Digital Gold Price Prediction on Indogold Platform Using Generalized Autoregressive Conditional Heteroskedasticity Model

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ABSTRACT

The digital gold market in Indonesia has experienced significant growth, with transaction values reaching IDR 53.3 trillion during January–November 2024, representing a 556 percent increase compared to the previous year. Despite this rapid growth, digital gold prices exhibit high volatility characterized by volatility clustering and conditional heteroskedasticity that conventional time series models cannot adequately capture. Although the GARCH model has been widely applied to predict physical gold prices, no prior study has specifically examined digital gold price volatility on Indonesian fintech-based trading platforms. This study aims to construct a univariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model based solely on historical price movements to predict digital gold prices on the Indogold platform and evaluate its predictive accuracy. Accordingly, the proposed model relies exclusively on historical price data and does not incorporate external macroeconomic variables, such as exchange rates, inflation, interest rates, or international gold prices. The data used consisted of weekly closing prices of digital gold on the Indogold platform from January 5, 2020, to December 29, 2024, totaling 261 observations. Analysis was conducted using RStudio software through logarithmic return calculation, data splitting via trial and error (selected proportion 80%:20%), Augmented Dickey-Fuller stationarity testing, ARMA order identification through ACF and PACF plots followed by AIC-based model selection, ARCH-LM effect testing, GARCH model estimation, and Ljung-Box and ARCH-LM diagnostic testing. The best model identified was ARMA(2,2)-GARCH(1,1) with the conditional variance equation $\sigma_t^2 = 0.000073 + 0.405334\varepsilon_{t-1}^2 + 0.476482\sigma_{t-1}^2$. The model passed all diagnostic tests with Ljung-Box p-value = 0.3362 and ARCH-LM p-value = 0.9999. Prediction accuracy evaluation on the test data yielded MAPE = 1.8141%, which is categorized as highly accurate according to Lewis (1982), indicating strong price forecasting performance; however, its suitability as an investment decision-making tool requires further evaluation of return, risk, and trading strategy performance beyond price accuracy alone.

I. INTRODUCTION

The rapid advancement of digital technology has significantly transformed the global financial sector, marked by the emergence of financial technology (fintech)-based investment instruments that change how people access and manage their investments. In Indonesia, this growth has accelerated alongside high internet penetration, rising digital literacy, and the widespread availability of investment applications. According to Bank Indonesia [1], the value of digital transactions, including stocks, bonds, mutual funds, and alternative assets, reached IDR 1,200 trillion in 2022, indicating strong public confidence in digital investing.

Among various digital investment instruments, digital gold has emerged as one of the fastest-growing innovations, combining the safe-haven characteristics of gold with the convenience of digital technology. Data from the Commodity Futures Trading Supervisory Agency (Bappebti) [2] recorded digital gold transaction values of IDR 53.3 trillion during January–November 2024, an increase of 556 percent compared to IDR 8.1 trillion in the same period of 2023, with volume reaching 43.9 tonnes or an increase of 430.6 percent. This surge positions digital gold as the fastest-growing investment instrument in Indonesia, while also reflecting growing public demand for investment vehicles that are easily accessible yet preserve intrinsic value.

However, behind this rapid growth, digital gold prices are highly volatile and difficult to predict. Global gold prices, as the primary benchmark for digital gold, respond dynamically to market sentiment and geopolitical conditions. Pegadaian [3] noted that gold prices surpassed US$2,000 per troy ounce in 2020 amid global uncertainty during the pandemic, fell to around US$1,800 in 2023 following the Federal Reserve's tightening, and surged by 29.5% in 2024, driven by geopolitical tensions and expectations of global rate cuts. On digital platforms, this volatility is further amplified by retail investor behavior that tends to be reactive to short-term price changes, the ease of instant transaction features on applications, and variations in price-setting mechanisms across platforms. As a result, digital gold investors, particularly retail investors who dominate platforms such as Indogold, are highly vulnerable to suboptimal investment decisions due to their inability to anticipate future price movements.

