linear trend and to take the second-order differences in the presence of a quadratic trend. If higher orders of differences are required, other model options, such as smoothing, are considered. If the graph of the time series has a concave upward trend accompanied by an increase in variance, logarithmisation or taking the square root of the indicator values is used [16]. With this in mind, the ARIMA(p,d,q) process integrated at the dth level is described by Eq:

$$(1-L)^d Y_t = c + \left(\sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d Y_t + \left(1+\sum_{j=1}^{q} \theta_j L^j\right)\varepsilon_t. \qquad (2)$$

When studying financial time series, their volatility plays a special role. In the study of risk, volatility is expressed as the root of the variance, i.e. the measure of the spread of the values of an indicator from its mathematical expectation [12]. In the case of non-stationary time series with conditional heteroscedasticity, the variance is not a constant and depends on time, while ARIMA models solve the problem of non-stationarity of the mathematical expectation, their failure to take conditional heteroscedasticity into account does not allow for a comprehensive analysis and forecasting of financial time series (Stehlíková). In addition, volatility is characterised by the so-called clustering, i.e. a spike in certain periods and, due to the high level of volatility in that period, its high levels in the future. Thus, correct modelling of volatility makes it possible to come as close as possible to the actual processes taking place in financial markets. For this purpose, the GARCH (General Autoregressive Conditional Heteroskedasticity) model is used in practice, which was formulated by T. Bollerslev in 1986 [9, 10] as a generalisation of the ARCH model by R. Engle.

As is well known, the ARCH(q) process describes a set of two equations that define the mathematical expectation and variance. Thus, for AR(1) they are as follows:

$$Y_t = c + \phi_1 Y_{t-1} + \varepsilon_t.$$
$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \cdots + \alpha_q\varepsilon_{t-q}^2 = \alpha_0 + \left(\sum_{i=1}^{q}\alpha_i L^i\right)\varepsilon_t^2, \qquad (3)$$

Where: Y_t – time series, $L^i\varepsilon^2_t$ – square of the *i*-th relative change of the indicator, c – conditional mean Y_t, σ^2_t – conditional variance, α_i – coefficients of the model.

The variance equation parameter is restricted to $0<\alpha_i<1$ to ensure that the variance is positive while maintaining its stationarity [13]. GARCH models are a generalisation of the ARCH class of models. Its application has been studied by T. Andersen, L. Bauwens, A. Bera, T. Bollerslev, S. Deghiannakis, F. Diebold, R. Engle, A. Pagan, F. Palm, N. Shepherd, and T. Teräsvirta [1, 2, 6, 7, 9, 10, 18, 19, 23-25, 45, 46, 50, 54].

The variance of ARCH(q) is characterised by conditional heteroscedasticity, which allows it to be used to model time-dependent volatility [23]. Since the ARCH model requires estimation of the q+1 parameter to track the effect of q lags of disturbances, it can make it difficult to analyse the effects of a large number of lags. GARCH models allow to reduce the number of parameters while maintaining the accuracy of the estimation. The notation GARCH(p, q) means taking p lags for the variance and q lags for the disturbances. The equation of variance in the GARCH(1,1) model is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \gamma_1\sigma_{t-1}^2 = \alpha_0 + \alpha_1 L\varepsilon_t^2 + \gamma_1 L\sigma_t^2, \qquad (4)$$

Where: σ^2_t – conditional variance, $L\varepsilon^2_t$ – square of the last relative change in the indicator, α_i, γ_j – coefficients of the ARCH and GARCH models, respectively.

Thus, it is possible to track volatility as a dependent variable not only on disturbances, but also on its lagged value, estimating only three parameters. The most commonly used model specification in financial time series analysis is GARCH(1,1) [36].

