Research article
DOI: https://doi.org/10.48554/SDEE.2023.2.1

Development of Instrumental Approaches to Forecasting the Volatility of the Return of Financial Assets

John Guyomey[1*], Andrey Zaitsev[2]

[1] Tamale Technical University, Tamale, Ghana, gayomey@hotmail.com
[2] Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russian Federation, andrey_z@mail.ru
[*] Corresponding author: gayomey@hotmail.com

Abstract

Measurement and forecasting of volatility and income correlation are achieved by non-parametric methods using high-frequency price data. Due to accurate calculations of conditional volatility and correlation forecasting, it is possible to correctly identify financial derivatives and make risk decisions and relative asset allocation decisions. This article systematises the methods for modelling the volatility of financial asset returns, considers the theoretical foundations of the generalised autoregressive conditional heteroscedasticity model, and predicts and analyses the volatility of US stock indices and stocks using high-frequency volatility estimates (realised volatility indicators). The stock indices studied are the Dow Jones Industrial Average (DJI), Standard and Poor's 500 (SP500), and the Nasdaq Composite Index (NASDAQCOMP). Stocks analysed include stocks in Microsoft, Bank of America, and Coca-Cola. The results of the study support conclusions regarding the effectiveness of volatility estimators within two Bank of America volatility forecasting models, the superiority of the HAR-RV model for trading options in a specific market, and the best model for Microsoft. Thus, systematic analysis of news information is useful for predicting the volatility of returns on financial assets, but its effectiveness depends on the individual company. Future studies should explore the usefulness of the systematic analysis of news information in predicting the volatility of returns on financial assets in other markets and for other asset classes.

Keywords: volatility, high-frequency volatility estimates, modelling and forecasting methods, yield volatility, financial assets, stock indices, US stocks, information environment

Citation: Guyomey, J., Zaytsev, A., 2023. Development of Instrumental Approaches to Forecasting the Volatility of the Return of Financial Assets. Sustainable Development and Engineering Economics 2, 1. https://doi.org/10.48554/SDEE.2023.2.1

Научная статья

УДК 519.862.6

DOI: https://doi.org/10.48554/SDEE.2023.2.1

Развитие Инструментальных Подходов к Прогнозированию Волатильности Доходности Финансовых Активов

Джон Гайомей[1*], Андрей Зайцев[2]

[1] Технический университет Тамале, Тамале, Гана, gayomey@hotmail.com
[2] Санкт-Петербургский политехнический университет Петра Великого, Санкт-Петербург, Российская Федерация, andrey_z@mail.ru
[*] Автор, ответственный за переписку: gayomey@hotmail.com

Аннотация

Измерение и прогнозирование волатильности и корреляции доходности активов осуществляется непараметрическими методами, для которых используются высокочастотные ценовые данные. Благодаря точным моделям прогнозирования условной волатильности и корреляции возможно корректное определение производных финансовых инструментов, управление рисками и принятие решений относительно распределения активов. В данной статье проведена систематизация методов моделирования волатильности доходности финансовых активов, рассмотрены теоретические основы общей модели GARCH, а также спрогнозированы и проанализировали волатильность фондовых индексов и акций США при помощи высокочастотных оценок волатильности (показатели реализованной волатильности). Изучаемыми фондовыми индексами являются индексы Dow Jones Industrial Average (DJI), Standard and Poor's 500 (SP500) и Nasdaq Composite Index (NASDAQCOMP). Акции, с другой стороны, включают акции Microsoft, Bank of America и Coca-Cola. Результатами исследования стали выводы касательно эффективности оценщиков волатильности в рамках двух моделей прогнозирования волатильности акций Bank of America, превосходство HAR-RV модели для торговли опционов определенного рынка, найден наилучшая модель для акций Microsoft. В свете приведенных выше результатов был сделан вывод о том, что систематический анализ новостной информации полезен для прогнозирования волатильности доходности финансовых активов, однако его эффективности зависит от конкретной компании. Было рекомендовано, чтобы в будущих исследованиях изучалась полезность систематического анализа новостной информации для прогнозирования волатильности доходности финансовых активов на других рынках и для других классов активов.

Ключевые слова: волатильность, высокочастотные оценки волатильности, методы моделирования и прогнозирования, волатильность доходности, финансовые активы, фондовые индексы, акции США, информационная среда.

Цитирование: Гайомей, Д., Зайцев, А., 2023. Развитие Инструментальных Подходов к Прогнозированию Волатильности Доходности Финансовых Активов. Sustainable Development and Engineering Economics 2, 1. https://doi.org/10.48554/SDEE.2023.2.1

1. Introduction

The trend towards measuring and predicting volatility and correlation of asset returns using non-parametric methods has two directions for study: continued research and development of methods for using volatility information in high-frequency data, and modelling and forecasting volatility in a multidimensional environment that is relevant to practical financial economics. The realised volatility approach, which is the most obvious nonparametric measure of volatility, deals with both directions. The benefit is the lack of modelling of intraday observations of returns, which allows for the accurate measurement and prediction of volatility in multidimensional environments. The inherent problem with modelling and forecasting conditional volatility turns is that volatility is unobservable—what is found—modelling what should be indirect. The problem of lagging returns volatility is frequently addressed by inferring volatility based on characteristic assumption parameters, using, for example, autoregressive conditional heteroscedasticity–generalised autoregressive conditional heteroscedasticity "ARCH-GARCH" or a stochastic volatility model. Therefore, it is necessary to develop alternative approaches that would allow for expanding the available price indicators with additional data available for prompt receipt and research. Such data are indicators of the news, information, and digital components that have an impact on financial market participants (Kulakov, 2004a; Kulakov, 2004b).

The main aim of this study is to develop instrumental approaches to forecasting the volatility of return on financial assets. In common parlance, volatility refers to fluctuations observed in a phenomenon over time. This is the change in the results of an uncertain variable, such as the return on assets. Volatility is a statistical measure of the degree to which a trading price changes over a given period. In terms of returns on financial assets, volatility is the standard deviation of returns on investments on an annualised basis. Alexander (2008) defined volatility as "an annual measure of dispersion in a stochastic process that is used to model logarithmic returns". Andersen et al. (2010) classified approaches to the empirical quantification of volatility into two categories: procedures based on the evaluation of parametric models (parametric measurement and volatility modelling), and direct non-parametric measurements (non-parametric measurement and volatility modelling).