This condition underscores the urgent need for a reliable digital gold price prediction model as a decision-support tool for investment. The ability to predict prices enables investors to plan buying and selling strategies more systematically, minimize loss risk exposure, and optimize portfolio returns [4]. Beyond individual benefit, accurate digital gold price prediction is also relevant for platform managers in maintaining liquidity stability and for regulators in formulating more effective supervisory policies. Therefore, the development of an appropriate prediction model for digital gold prices represents a pressing need from both academic and practical perspectives.

Despite this urgency, empirical research specifically focused on predicting digital gold prices on Indonesian fintech platforms remains extremely limited. Previous studies have generally focused on physical gold as a safe-haven asset and its relationship with stock markets [5], or the influence of macroeconomic variables on global gold prices [6]. More recent works have applied the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to predict physical gold prices in Indonesia, including Sanusi et al. [7], who predicted Antam gold prices using GARCH, and Sari et al. [8], who applied the ARIMA-GARCH model to predict Indonesian gold prices. However, these studies remain limited to physical gold traded in conventional markets. To date, no study has specifically applied the GARCH model to predict digital gold prices on fintech-based investment platforms in Indonesia.

This research gap remains significant. Although digital gold prices on platforms such as Indogold reference physical gold prices as a benchmark, their time-series behavior exhibits distinct characteristics. Prices formed on fintech platforms are influenced by each platform’s own pricing mechanism, service fees, platform liquidity, and the behavior of retail investors who dominate digital transactions factors not fully reflected in physical gold prices in conventional markets. Furthermore, the absence of a prediction model built specifically from Indonesian digital gold platform historical data makes this research academically and practically urgent, particularly for retail investors who rely on such platforms as a reference for investment decision-making.

To address the challenge of digital gold price prediction, a method is needed that can capture two statistical characteristics commonly found in high-frequency financial data: volatility clustering and conditional heteroskedasticity. Conventional time series models, such as ARIMA, can only model the conditional mean and assume constant variance, thereby failing to capture volatility clustering and conditional heteroskedasticity prevalent in financial asset price data [9]. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, developed by Bollerslev [10], addresses this limitation by modeling time-varying conditional variance, making it well suited for financial time-series exhibiting volatility clustering and conditional heteroskedasticity. This superiority has been empirically demonstrated by Sanusi et al. [7] and Sari et al. [8], who found that ARIMA-GARCH models produced more accurate gold price predictions than conventional ARIMA models, and by Chuang et al. [11], who demonstrated the effectiveness of GARCH variants in capturing gold market dynamics amid global financial uncertainty.

In this context, Indogold was selected as the research subject for several scientific reasons. Indogold (PT Indogold Makmur Sejahtera) is the first digital gold platform in Indonesia to receive official Bappebti licensing as a Physical Digital Gold Trader, making it the most comprehensive representation of the Indonesian digital gold ecosystem [12]. Most importantly, from a methodological standpoint, Indogold has maintained price data records since 2009, providing a long and well-structured time series dataset, the primary prerequisite for obtaining stable and reliable GARCH model estimates [13]. Based on these considerations, this study helps fill the existing research gap while providing practical benefits for investors, platform managers, and regulators in the Indonesian digital gold investment ecosystem. The novelty of this study lies in the application of the ARMA-GARCH framework to model the volatility of digital gold prices on the Indogold platform using recent weekly data (2020–2024), providing empirical evidence on the volatility characteristics of Indonesia's digital gold market. Nevertheless, this study focuses specifically on the Indogold platform as a case study. Therefore, the findings should be interpreted within the context of this platform and may not necessarily represent the behavior of other digital gold trading platforms with different pricing policies or market structures.