– GARCH (1,1) – the process is stationary if the condition $\alpha_i+\gamma_j<1$ is met. In general, the GARCH (p, q) model has the following specification:

$$\varepsilon_t = \sigma_t u_t, \text{ where } u_t \sim N(0,1)$$
$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_q\varepsilon_{t-q}^2 + \gamma_1\sigma_{t-1}^2 + \cdots \gamma_p\sigma_{t-p}^2 = \alpha_0 +$$
$$+\left(\sum_{i=1}^{q}\alpha_i L^i\right)\varepsilon_t^2 + \left(\sum_{j=1}^{p}\gamma_j L^j\right)\sigma_t^2, \qquad (5)$$

The standard GARCH is characterised by symmetry [43], i.e. the same effect of positive ($\varepsilon^2_t>0$) and negative ($\varepsilon^2_t<0$) shocks on volatility (variance) in period t. In practice, however, the reaction of financial market participants to negative shocks can only increase volatility through massive deposit withdrawals, which leads to a further collapse in loan prices and increases turbulence. Therefore, it is very important in practice to specify GARCH models that take into account the asymmetry of the impact of shocks of different signs, in particular

– Threshold GARCH [59]. Its peculiarity is that it takes into account conditional standard deviations. This model can respond to positive and negative shocks asymmetrically, which is not accounted for in the original models:

$$\sigma_t^2 = \alpha_0 + (\sum_{i=1}^{q} \alpha_i L^i)\, \varepsilon_t^2 + \tau_i L \varepsilon_t d_{t-1} + (\sum_{j=1}^{p} \gamma_j L^j)\, \sigma_t^2, \qquad (6)$$

Where: d_{t-1} – dummy variable defined as:

$$d_{t-1} = \begin{cases} 1, \varepsilon_{t-1} < 0 \\ 0, \ \varepsilon_{t-1} \geq 0 \end{cases}. \qquad (7)$$

At the same time, the requirements for a positive variance value must be met: $\alpha_0>0$, $\alpha_i>0$, $\gamma_j\geq0$, $\alpha_i+\tau_i\geq0$.

– GJR-GARCH [28]. It differs from TGARCH by using conditional variance instead of deviations:

$$\sigma_t^2 = \alpha_0 + (\sum_{i=1}^{q} \alpha_i L^i)\, \varepsilon_t^2 + \tau_i L \varepsilon_t^2 d_{t-1} + (\sum_{j=1}^{p} \gamma_j L^j)\, \sigma_t^2 \qquad (8)$$

The effect of a positive shock on the conditional variance is determined by the coefficient α, while the effect of a negative shock is determined by the coefficients α+τ, which reflects the asymmetry of the impact of shocks of different signs and the increase in volatility in the case of negative shocks. In the case of the GJR-GARCH specification of the GARCH model, the coefficient τi should be statistically significant [43].

Within each of the model specifications, the distribution function of the model residuals is set. The most common options within GARCH are the normal distribution, the Student's distribution, or the so-called skewed Student's distribution. For this purpose, the concepts of skewness and kurtosis are used to describe the distribution of values (both residuals and initial data).

RESULTS

The analysis of the behaviour of the indicator under study shows a nonlinear hyperbolic trend, as well as a variable variance with significant outliers in the first and second quarters of 2020 and the beginning of the first quarter of 2021, and less significant disturbances in the second and third quarters of 2020 and the first quarter of 2022 (Fig. 1).