Table 1 summarises the various methods for empirically quantifying return volatility within parametric and non-parametric approaches.

Table 1. Approaches to measuring and modelling the volatility of returns on financial assets

Source: compiled by the authors

Parametric measurement and volatility modelling	**Non-parametric measurement and volatility modelling**
Discrete-time parametric volatility models **Continuous time parametric volatility models** **Implied volatility based on a parametric model**	**Measures of instantaneous volatility,** $h \to 0$: 1. ARCH filters and smoothers (ARCH filters and smoothers are used to measure instantaneous volatility; filters only use information up to time σ_t^2 .τ = t while smoothers are based on τ > t. **Implemented measures of volatility, h > 0** 1. The implemented volatility methods directly measure conditional volatility over fixed time intervals. 2. They can be classified based on whether the notional volatility measurement uses only the price data contained within the [t-h,t] interval itself, or whether filtering/smoothing techniques are used to also include returns outside [t-h,t]. 3. The most obvious non-parametric measure of volatility is the "ex-post return squared spanning the time interval [t-h,t], that is, measures of realised volatility".
Methods for parametric measurement of volatility	
Volatility models in continuous time	**Discrete Time Models**

Continuous diffusion along the sampling path 1. Invariant diffusion in time 2. Ornstein-Uhlenbeck (OU) and Cox-Ingersoll-Ross (1985) processes (CIR) 3. Square root volatility model **Hopping diffusions and processes controlled by the levy**	**ARCH-GARCH models** 1. ARCH (m) (Engle, 1986) 2. GARCH (1,1) (Engle, 1986) 3. GARCH (p,q) 4. Symmetric normal GARCH Model 5. Asymmetric GARCH models 5.1 GJR-GARCH (Glosten, 1993) 5.2 Exponential GARCH (E-GARCH) (Nelson, 1991) 5.3 Asymmetric power ARCH model ("apARCH") (Ding, 1993) 5.4 Component sGARCH model ('csGARCH') (Lee and Engle, 1999) 5.5 GARCH family model ("fGARCH") (Hentschel, 1995) 6. Abnormal GARCH models 6.1 Student tGARCH (Bollerslev, 1987) 6.2 Normal mixture GARCH 6.3 Markov switching GARCH (Hamilton and Susmel, 1994) 7. Multivariate GARCH models 7.1 The VECH model presented by Bollerslev et al. (1988) 7.2 Baba-Engle-Craft-Kroner (BEKK) model formalised by Engle and Kroner (1995) 7.3 Factorial and orthogonal GARCH models 7.4 The class of constant conditional correlation (CCC) models proposed by Bollerslev (1990) 7.5 Dynamic conditional correlation (DCC) proposed by Engle III and Sheppard (2001) **Stochastic volatility models** 1. Autoregressive volatility model, or SARV(p) model: 1.1 Lognormal stochastic autoregressive volatility model 1.2 Stochastic autoregressive square root model or SR-SARV
Approaches to Modeling Financial Asset Return Volatility Using High-Frequency Data	
Method/Evaluator	**Description**
Realised variance or realised volatility (rRVar) (Andersen, 2003)	This estimator calculates daily realised variance or realised volatility (RV)
Realised covariances using subsample averaging (rAVGCov)	It calculates realised variances by averaging RV over partially overlapping grids (Zhang et al., 2005)
Modulated realised covariance (rMRCov)	The modulated realised covariance computes a univariate or multivariate pre-averaged estimator by Hautsch and Podolskij (Hautsch and Podolskij, 2013).
Two-time scale of covariance estimation (rTSCov)	It calculates the covariance matrix on a two-time scale (Zhang et al., 2005; Zhang, 2011).
Reliable estimation of covariance on a two-time scale (rRTSCov)	It calculates the robust two-time covariance matrix (Boudt and Zhang, 2015)
Implemented kernel estimator (rKernelCov)	It calculates the realised covariance using the kernel estimator
Realised two power covariance (rBPCov)	It calculates the realised BiPower covariance (rBPCov) (Barndorff-Nielsen and Shephard, 2004)
Minimum realised variance (rMinRVar)	It calculates rMinRVar (Andersen et al., 2012)
Median realised variance (rMedRVar,)	It calculates rMinRVar (Andersen et al., 2012)
Threshold Covariance (rThresholdCov)	It calculates the threshold covariance matrix (Mancini and Gobbi, 2012)
Hayashi-Yoshida Covariance (rHYCov)	It calculates the Hayashi-Yoshida covariance estimate (Hayashi and Yoshida, 2005)

Realised appearance weighted covariance (rOWCov)	It calculates the realised distance weighted covariance (rOWCov) (Boudt and Zhang, 2015)
Realised semi-dispersion of high-frequency reciprocal series (rSVar)	It calculates the realised semivariances (Barndorff-Nielsen et al., 2008)
Realised range based variance (RRV)	It computes a range-based realised estimator (Christensen and Podolskij, 2007)
Quantile-based realised variance (QRV)	It calculates the quantile realised variance (Christen et al., 2010)
Estimating duration based realised variance (DRV) in Andersen, Dobrev, and Schaumburg (2009)	It calculates the long-term realised variance (Andersen et al., 2009)

Let σ_n^2 and σ_n be the variance and volatility of the market variable on day n, respectively. Let ***S*** denote the value of the variable at the end of the *i-th* day. For σ_n, there will be dispersion and volatility will rush to day n respectively. Let ***S*** denote the value of the variable at the end of the *i-th* day. Let u_i be the continuously added variable returns during the *i-th* day:

$$u_i = ln\frac{S_i}{S_{i-1}}(1) \tag{1}$$

An objective estimate of the daily variance, σ_n^2, based on the most recent observations at u_i is:

$$\sigma_n^2 = \frac{1}{m-1}\sum_{i=1}^{m}\left(u_i - \underline{u}\right)^2 \tag{2}$$

Let's make the following changes to the above formula for estimating the variance, σ_n^2,:

- u_i is defined as the percentage change in the market variable between the end of day *i*-1 and the end of day *i*, so that

$$u_i = \frac{S_i - S_{i-1}}{S_{i-1}} \tag{3}$$

- $u_i = 0$;