II. METHOD

A. Data and Data Source

The data used in this study are weekly closing prices of digital gold on the Indogold platform (indogold.com) from January 5, 2020, to December 29, 2024, comprising 261 weekly observations. Weekly data were selected over daily observations to reduce short-term price noise arising from micro-level platform mechanisms, thereby providing a clearer representation of the underlying volatility dynamics relevant for medium-term investment analysis. This study is applied research using secondary data obtained from the official Indogold website. All analyses were conducted using RStudio software.

B. Data Analysis Procedure

This study employed a quantitative time-series approach to model and forecast digital gold prices using the GARCH framework. Weekly digital gold prices were first transformed into logarithmic returns to obtain a more stationary series. The return data were then divided into training and testing datasets using a trial-and-error approach to determine the optimal proportion. Stationarity was examined using the Augmented Dickey-Fuller (ADF) test. The ACF and PACF plots were first used to identify candidate ARMA orders. These candidate models were subsequently estimated and evaluated using the Akaike Information Criterion (AIC), with parameter significance also considered to determine the most appropriate mean model. The presence of ARCH effects was then tested using the ARCH-LM test. Candidate GARCH models were estimated and compared using the Akaike Information Criterion (AIC) to obtain the best model. Diagnostic checks were performed using the Ljung–Box test and the ARCH-LM test to assess model adequacy. Finally, the selected model was used to generate rolling forecasts on the testing dataset, and forecasting performance was evaluated using the Mean Absolute Percentage Error (MAPE).

C. GARCH(p,q) Model

The GARCH(p,q) model introduced by Bollerslev [10] as a generalization of the ARCH model [14] specifies the conditional variance equation as:

$$\sigma_t^2 = \omega + \Sigma\beta_j\sigma_{t-j}^2 + \Sigma\alpha_i\varepsilon_{t-i}^2$$

where σ_t^2 is the conditional variance, ε_{t-i}^2 represents past squared error shocks (ARCH component), and σ_{t-j}^2 represents past conditional variances (GARCH component). The ARMA model serves as the mean equation, generating residuals ε_t as input for the conditional variance equation. Parameters are estimated jointly using Maximum Likelihood Estimation (MLE)[15].

D. Accuracy Measures

Forecasting performance was comprehensively evaluated using three complementary accuracy measures: Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Based on Lewis [16], MAPE < 10% is considered highly accurate, 10–20% accurate, 20–50% reasonable, and ≥ 50% inaccurate.

III. Result and Discussion

A. Data Description

Digital gold prices on the Indogold platform exhibited a general upward trend throughout 2020–2024, rising from approximately IDR 700,000 per gram in early 2020 to approximately IDR 1,400,000 per gram by late 2024. Notable price fluctuations occurred in mid-2020, coinciding with global market uncertainty caused by the COVID-19 pandemic, and significant price surges throughout 2024 driven by global geopolitical tensions and expectations of Federal Reserve rate cuts. This non-homogeneous price movement pattern indicates time-varying volatility, which is the fundamental motivation for applying the GARCH model in this study.

B. Logarithmic Return

Logarithmic returns were calculated using. $r_t = \ln(P_t) - \ln(P_{t-1})$. The return series exhibits considerable fluctuations, indicating substantial volatility in digital gold prices. The return plot clearly demonstrates volatility clustering, where periods of high volatility tend to be followed by high volatility and periods of low volatility tend to be followed by low volatility. This phenomenon violates the constant variance assumption of conventional ARIMA models and provides empirical evidence that volatility is time-varying. Therefore, the GARCH model is considered appropriate because it explicitly models conditional variance and captures volatility dynamics more effectively than conventional linear time-series models. The presence of volatility clustering also provides preliminary evidence of conditional heteroskedasticity, which is a key characteristic addressed by the GARCH framework.

C. Data Splitting and Stationarity Test

Data splitting was carried out via trial and error across four different proportions. Each candidate split proportion was evaluated using the same out-of-sample rolling forecast procedure applied in the final model evaluation, rather than in-sample fitting, thereby reducing the risk of look-ahead bias in the split selection process. The MAPE comparison results are presented in Table I.