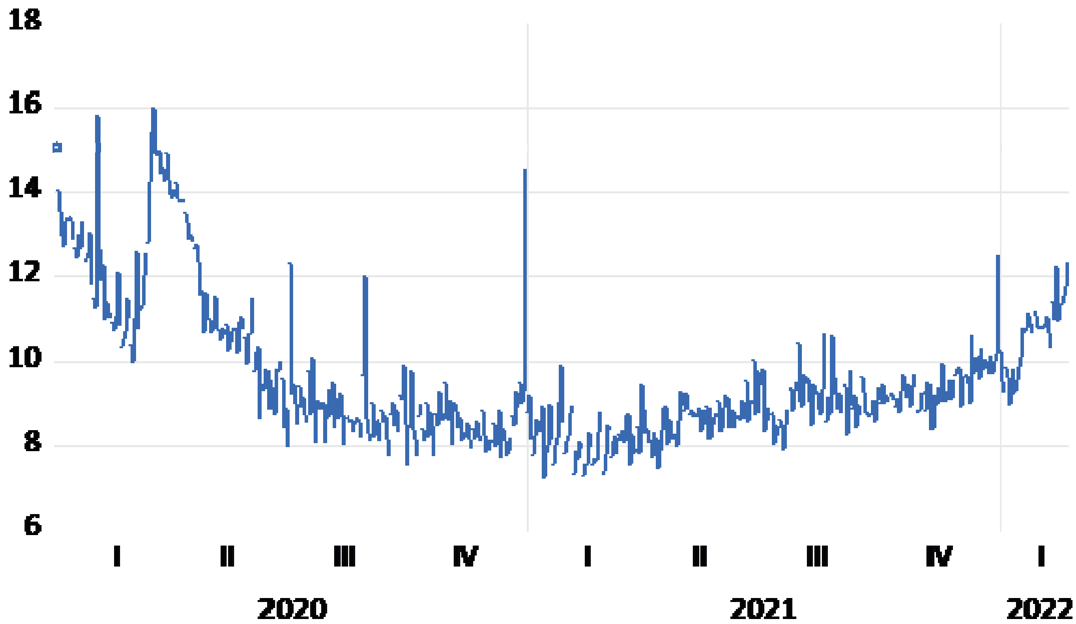

Figure 1. **Dynamics of interest rates on loans granted to business entities (03.01.2020-23.0222)**

Source: authors' calculations in EViews 12.

The analysis indicates that the variance is non-stationary and clustered, as the nature of the disturbances (degree of volatility) of interest rates at the beginning of each financial year tends to increase sharply in the first decade and decrease gradually. It can be assumed that there is an ARCH effect due to the conditional heteroscedasticity of the time series and the autocorrelation of the residuals, which is why the use of ARIMA alone will be insufficient for approximation, which was confirmed by further verification using statistical tests.

In particular, to confirm the assumption of autocorrelation and heteroscedasticity of the interest rate series, a number of formal statistical and econometric tests were applied. The time series was tested for stationarity of the mathematical expectation using the Augmented Dickey-Fuller (ADF) test. Its results indicate that the original interest rate series is non-stationary (Table 1).

Table 1. **Dickie-Fuller Test (*ADF*) Results**

Indicator	Meaning
Dickie-Fuller Stats	-2,309855
The Critical Importance of the Student's Distribution	-2,35
p-value	0,1692

Source: authors' calculations in EViews 12.

Thus, the ADF statistic with a confidence level of 0.1695>0.05 indicates that the observed value is less than the critical value (-2.309855<-2.31). This confirms the null hypothesis of unit roots. With this in mind, the first differences of the original series were taken. The repeated ADF test showed that for the difference series I(1), the Dickey-Fuller statistic is -7.435154, which is less than the critical value of the Student's distribution, and therefore, with a p-value below 0.05, the stationarity of I(1) should be stated.

Subsequently, based on the values and graphs of ACF and PACF autocorrelation generated in EViews 12 for the first integration of I(1) of the original series, the order of the model was established and its parameters were estimated (Fig. 2).