- m-1 is replaced by m**.**

The above changes simplify the original variance formula to:

$$\sigma_n^2 = \frac{1}{m}\sum_{i=1}^{m}u_{n-i}^2 \tag{4}$$

However, there is still a problem with this. The problem with the above simplified formula for calculating the variance is that it gives a high weight density $u_{n-1}^2, u_{n-2}^2 ...., u_{n-m}^2$.,,, (i.e. profitability). Our goal is to conditionally estimate volatility, and predictively assign large amounts of losses. The model that adopts this is:

$$\sigma_n^2 = \sum_{i=1}^{m}\alpha_i u_{n-i}^2 \tag{5}$$

The variable α_i is the amount of weight assigned to the observation ***i*** days ago. α_i are positive and must sum to one, that is:

$$\sum_{i=1}^{m}\alpha_i = 1 \tag{6}$$

An extension of the idea in the above weighting schemes is to assume that there is a long-term average variance and that some weight should be given to it. The result is a model that takes the following form:

$$\sigma_n^2 = \gamma V_L + \sum_{i=1}^{m} \alpha_i u_{n-i}^2 \tag{7}$$

where V_L is the unconditional variance and γ is the weight given to V_L. The sum of the weights must be equal to one, so we have

$$\gamma + \sum_{i=1}^{m} \alpha_i = 1 \tag{8}$$

The above model is called the ARCH(m) model. It was introduced by Engle (1982). It estimates the variance based on the long-term mean variance, V_L, and ***m*** observations. If we $\omega = \gamma V_L$, the ARCH(m) model becomes

$$\sigma_n^2 = \omega + \sum_{i=1}^{m} \alpha_i u_{n-i}^2 \tag{9}$$

A generalisation of the above model is the GARCH model. The GARCH model generalises Engle's (1982) ARCH model. In GARCH (1,1), σ_n^2 is calculated based on the following equation:

$$\sigma_n^2 = \lambda V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-i}^2 \tag{10}$$

where λ is the weight assigned to V_L, α is the weight assigned to u_{n-1}^2, and β is the weight assigned to σ_{n-i}^2. The sum of the weights must be equal to one, so it follows that:

$$\gamma + \alpha + \beta = 1 \tag{11}$$

If we set $\omega = \gamma V_L$, GARCH(1,1) becomes:

$$\sigma_n^2 = \omega + \alpha u_{n-1}^2 + \beta \sigma_{n-i}^2 \tag{12}$$

The given estimated values ω,α and β, γ can be calculated as:

$$\gamma = 1 - \alpha - \beta \tag{13}$$

The long-term variance V_L will then be given as:

$$V_L = \frac{\omega}{\gamma} \tag{14}$$

To ensure a stable GARCH (1,1) process, it is required that:

$$\alpha + \beta < 1 \tag{15}$$

"(1, 1)" in GARCH (1,1) indicates that σ_n^2 is calculated based on the most recent observation u^2 and the most recent variance estimate, that is, σ_n^2 is calculated u_{n-1}^2 and σ_{n-i}^2. The general GARCH (p, q) model computes σ_n^2 using the most recent p observations on u^2 and the most recent q variance estimates (Hull, 2018). The main difference between parametric and non-parametric approaches is related to the choice of the time interval to which the measure of volatility refers, for example, a discrete interval, where h > 0, or a point in time (instantaneous) measure, where h → 0.

Considering the ARCH-GARCH models, there are times when volatility is unusually high, and there are times when volatility is unusually low. There is extensive empirical evidence for the clustering of volatility in financial markets, dating back to Mandelbrot (1963). Volatility clustering has significant implications for option pricing, hedging, and risk measurement (Andersen et al., 2006.; Kornikov et al., 2002). A big shock to markets leads to changes in volatility and further increases the likelihood of another big shock. This must be considered when pricing options and assessing portfolio risks (Egorova, 2002; Senko, 2001).

GARCH models have been introduced to capture the clustering of returns volatility (Chekulaev et al., 2004). Given that GARCH models reflect volatility clustering, their predictions are not equal to the current estimate. GARCH volatility can be above or below average in the short term, but as the forecast horizon increases, GARCH volatility forecasts converge towards long-term volatility. The advantage of GARCH is that it calculates short- and medium-term volatility forecasts based on a robust econometric model. GARCH models have been very successful in predicting notional return volatility. They have been finalised and expanded to include additional features. Traditional GARCH models have been extended by incorporating implemented measures into the GARCH equation to enhance their predictive capabilities. Important works in this direction include Engle and Gallo (2006), Hansen (2012), Shepard and Sheppard (2010).

2. Materials and Methods

We estimated, predicted, and analysed the volatility of US stock indices and stocks using existing high-frequency volatility estimates (realised volatility measures). The stock indices studied are the Dow Jones Industrial Average (DJI), Standard and Poor's 500 (SP500), and the Nasdaq Composite Index (NASDAQCOMP). Stocks include stocks in Microsoft, Bank of America, and Coca-Cola. We also valued call and put options on Bank of America, Coca-Cola, and Microsoft using various high-frequency volatility forecasts. The study used both primary and secondary data sources. Daily and intraday data on the prices of the studied stocks and indices, as well as data on option contracts, were obtained from official foreign sources that are participants in the US financial market. Secondary data were obtained based on an in-depth study of scientific periodicals, as well as reference books, monographs, and textbooks in the subject area of research.

To evaluate and predict the volatility of the above stocks and stock indices, we downloaded historical closing price data (data for 5 minutes) for these assets from Finam (Broker Finam, 2022)1. The sample data covered the period 2020.02.06–2021.09.02. We also downloaded option chains for Microsoft (MSFT), Bank of America (BAC), and Coca-Cola (KO) at the end of each trading day from Yahoo Finance2. Option chains covered the period from 2021.08.02 to 2021.09.02. To estimate the volatility of stocks underlying option contracts, this study used the recently proposed high-frequency volatility estimates available in the volatility literature. Table 1 provides data to describe these volatility estimates. To keep tabular presentations simple, we have abbreviated the above high-frequency volatility estimates as follows: RV, AV, MRC, TS, RTS, Epa, Par, mTH, BP, MiRV, MeRV, Thr, HY, OW, SV.do, SV.up, RRV, QRV, and mQRV.

To predict realised volatility, this study used Corsi's (2009) heterogeneous autoregressive model of realised variance (HAR-RV model). The dynamics of the HAR-RV model are represented by:

$$RV_{t+1d}^{(d)} = c + \beta^{(d)} RV_t^{(d)} + \beta^{(w)} RV_t^{(w)} + \beta^{(m)} RV_t^{(m)} + \varepsilon_{t+1d}^{(d)} \tag{16}$$

$RV_t^{(d)}$ is the realised volatility for day *t*.