TABLE I
TRIAL AND ERROR DATA SPLITTING RESULT

Training	**Testing**	**N Train**	**MAPE (%)**
70%	30%	182	1.7677
75%	25%	196	1.8755
80%*	20%	208	**1.6172***
85%	15%	221	1.8579

*Selected proportion

The 80%:20% split yielded the lowest MAPE (1.6172%) and was therefore selected as the final partition: 208 observations as training data (January 5, 2020–December 22, 2023) and 52 observations as testing data (December 29, 2023–December 29, 2024).

The ADF test on the training data yielded a t-statistic of -5.307 with a p-value of $0.01 < 0.05$, leading to the rejection of H_0 and confirming that the logarithmic return series is stationary. No further differencing was required. The stationarity result implies that the statistical properties of the return series, particularly its mean and variance, remain relatively stable over time. Consequently, the series satisfies the fundamental assumption required for ARMA-GARCH modeling and can be used directly in the subsequent modeling process.

D. ARMA Model Identification and Estimation

ACF plot analysis revealed significant autocorrelations at lags 1 and 5, indicating an MA order of 2. The PACF plot showed two lags exceeding the significance boundary, indicating an AR order of 2. The ACF and PACF analyses were used to identify candidate ARMA orders, while the final model was selected based on the lowest AIC value together with parameter significance, as shown in Table II.

TABLE II
COMPARISON OF ARMA CANDIDATE MODELS

Model	AIC	Log-Lik	Sig. Param.
ARMA(1,0)	-1013.909	508.95	Significant
ARMA(0,1)	-1011.080	507.54	Significant
ARMA(2,0)	-1013.056	509.53	Not Sig.
ARMA(1,1)	-1012.728	509.36	Not Sig.
ARMA(1,2)	-1011.135	509.68	Not Sig.
ARMA(2,1)	-1011.135	509.57	Not Sig.
ARMA(2,2)*	-1017.342	513.67	Significant

*Selected model

ARMA(2,2) was selected as the best mean equation with the lowest AIC value (−1017.342) and all parameters statistically significant. The resulting mean equation is:

$$r_t = -0.8083 r_{t-1} - 0.8583 r_{t-2} + \varepsilon_t + 0.7361\varepsilon_{t-1} + 1.0000\varepsilon_{t-2}$$

E. ARCH-LM Test and GARCH Model Construction

The ARCH-LM test on residuals from ARMA(2,2) yielded Chi-squared = 38.9145 with p-value = 0.000 < 0.05, rejecting H_0 and confirming the presence of ARCH effects in the residuals. Conditional heteroskedasticity was also visually confirmed by the non-homogeneous residual plot, which displayed volatility clustering characteristic of financial time series data [13].

GARCH order identification from squared residual ACF and PACF plots indicated q = 2 (ARCH component) and p = 1 (GARCH component). An overfitting procedure was conducted across four candidate models. Results are presented in Table III.

TABLE III
COMPARISON OF ARMA(2,2)-GARCH CANDIDATE MODELS

Model	AIC	Log-Lik	Sig Param.
GARCH(1,1)*	-5.0367	530.82	α1, β1 Sig.
GARCH(1,2)	-5.0303	531.15	β2 Not Sig.
GARCH(2,1)	-5.0853	536.87	β1 Not Sig.
GARCH(2,2)	-5.0668	535.95	β1,β2 Not Sig.