Date: 02/05/24 Time: 18:49
Sample (adjusted): 1/08/2020 2/23/2022
Included observations: 535 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.416	-0.416	93.034	0.000
		2	-0.016	-0.229	93.173	0.000
		3	-0.067	-0.217	95.569	0.000
		4	-0.035	-0.224	96.214	0.000
		5	0.194	0.066	116.65	0.000
		6	-0.096	0.013	121.67	0.000
		7	0.006	0.012	121.68	0.000
		8	-0.045	-0.021	122.80	0.000
		9	0.004	-0.030	122.81	0.000
		10	0.078	0.028	126.10	0.000
		11	-0.044	0.008	127.14	0.000
		12	0.005	0.007	127.15	0.000
		13	-0.068	-0.064	129.69	0.000
		14	0.060	-0.005	131.67	0.000
		15	0.004	-0.013	131.68	0.000
		16	0.008	0.012	131.71	0.000
		17	-0.035	-0.024	132.41	0.000
		18	0.007	0.009	132.44	0.000
		19	0.019	0.011	132.64	0.000
		20	-0.039	-0.048	133.47	0.000
		21	0.072	0.040	136.35	0.000
		22	-0.051	0.010	137.81	0.000
		23	-0.002	-0.010	137.81	0.000
		24	-0.004	-0.024	137.83	0.000
		25	0.051	0.058	139.28	0.000
		26	-0.031	-0.009	139.81	0.000
		27	-0.034	-0.036	140.45	0.000
		28	-0.011	-0.059	140.52	0.000
		29	0.006	-0.052	140.54	0.000
		30	0.073	0.029	143.58	0.000
		31	-0.043	0.008	144.66	0.000
		32	-0.055	-0.057	146.38	0.000
		33	0.032	-0.014	146.97	0.000
		34	0.029	0.038	147.46	0.000
		35	-0.003	-0.013	147.46	0.000
		36	-0.064	-0.076	149.84	0.000

Figure 2. **Diagram of the autocorrelation (ACF) and partial autocorrelation (PACF) function for the time series of interest rates during 01.01.20-23.02.22**

Source: authors' calculations in EViews 12.

The AR lags that are candidates for inclusion in the model are selected based on their deviation above the critical value according to the PACF schedule. A similar approach is used for the MA according to the ACF schedule. For an optimal ARIMA, all values of autocorrelation between the residuals should be insignificant. Since this statement is violated (Fig. 2), the model was further investigated for the presence of an ARCH effect in the residuals. Given the existence of several correct ARIMA models, the following criteria were used to select the optimal one

– the smallest number of parameters;
– minimum value of standard errors for forecast values;
– information criteria.

It should be noted that the least squares method (OLS) was used to estimate the order of AR and MA. However, its use is not entirely correct for ARIMA, as it can give biased parameter estimates. Therefore, after determining the preliminary specification of the model, it was re-estimated using the non-linear least squares (NLS) method. Based on the results, ARIMA(4,1,1) has the lowest AIC value (Table 2).

Table 2. **Evaluation of the optimality of the ARIMA model by the AIC criterion**

Model *ARIMA*	Meaning of *AIC*
ARIMA(4,1,1)	2,112429
ARIMA(4,1,2)	2,121118
ARIMA(4,1,3)	2,132072

Source: authors' calculations in EViews 12.

Obtaining the optimal model specification based on penalty criteria was preceded by checking its residuals for the presence of autocorrelation, conditional heteroscedasticity, which violate the requirement of the residuals being distributed according to white noise. For this purpose, the following hypotheses were tested using the Lagrange multiplier LM test:

H0: no ARCH effect in the residuals of the ARIMA model,

H1: the presence of ARCH in the ARIMA residuals.

The test statistic has a $\chi 2$ distribution. If the value of the ARCH LM-test statistic exceeds the critical value of $\chi 2$ (or if the p-value is < 0.05), the hypothesis of homoscedasticity of the ARIMA residuals is rejected. Based on these prerequisites, it is established that the ARIMA(4,1,1) residuals contain an ARCH effect, and therefore it is insufficient for time series approximation (Table 3).

Table 3. **LM test results for ARCH effect for ARIMA(4,1,1)**

Indicator (criterion)	Meaning
Observational $\chi 2$	17,91884
Critical value of $\chi 2$	3,25
p-value	$2{,}2\times10^{-16}$
The presence of the ARCH effect	Existing

Source: authors' calculations in EViews 12.