$RV_t^{(w)}$ is the average realised volatility for the last week (last 5 trading days), calculated as follows:

$$RV_t^{(w)} = \frac{1}{5}\left(RV_t^{(d)} + RV_{t-1}^{(d)} + RV_{t-2}^{(d)} + RV_{t-3}^{(d)} + RV_{t-4}^{(d)}\right) \tag{17}$$

$RV_t^{(m)}$ is the average realised volatility for the last month (last 22 trading days), calculated as follows:

$$RV_t^{(m)} = \frac{1}{22}\left(RV_t^{(d)} + RV_{t-1}^{(d)} + \ldots + RV_{t-20}^{(d)} + RV_{t-21}^{(d)}\right) \tag{18}$$

The HAR-RV model was estimated using the ordinary least squares method, assuming that at

[1] Broker Finam. URL: http//finam.ru/. Access date 04/10/2022
[2] Information about financial instruments. URL: https://finance.yahoo.com/. Access date 04/10/2022

time *t* the conditional mean value ε_(t+1d)^((d)) is zero. For our study, we used a HAR-RV model with the following characteristics: Type, HAR; Lags, 1 5 22; Window Type, "rolling"; and Maximum lags, 22.

We used a 5-minute series of returns (30,808 5-returns) to estimate and predict stock volatility. We were of the opinion that almost all information from high-frequency data is contained in 5-minute data, so we decided to estimate and predict stock volatility using a 5-minute sampling rate. To value option contracts, this study used the Black–Scholes–Merton formulas for the prices of European call and put options in determining the price of option contracts.

3. Results and Discussion

The most popular stock indices for tracking the dynamics of the US stock market are the Dow Jones Industrial Average (DJIA), the Standard and Poor's 500 (S&P500), and the Nasdaq Composite (NASDAQCOM). We estimated the realised volatility of these stock indices for the period 2020.01.06-2021.10.15 using high-frequency volatility estimates. The figures below show volatility estimates obtained for the period under review (Figure 1) (Gayomey, 2022).

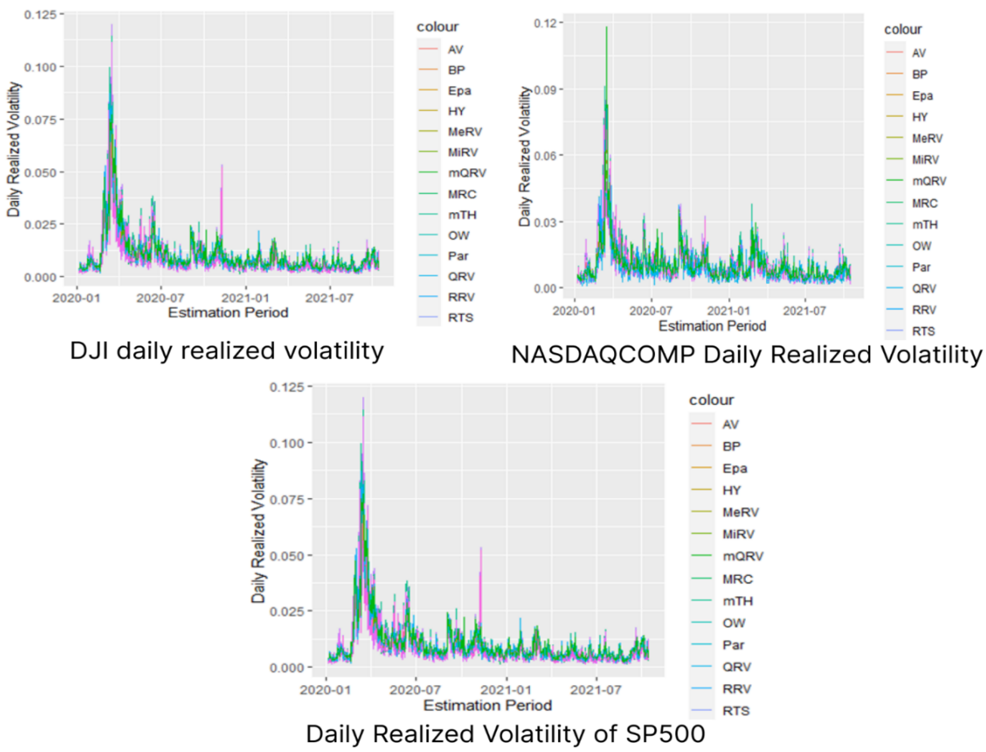


Figure 1. DJI daily realised volatility, NASDAQCOMP Daily Realised Volatility, Daily Realised Volatility of SP500

The realised volatility of all three stock indices shows that the US stock market was volatile towards the end of the first quarter of 2020 (volatility of 10% and above). The figure also shows that from the beginning of the second quarter of 2020 until the end of the evaluation period (2021.10.15), realised volatility has consistently been below 5%, indicating a stable price level in the market. Estimates, however, show that volatility changes over time. Volatility clustering was also observed. We then projected volatility for the Dow Jones Industrial Average, S&P 500, and Nasdaq Composite for the next 30 days (2021.10.18–2021.11.26) using high-frequency volatility estimates. We also compared the volatility forecasts with the CBOE Volatility Index (VIX) for the next 30 days (2021.10.18–2021.11.26) to assess the accuracy of the forecast. The CBOE Volatility Index (VIX) is a popular measure of expected stock market volatility based on S&P 500 index options. It is based on the prices of options on the SPX index with the nearest expiration dates and thus gives a 30-day forecast of volatility in advance (Gayomey, 2022a).

Figures 2-4 show the expected annual change in the Dow Jones Industrial Average, Nasdaq Composite, and S&P500 over the next 30 days: 2021.10.16–2021.11.26, according to the realised volatility approach.