Thus, there is a need to build a GARCH model and analyse the time series using it (Naika et al., 2020). In the process of testing models of interest rate dynamics, the GJR-GARCH (1,1) model was identified as the optimal one. To approximate this time series, the optimal model is ARIMA(4,1,1)-GJR-GARCH(1,1), which has the form:

$$Y_t = -0{,}013 - 0{,}817Y_{t-1} - 0{,}572Y_{t-2} - 0{,}459Y_{t-3} - 0{,}322Y_{t-4} + 0{,}197\varepsilon_{t-1}$$
$$\varepsilon_t = \sigma_t u_t, \quad (9)$$

In the case of positive news (shocks), the specification is used to estimate the variation (σ_t^2):

$$\sigma_t^2 = 0{,}105 + 0{,}527\sigma_{t-1}^2 + 0{,}344\varepsilon_{t-1}^2 \ (\varepsilon t \geq 0) \quad (10)$$

Instead, in the case of negative shocks, specification (19) takes the form of leverage effect:

$$\sigma_t^2 = 0{,}105 + 0{,}527\sigma_{t-1}^2 + (0{,}344 - 0{,}238)\varepsilon_{t-1}^2 \ (\varepsilon t<0) \quad (11)$$

The analysis of the model shows that the first lag of interest rates and the first lag of shocks have the greatest impact on the dynamics of interest rates (coefficient values are -0.817 and 0.197, respectively). The variance of interest rates depends most on its first lag and the lag of the shock (coefficient values are 0.527 and 0.344). The variance equation reflects the existence of the influence of the Boolean skewness variable, depending on the sign of the shock lag, on the variance of interest rates - the value of the parameter was 0.238. The variance equation is stationary, since $\alpha + \gamma = 0.871 < 1$. The value of the kurtosis coefficient at 4.77 indicates that the residuals within the GARCH model are leptokurtotic, which is a characteristic feature of financial time series.

When analysing the quality of the model, it was tested for correctness in accordance with the requirements of the absence of an ARCH effect in general and autocorrelation in the model residuals (Table 4).

Table 4. **LM test results for ARCH effect for ARIMA(4,1,1)-GJR-GARCH(1,1)**

Indicator (criterion)	Meaning
Observational $\chi 2$	0,045723
Critical value of $\chi 2$	3,25
p-value	0,8307
The presence of the ARCH effect	Missing

Source: authors' calculations in EViews 12.

The test confirmed the correctness of the selected GARCH model for a number of interest rates, which allows using the results for further analysis and modelling of time series, in particular, retrospective analysis of the indicator's dynamics. For this purpose, the results of the models were analysed and their graphical analysis was carried out using the function. When comparing the built models and their results, the asymmetric GJR-GARCH model showed better results than the standard GARCH model based on the assumption of symmetry of the impact of shocks on variance regardless of their sign, as indicated by the values of a number of information criteria (Table 5).

Table 5. **Reliability testing of ARIMA and ARIMA-GARCH models**

Model	The Law of Distribution	Information criterion		
		Akaike	Schwartz	Hannan-Quinn
ARIMA(4,1,1)	Normal distribution	2,1011	2,0670	1,9855
ARIMA(4,1,1)-GJR-GARCH(1,1)	Normal distribution	2,0600	2,1324	2,1324
ARIMA(4,1,1)-GJR-GARCH(1,1)	Student's t-distribution	1,6374	1,7259	1,6720

Source: authors' calculations in EViews 12.

The Student's distribution was used for the model residuals, which confirmed the assumption of asymmetry of the impact of shocks on volatility depending on their sign. At the same time, the use of a normal distribution sharply worsens the quality of the model according to the Pearson test for specification optimality and penalty criteria. Thus, we have another confirmation of the need to use GARCH models, since the residuals of the ARIMA model do not have a normal distribution.

When choosing a model, the NBU also compared the options with symmetric and asymmetric accounting for the impact of the sign of shocks on interest rate volatility, and found that the models with asymmetric accounting for volatility were of higher quality according to the information criteria. In addition to the selected GIR-GARCH(1,1)-model, the analysis showed good results for the GIR-GARCH(2,1), E-GARCH(2,1), and GJR-GARCH(1,2) models with the Student's distribution for the modelled residuals. As in the previous case, the versions of the models assuming a normal distribution of the simulated residuals within the GARCH model showed significantly worse results according to the information criteria and the necessary statistical tests (Fig. 3).

The analysis of interest rate series and their volatility shows that the latter influenced the mathematical expectation of the analysed indicator, but the mathematical expectation of the I(1) series remains close to 0 and does not undergo significant changes. Thus, the impact of volatility on interest rates is always present in the financial market, and in some periods it is more pronounced than in others. For example, the first quarter of 2021 was a period of heightened volatility due to deposit outflows caused by the coronavirus pandemic, and the effect of this surge was noticeable in the following months. However, as business picked up compared to the beginning of the pandemic, expectations for loans and deposit opportunities stabilised and volatility returned to previous levels.

An analysis of the distribution of residuals of the ARIMA(4,1,1)-GJR-GARCH(1,1) model showed that the results of using its form with a normal distribution of residuals are worse than those with a Student's distribution (Fig. 4).

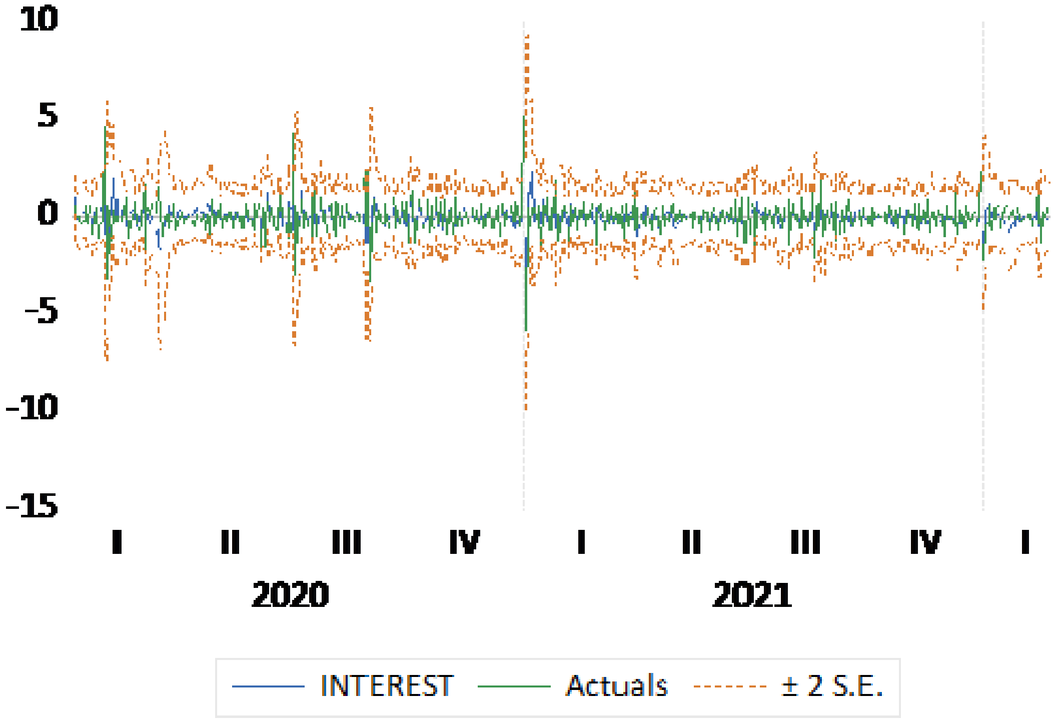

Figure 3. **Integrated dynamics of interest rates on loans granted to business entities I(1) with the imposition of volatility series**
Source: authors' calculations in EViews 12.