Expected annual change in the DJIA over the next 30 days: 2021.10.16-2021.11.26

Implemented measures	Volatility forecast	CBOE Volatility Index	Forecast Loss
RV	16.2897	16.3000	0.0103
AV	12.3653	16.3000	3.9347
MRC	8.8899	16.3000	7.4101
TS	10.7024	16.3000	5.5976
RTS	9.4100	16.3000	6.8900
Epa	14.8305	16.3000	1.4695
Par	14.8305	16.3000	1.4695
mTH	14.8305	16.3000	1.4695
BP	12.4816	16.3000	3.8184
MiRV	11.5836	16.3000	4.7164
MeRV	11.2091	16.3000	5.0909
Thr	10.2701	16.3000	6.0299
HY	10.9682	16.3000	5.3318
OW	8.7731	16.3000	7.5269
SV.do	9.9558	16.3000	6.3442
SV.up	12.4042	16.3000	3.8958
RRV	13.7790	16.3000	2.5210
QRV	12.9370	16.3000	3.3630
mQRV	12.7933	16.3000	3.5067

Note: The highlighted cell indicates high-frequency volatility estimators whose volatility forecast was close to that of the CBOE Volatility Index (VIX).)

Figure 2. Expected annual change in the DJIA over the next 30 days: 2021.10.16–2021.11.26

Expected annual change in the NASDAQ COMP over the next 30 days: 2021.10.16-2021.11.26

Implemented measures	Volatility forecast	CBOE Volatility Index	Forecast Loss
RV	16.2312	16.3000	0.0688
AV	22.6563	16.3000	-6.3563
MRC	11.5679	16.3000	4.7321
TS	12.3602	16.3000	3.9398
RTS	10.9333	16.3000	5.3667
Epa	16.9672	16.3000	-0.6672
Par	16.9672	16.3000	-0.6672
mTH	16.9672	16.3000	-0.6672
BP	11.1340	16.3000	5.1660
MiRV	10.5268	16.3000	5.7732
MeRV	10.4024	16.3000	5.8976
Thr	9.6806	16.3000	6.6194
HY	11.0299	16.3000	5.2701
OW	8.7697	16.3000	7.5303
SV.do	10.3777	16.3000	5.9223
SV.up	12.1616	16.3000	4.1384
RRV	13.4633	16.3000	2.8367
QRV	10.3678	16.3000	5.9322
mQRV	11.8126	16.3000	4.4874

Note: The highlighted cell indicates high-frequency volatility estimators whose volatility forecast was close to that of the CBOE Volatility Index (VIX).)

Figure 3. Expected annual change in the NASDAQ COMP over the next 30 days: 2021.10.16-2021.11.26

Expected annual change in the SP500A index over the next 30 days:
2021.10.16-2021.11.26

Implemented measures	Volatility forecast	CBOE Volatility Index	Forecast Loss
RV	14.8594	16.3000	1.4406
AV	20.4546	16.3000	-4.1546
MRC	9.2252	16.3000	7.0748
TS	10.2678	16.3000	6.0322
RTS	9.0695	16.3000	7.2305
Epa	15.2176	16.3000	1.0824
Par	15.2176	16.3000	1.0824
mTH	15.2176	16.3000	1.0824
BP	9.9485	16.3000	6.3515
MiRV	9.5236	16.3000	6.7764
MeRV	9.3557	16.3000	6.9443
Thr	8.6203	16.3000	7.6797
HY	9.5312	16.3000	6.7688
OW	7.9498	16.3000	8.3502
SV.do	8.9054	16.3000	7.3946
SV.up	11.4562	16.3000	4.8438
RRV	11.6070	16.3000	4.6930
QRV	8.6699	16.3000	7.6301
mQRV	10.1537	16.3000	6.1463

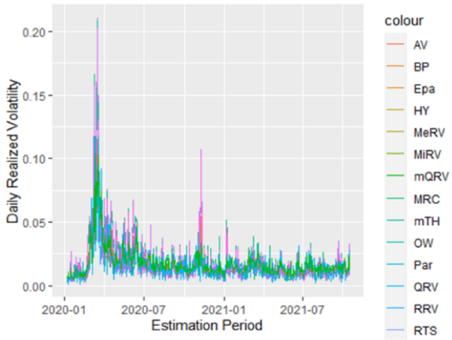
Note: The highlighted cell indicates high-frequency volatility estimators whose volatility forecast was close to that of the CBOE Volatility Index (VIX).)

Figure 4. Expected annual change in the SP500A index over the next 30 days: 2021.10.16-2021.11.26

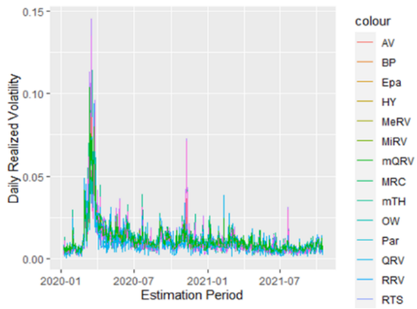
According to Figures 2–4, for the DJI and NASDAQCOMP indices, the realised volatility (RV) estimate had the lowest forecast error compared to the CBOE Volatility Index, while for the SP500 index, the realised core estimates (Epa, Par, and MTH) performed the best. The results in the tables also show that the projections for the realised volatility and the realised core estimates for the three indices are, in most cases, very close to the forecast for the CBOE volatility index; that is, the forecast of these two estimates is very similar to the CBOE Volatility Index forecast. The tables also show that more high-frequency volatility estimators provide lower volatility forecasts for the US stock market during the period under review. Consider specific examples (Gayomey, 2022b).

Estimating and predicting the volatility of Bank of America, Coca-Cola, and Microsoft stocks

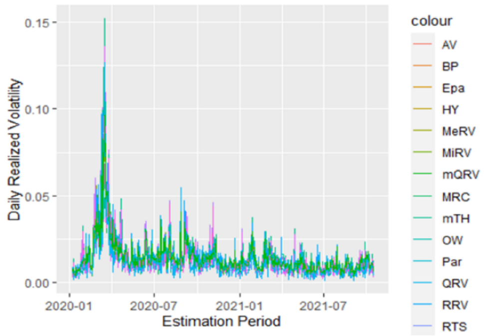
We predicted and analysed the annual volatility of these stocks. The figures below show the implemented volatility estimates for Bank of America, Coca-Cola, and Microsoft for the period 2020.01.06–2021.10.15 (fig. 5).



Daily realized volatility for Bank of America



Daily realized volatility for Coca-Cola



Daily realized volatility for Microsoft

Figure 5. Daily realised volatility for Bank of America, for Coca-Cola, and Microsoft

The charts above show the realised volatility, confirming the volatility situation in the US stock market at the end of the first quarter of 2020, which remains relatively stable during the remainder of the forecast period. Of all three stocks, Microsoft shares experienced the least volatility during the remainder of the forecast period (Gayomey, 2022a).