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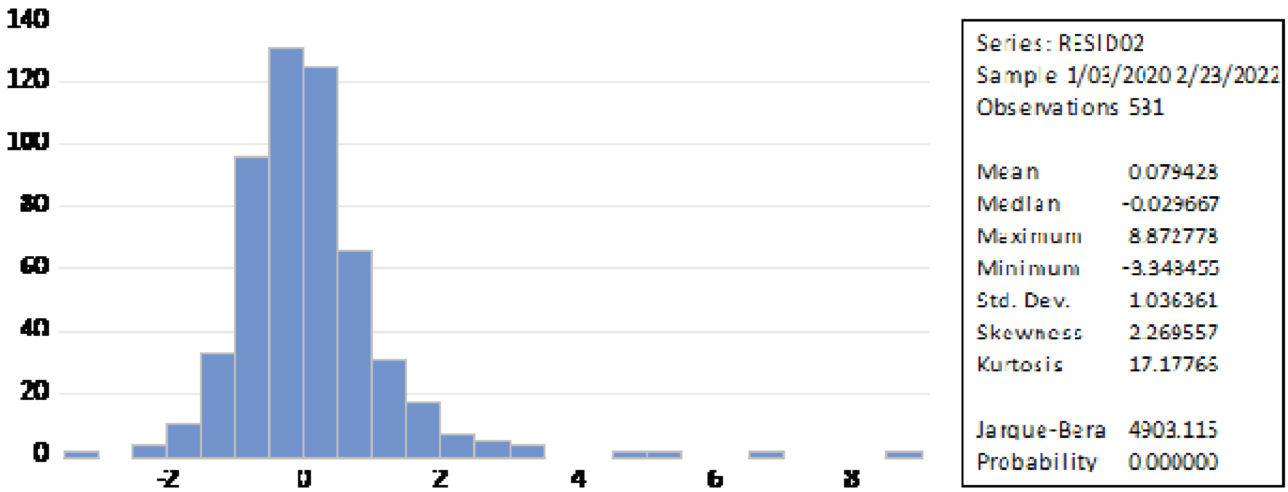

Figure 4. **Diagram of the distribution of residuals of the ARIMA(4,1,1)-GJR-GARCH(1,1) model**
Source: authors' calculations in EViews 12.

This is a consequence of the models' kurtosis coefficient of 15.2, when a larger proportion of values are concentrated near the mathematical expectation than required by the law of normal distribution. This situation is typical for interest rates and is driven by banks' desire to minimise risk when investing, which indirectly affects interest rates and their volatility. At the same time, among the negative values of the I(1) series, about 50 percent are significantly close to the mathematical expectation (see Figure 3). The situation is similar with the positive values of the dynamics: most of them are insignificant in absolute terms, and thus have a moderate impact on the cost of credit. Together with the wider tails compared to the requirements of the normal distribution, we conclude that the interest rate residuals have a leptokurtosis distribution.

The overlay of the modelled volatility on the dynamics of interest rates over the period under study showed that the modelled volatility is consistent with historical dynamics and retains all the main patterns, with no periods of significant discrepancy between the modelled and actual dynamics of indicators (Fig. 5).

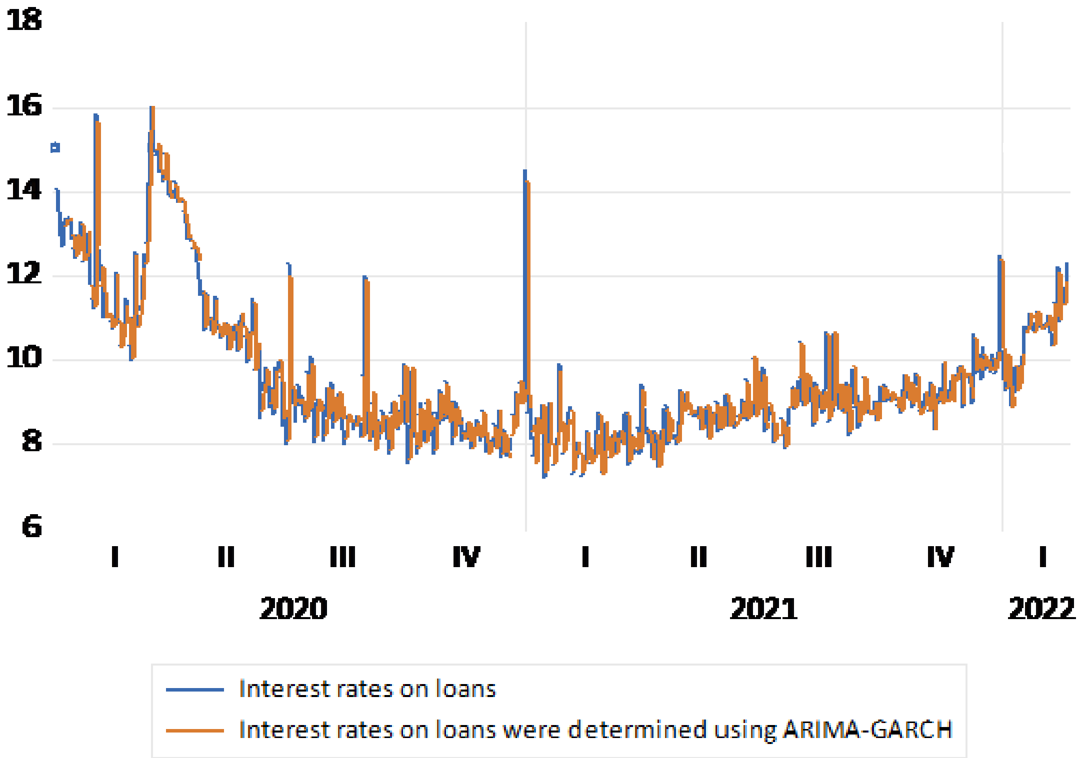

Figure 5. **Dynamics of actual and expected values of interest rates on loans granted to business entities (03.01.2020-23.0222)**

Source: authors' calculations in EViews 12.

Thus, different specifications of ARMA-GARCH models were built based on daily interest rate data. The obtained models were tested for correctness by various statistical tests, and the optimal specifications among many models were chosen according to information criteria. This model is ARIMA(4,1,1)-GJR-GARCH(1,1). The model considers the asymmetry of the impact of disturbances of different signs on the variance of rates and, hence, on volatility.

CONCLUSIONS

The established model for predicting the value of financial instruments in the corporate market approximates well the trends in interest rates and their volatility. Still, its drawback is that the model mainly describes the subjective nature of the mechanisms of the formation of distributions of market characteristics. These ideas are based on the concept of nonlinear perception and implementation of information on the state of value of financial assets. Therefore, a balanced approach should be taken to assess different (short-term and long-term) forecasting horizons when modelling.

The risky nature of financial markets is a prerequisite for analysing and modelling the volatility of their dynamics to respond correctly to possible volatility spikes and predict their duration. The best option for this is to use time series models. The high statistical reliability of ARIMA-GARCH models is the reason why they are widely used for this purpose. Various modifications of this method were implemented in this paper in the EViews 12.

The analysis was based on daily data for 2020-2022 on interest rates in the corporate credit market. The initial time series was plotted, autocorrelation functions were plotted, and the series was tested for stationarity using the Dickey-Fuller test, which led to its differentiation and subsequent formation of the optimal ARIMA specification. When testing the residuals for autocorrelation and ARCH effect, positive results were obtained, which led to the use of the GARCH model.

The search for various GARCH specifications allowed us to choose GJR-GARCH for modelling, which considers the asymmetry of the impact of information shocks on managing the profitability of banks' active operations.

The resulting model was tested using the Leung-Box test, ARCH LM test, and Pearson test for the optimality of the specification. The model was compared with actual time series data. All the results confirmed the built models' correctness, allowing them to be used for analysis and forecasting for further periods. Further research should be directed at assessing the asymmetric flow of shocks on the volatility of the cost of borrowed resources on the part of the plaintiff, as well as assessing the dynamics of interest rate models according to the Value at Risk (VaR) concept.

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