Figure 6 shows the annual volatility forecast for Bank of America, Coca-Cola, and Microsoft.

Annual Volatility Forecast for BAC, KO and MSFT: Realized Volatility Metrics

Implemented measures	BAC	KO	MSFT
RV	0.2922	0.1802	0.2145
AV	0.2327	0.1454	0.1816
MRC	0.1955	0.1045	0.1385
TS	0.2213	0.1352	0.1809
RTS	0.2069	0.1174	0.1516
Epa	0.2945	0.1689	0.2094
Par	0.2945	0.1689	0.2094
mTH	0.2945	0.1689	0.2094
BP	0.2377	0.1567	0.1833
MiRV	0.2372	0.1546	0.1828
MeRV	0.2294	0.1474	0.1788
Thr	0.2194	0.1309	0.1667
HY	0.2245	0.1432	0.1814
OW	0.2060	0.1147	0.1517
SV.do	0.2030	0.1335	0.1653
SV.up	0.2060	0.1248	0.1453
RRV	0.2608	0.1708	0.2227
QRV	0.1961	0.1438	0.1762
mQRV	0.2397	0.1639	0.1939

Note: Cells highlighted in blue indicate the minimum volatility forecast, while cells highlighted in pink indicate the maximum volatility forecast

Figure 6. Annual volatility forecast for BAC, KO, and MSFT: Realised volatility metrics

Figure 6 shows that the minimum volatility prediction for all three stocks is given by a modulated realised covariance (MRC) estimate. The table also shows that the maximum volatility forecast for Bank of America, Coca-Cola, and Microsoft was derived using realised variance (RV), realised core (Epa, Par, and mTH), and realised range (RRV) volatility estimates, respectively. Table 5 further confirms that all volatility estimates project high volatility for Bank of America (annualised volatility forecast of at least 19% and a maximum of 29%). It can also be seen that Coca-Cola's year-on-year volatility forecast across all volatility estimates is less than 19%, with a minimum volatility forecast of 10%. For Microsoft's stock, the year-on-year volatility forecast ranges from 13.8% to 22%. The forecast above clearly shows that Bank of America is expected to be more volatile over the coming year compared to other stocks, while Coca-Cola is expected to remain more stable over the same period (Gayomey, 2022b).

4. Conclusion

The purpose of this article was to develop methods for modelling and forecasting the volatility of financial asset returns based on the assessment of high-frequency data and the dynamics of the information environment. To this end, we reviewed and systematised theoretical and methodological approaches to measuring and forecasting the volatility of return on financial assets. We also estimated, predicted, and analysed the volatility of stock indices and US stocks using existing high-frequency volatility estimates (realised volatility measures). The stock indices studied are the Dow Jones Industrial Average (DJI), Standard and Poor's 500 (SP500), and the Nasdaq Composite Index (NASDAQCOMP). Stocks, on the other hand, include stocks in Microsoft, Bank of America, and Coca-Cola. We also valued call and put options on Microsoft, Bank of America, and Coca-Cola using various high-frequency volatility forecasts.

The results of the analysis and systematisation of theoretical and methodological approaches to measuring and forecasting the volatility of the profitability of financial assets have shown that the existing approaches and methods for assessing and forecasting the volatility of the profitability of financial assets have some limitations that make the use of these methods for predicting volatility unsatisfactory. In particular, within the framework of the GARCH model and stochastic volatility, the following are salient:

- Volatility is usually derived from daily returns squared, which are objective but noisy estimates of daily conditional volatility.

- High-frequency data are rarely used.

- Evaluation of GARCH and stochastic volatility models is difficult.

- Evaluation of these models often gives unsatisfactory results. Forecasts are inaccurate.

- Standardised returns usually have fat tails, which leads to the search for suitable error distributions that can adequately reflect the empirical distributions of returns.

- Multivariate modelling of volatility and correlation can be extremely complex, and practical models are often only applicable to very small dimensions.

- These volatility methods do not take into account changes in the news background of the digital information environment.

In the high-frequency volatility approach (HAR-RV model), the realised volatility plotted from the highest frequency data should give the best possible estimate of the cumulative volatility, that is, *Iv* as $m \rightarrow \infty$. However, in practice, the sampling rate is limited by the actual supply or transaction frequency. Moreover, very high-frequency prices are affected by market microstructure, such as supply and demand rebound effects, price discreteness, etc., leading to bias and inconsistency in realised volatility. These methods for assessing volatility also do not consider changes in the news background of the digital information environment.

These findings prompt the conclusion that the systematic analysis of news information is useful for predicting the volatility of returns on financial assets, but its effectiveness depends on the individual company. Future studies are encouraged to explore the usefulness of the systematic analysis of news information in predicting the volatility of returns on financial assets in other markets and for other asset classes.

Acknowledgments

The research was financed as part of the project “Development of a methodology for instrumental base formation for analysis and modeling of the spatial socio-economic development of systems based on internal reserves in the context of digitalization” (FSEG-2023-0008)

References

Alexander, C., 2008. Market risk analysis, practical financial econometrics, second ed. John Wiley & Sons.

Andersen, T.G., Bollerslev, T., Christoffersen, P.F., Diebold, F.X., 2006. Volatility and correlation forecasting. Handbook of Economic Forecasting 1, 777–878.

Andersen, T.G., Bollerslev, T., Diebold, F.X., 2010. Parametric and nonparametric volatility measurement, in: Handbook of financial econometrics: Tools and techniques. North-Holland, pp. 67–137.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Labys, P., 2003. Modeling and forecasting realized volatility. Econometrica 71 (2), 579 625.

Andersen, T.G., Dobrev, D., Schaumburg, E., 2009. Duration-based volatility estimation. Institute of Economic Research, Hitotsubashi University.

Andersen, T.G., Dobrev, D., Schaumburg, E., 2012. Jump-robust volatility estimation using nearest neighbor truncation. Journal of Econometrics 169 (1), 75–93.

Barndorff-Nielsen, O.E., Hansen, P.R., Lunde, A., Shephard, N., 2008. Designing realized kernels to measure the ex post variation of equity prices in the presence of noise. Econometrica 76 (6), 1481–1536.

Barndorff-Nielsen, O.E., Shephard, N., 2004. Measuring the impact of jumps in multivariate price processes using bipower covariation. Discussion paper, Nuffield College, Oxford University.

Bollerslev, T., 1987. A conditionally heteroskedastic time series model for speculative prices and rates of return. The Review of Economics and Statistics 542–547.

Bollerslev, T., Engle, R.F., Wooldridge, J.M., 1988. A capital asset pricing model with time-varying covariances. Journal of Political Economy 96 (1), 116–131.

Boudt, K., Zhang, J., 2015. Jump robust two time scale covariance estimation and realized volatility budgets. Quantitative Finance 15 (6), 1041–1054.

Chekulaev, M., 2004. Volatility cannot be understood with the mind. Currency Speculator 7(57), 22-25.

Christensen, K., Oomen, R., Podolskij, M., 2010. Realised quantile-based estimation of the integrated variance. Journal of Econometrics 159 (1), 74–98.

Christensen, K., Podolskij, M. (2007). Realized range-based estimation of integrated variance. Journal of Econometrics 141 (2), 323–349.

Corsi, F., 2009. A simple approximate long-memory model of realized volatility. Journal of Financial Econometrics 7 (2), 174–196.

Ding, Z., Granger, C.W., Engle, R.F., 1993. A long memory property of stock market returns and a new model. Journal of Empirical Finance 1(1), 83–106.

Egorova, E.E., 2002. Once again about the essence of risk and a systematic approach. Risk management, 2, 9-12.

Engle III, R.F., Sheppard, K., 2001. Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH.

Engle, R., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics 20(3), 339–350.

Engle, R.F., Bollerslev, T., 1988. Modelling the persistence of conditional variances. Econometric Reviews 5 (1), 1–50.

Engle, R.F., Kroner, K. F., 1995. Multivariate simultaneous generalized ARCH. Econometric theory, 11(1), 122–150.

Engle, R. F., Gallo, G.M., 2006. A multiple indicators model for volatility using intra-daily data. Journal of Econometrics 131 (1–2), 3–27.

Gayomey, D., 2022a. Forecasting the volatility of US stock market indices using GARCH models and high-frequency volatility estimates. Economic Sciences 208, 59–64.

Gayomey, D., 2022b. High-frequency volatility assessment and option pricing. Bulletin of the Altai Academy of Economics and Law 4, 138–149.

Glosten, L. R., Jagannathan, R., Runkle, D. E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance, 48, 1779–1801.

Grigoryeva, I.L., Filippov L.A., 2001. Estimation of economic risk. Risk Management 3, 6-12.

Hamilton, J.D., Susmel, R., 1994. Autoregressive conditional heteroskedasticity and changes in regime. Journal of Econometrics 64 (1–2), 307–333.

Hansen, P. R., Huang, Z., Shek, H. H., 2012. Realized GARCH: A joint model for returns and realized measures of volatility. Journal of Applied Econometrics 27 (6), 877–906.

Hautsch, N., Podolskij, M., 2013. Preaveraging-based estimation of quadratic variation in the presence of noise and jumps: theory, implementation, and empirical evidence. Journal of Business & Economic Statistics 31 (2), 165–183.

Hayashi, T., Yoshida, N., 2005. On covariance estimation of non-synchronously observed diffusion processes. Bernoulli 11 (2), 359–379.

Hentschel, L., 1995. All in the family nesting symmetric and asymmetric garch models. Journal of Financial Economics, 39 (1), 71–104.

Hull, J.C. (2018). Options, Futures, and other Derivatives, tenth ed. Pearson Education.

Kornikov, V.V., Seregin I.A., Khovanov N.V., 2002. Multi-criteria assessment of financial risks under conditions of uncertainty. St. Petersburg: Publishing house of St. Petersburg University, pp. 93.

Krutyakova, Y., 2006. Time of risk and risks of time. Risk 4, 46–48.
Kulakov, A.E., 2004a. Volatility of profitability and an approach to building a control and risk management system. Banking 6, 35–38.
Kulakov, A.E., 2004b. Yield volatility as an integral indicator of risk. Finance and credit 16(154), 25-30.
Lee, G.J., Engle, R.F., 1999. A permanent and transitory component model of stock return volatility. In cointegration causality and forecasting a festschrift in honor of Clive WJ Granger. Oxford University Press, pp. 475–497.
Mancini, C., Gobbi, F., 2012. Identifying the Brownian covariation from the co-jumps given discrete observations. Econometric Theory 28 (2), 249–273.
Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica: Journal of the Econometric Society 347–370.
Senko V., 2001 Changing approach to risk management in large companies. Risk Management 3, 3–5.
Shephard, N., Sheppard, K. 2010. Realising the future: Forecasting with high-frequency-based volatility (HEAVY) models. Journal of Applied Econometrics 25 (2), 197–231.
Subbotin, A., Buyanova, E., 2008. Volatility and correlation of stock indices on multiple horizons. Risk Management 3 (47).
Zhang, L. 2011. Estimating covariation: Epps effect, microstructure noise. Journal of Econometrics, 160 (1), 33–47.
Zhang, L., Mykland, P.A., Aït-Sahalia, Y., 2005. A tale of two time scales: Determining integrated volatility with noisy high-frequency data. Journal of the American Statistical Association, 100 (472), 1394–1411.

Список источников

Alexander, C., 2008. Market risk analysis, practical financial econometrics, 2d Editio. ed. John Wiley & Sons.
Andersen, T. G., Bollerslev, T., Christoffersen, P. F., Diebold, F. X., 2006. Volatility and correlation forecasting. Handbook of economic forecasting, 1, 777–878.
Andersen, T. G., Bollerslev, T., Diebold, F. X., 2010. Parametric and nonparametric volatility measurement, in: Handbook of financial econometrics: Tools and techniques. North-Holland, pp. 67–137.
Andersen, T. G., Bollerslev, T., Diebold, F. X., Labys, P., 2003. Modeling and forecasting realized volatility. Econometrica, 71(2), 579–625.
Andersen, T. G., Dobrev, D., Schaumburg, E., 2009. Duration-based volatility estimation. Institute of Economic Research, Hitotsubashi University.
Andersen, T. G., Dobrev, D., Schaumburg, E., 2012. Jump-robust volatility estimation using nearest neighbor truncation. Journal of Econometrics, 169(1), 75–93.
Barndorff-Nielsen, O. E., Shephard, N., 2004. Measuring the impact of jumps in multivariate price processes using bipower covariation. Discussion paper, Nuffield College, Oxford University.
Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A., Shephard, N., 2008. Designing realized kernels to measure the ex post variation of equity prices in the presence of noise. Econometrica, 76(6), 1481–1536.
Bollerslev, T., 1987. A conditionally heteroskedastic time series model for speculative prices and rates of return. The review of economics and statistics, 542–547.
Bollerslev, T., Engle, R. F., Wooldridge, J. M., 1988. A capital asset pricing model with time-varying covariances. Journal of political Economy 96(1), 116–131.
Boudt, K., Zhang, J., 2015. Jump robust two time scale covariance estimation and realized volatility budgets. Quantitative Finance 15(6), 1041–1054.
Chekulaev, M., 2004. Volatility cannot be understood with the mind. Currency Speculator 7(57), 22-25.
Christensen, K., Podolskij, M. (2007). Realized range-based estimation of integrated variance. Journal of Econometrics 141(2), 323–349.
Christensen, K., Oomen, R., Podolskij, M., 2010. Realised quantile-based estimation of the integrated variance. Journal of Econometrics 159(1), 74–98.
Corsi, F., 2009. A simple approximate long-memory model of realized volatility. Journal of Financial Econometrics 7(2), 174–196.
Ding, Z., Granger, C. W., Engle, R. F., 1993. A long memory property of stock market returns and a new model. Journal of empirical finance 1(1), 83–106.
Engle, R. F., Bollerslev, T., 1988. Modelling the persistence of conditional variances. Econometric reviews 5(1), 1–50.
Engle, R. F., Gallo, G. M., 2006. A multiple indicators model for volatility using intra-daily data. Journal of Econometrics 131(1-2), 3–27.
Glosten, L. R., Jagannathan, R., Runkle, D. E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. The journal of finance 48, 1779–1801.
Hansen, P. R., Huang, Z., Shek, H. H., 2012. Realized GARCH: a joint model for returns and realized measures of volatility. Journal of Applied Econometrics 27(6), 877–906.
Hayashi, T., Yoshida, N., 2005. On covariance estimation of non-synchronously observed diffusion processes. Bernoulli 11(2), 359–379.
Hentschel, L., 1995. All in the family nesting symmetric and asymmetric garch models. Journal of financial economics 39(1), 71–104.
Nelson, D. B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica: Journal of the Econometric Society, 347–370.
Lee, G.J., Engle, R.F., 1999. A permanent and transitory component model of stock return volatility.In Cointegration Causality and Forecasting A Festschrift in Honor of Clive WJ Granger, Oxford University Press, 475–497.
Hamilton, J. D., Susmel, R., 1994. Autoregressive conditional heteroskedasticity and changes in regime. Journal of econometrics 64(1-2), 307–333.
Engle, R. F., Kroner, K. F., 1995. Multivariate simultaneous generalized ARCH. Econometric theory 11(1), 122–150.
Engle III, R. F., Sheppard, K., 2001. Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH.
Engle, R., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics 20(3), 339–350.
Hautsch, N., Podolskij, M., 2013. Preaveraging-based estimation of quadratic variation in the presence of noise and jumps: theory, implementation, and empirical evidence. Journal of Business & Economic Statistics 31(2), 165–183.
Hull, J.C. (2018). Options, Futures, and other Derivatives. Tenth Edition, Pearson Education, Inc.
Mancini, C., Gobbi, F., 2012. Identifying the brownian covariation from the co-jumps given discrete observations. Econometric Theory 28(2), 249–273.

Shephard, N., Sheppard, K. 2010. Realising the future: forecasting with high-frequency-based volatility (HEAVY) models. Journal of Applied Econometrics 25(2), 197–231.
Subbotin, A., Buyanova, E., 2008. Volatility and correlation of stock indices on multiple horizons. Risk management, 3(47).
Zhang, L. 2011. Estimating covariation: Epps effect, microstructure noise. Journal of Econometrics, 160(1), 33–47.
Zhang, L., Mykland, P. A., Aït-Sahalia, Y., 2005. A tale of two time scales: Determining integrated volatility with noisy high-frequency data. Journal of the American Statistical Association 100(472), 1394–1411.
Гайомей, Д., 2022. Прогнозирование волатильности индексов фондового рынка США с использованием моделей GARCH и высокочастотных оценок волатильности. Экономические науки 208, 59–64.
Гайомей, Д., 2022. Высокочастотная оценка волатильности и ценообразование опционов. Вестник Алтайской академии экономики и права 4, 138–149.
Григорьева И.Л., Филиппов Л.А., 2001. Оценка экономического риска. Управление рисками 3, 6–12.
Егорова Е.Е., 2002. Еще раз о сущности риска и системном подходе. Управление рисками 2, 9–12.
Корников В.В., Серегин И.А., Хованов Н.В., 2002. Многокритериальная оценка финансовых рисков в условиях неопределенности. СПб.: Изд-во СПбГУ, 93 с.
Крутякова Ю., 2006. Время риска и риски времени. РИСК 4, 46–48.
Кулаков А.Е. 2004. Волатильность доходности и подход к построению системы контроля и управления рисками. Банковское дело 6, 35–38.
Кулаков А.Е., 2004. Волатильность доходности как интегральный показатель риска. Финансы и кредит 16(154), 25–30.
Сенько В., 2001 Изменение подхода к управлению рисками в крупных компаниях. Управление рисками 3, 3–5.
Субботин А., Буянова Е., 2008. Волатильность и корреляция фондовых индексов на нескольких горизонтах. Управление рисками 3 (47).

The article was submitted 02.05.2023, approved after reviewing 28.05.2023, accepted for publication 03.06.2023.

Статья поступила в редакцию 02.05.2023, одобрена после рецензирования 28.05.2023, принята к публикации 03.06.2023.

About authors:

1. John Gayomey, Lecturer, Department of Accountancy, Tamale Technical University, Tamale, Ghana. gayomey@hotmail.com

2. Andrey Zaytsev, Doctor of Economics, Professor, Graduate School of Industrial Economics, Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russian Federation. https://orcid.org/0000-0002-4372-4207, andrey_z7@mail.ru

Информация об авторах:

1. Джон Гайомей, преподаватель кафедры бухгалтерского учета Технического университета Тамале, Тамале, Гана. gayomey@hotmail.com

2. Андрей Зайцев, доктор экономических наук, профессор, Высшая инженерно-экономическая школа, Санкт-Петербургский политехнический университет Петра Великого, Санкт-Петербург, Российская Федерация. https://orcid.org/0000-0002-4372-4207, andrey_z7@mail.ru