*Selected model

Although ARMA(2,2)-GARCH(2,1) had the lowest AIC, its β_1 parameter was estimated as 0.000000 with p-value = 1.0000, indicating that the GARCH component did not meaningfully capture volatility dynamics, contradicting the fundamental principle of GARCH modeling [10]. In contrast, ARMA(2,2)-GARCH(1,1) had both α_1 and β_1 statistically significant. The non-significance of the parameter ω is a common phenomenon in high-frequency financial data due to its extremely small value near zero. It does not affect the overall model's validity [9], [10]. The resulting conditional variance equation is:

$$\sigma_t^2 = 0.000073 + 0.405334\varepsilon_{t-1}^2 + 0.476482\sigma_{t-1}^2$$

The estimated ARCH coefficient ($\alpha_1 = 0.405334$) indicates that recent market shocks strongly influence current volatility. This finding suggests that unexpected changes in digital gold prices can immediately affect future volatility levels. Meanwhile, the GARCH coefficient ($\beta_1 = 0.476482$) shows that past volatility also contributes substantially to current volatility dynamics, indicating that volatility patterns tend to persist over time. This result indicates a relatively high degree of volatility persistence in the digital gold market.

Furthermore, the stationarity condition is satisfied since $\alpha_1 + \beta_1 = 0.405334 + 0.476482 = 0.881816 < 1$. This implies that shocks occurring in the digital gold market do not disappear immediately but continue to influence future volatility for several subsequent periods before gradually dissipating. Such behavior is commonly observed in financial asset returns and confirms the suitability of the GARCH framework for modeling volatility in digital gold prices.

From an economic perspective, the persistence of volatility indicates that uncertainty in Indonesia's digital gold market tends to continue for some time following major price shocks. This suggests that investors may continue to experience elevated market risk even after the initial shock has occurred. Such behavior may reflect investors' gradual adjustment to new market information and the sensitivity of digital gold prices to changing economic conditions, making volatility an important consideration in investment decision-making.

These findings also have practical implications. Investors can use the volatility forecasts generated by the GARCH model to support portfolio risk management and determine more appropriate investment timing during periods of market uncertainty. Digital gold trading platforms may utilize the forecasting results to improve risk monitoring and provide more informative market insights for users. Furthermore, regulators can use volatility information as supporting evidence in monitoring market stability and developing policies aimed at strengthening investor protection in Indonesia's digital gold market.

F. Diagnostic Testing

Diagnostic tests were performed on the selected ARMA(2,2)-GARCH(1,1) model to verify its adequacy before forecasting. Results are presented in Table IV.

TABLE IV
DIAGNOSTIC TEST RESULT OF ARMA(2,2)-GARCH(1,1)

Test	Statistic	p-value	Decision
Ljung-Box (lag=10)	11.279	0.3362	Fail to Reject H_0
ARCH-LM (lag=5)	0.0772	0.9999	Fail to Reject H_0

The Ljung-Box test yielded a p-value of 0.3362 > 0.05, indicating that the standardized residuals contain no significant autocorrelation and behave as white noise. The ARCH-LM test yielded a p-value of 0.9999 > 0.05, confirming that the model has successfully captured all conditional heteroskedasticity patterns present in the data. These results indicate that the ARMA(2,2)-GARCH(1,1) model adequately captures both the mean and volatility dynamics of the return series. Therefore, no significant information remains unexplained by the model, and it is considered suitable for forecasting purposes.

G. Forecasting and Accuracy Evaluation

The ARMA(2,2)-GARCH(1,1) model was used to generate one-step-ahead forecasts of logarithmic returns for the 52 testing period observations via a rolling forecast. Predicted returns were then converted back to gold prices using the inverse formula $\widehat{P_t} = P_{t-1} \times e^{r_t}$ A selection of forecasting results is presented in Table V.

TABLE V
SELECTED FORECASTING RESULT OF DIGITAL GOLD PRICE

Period	Actual Price (IDR)	Predicted Price (IDR)	Error (%)
07 Jan 2024	1,040,221	1,035,338	0.4694
04 Feb 2024	1,054,634	1,038,212	1.5571
07 Apr 2024	1,210,195	1,151,311	4.8657
27 Oct 2024	1,416,947	1,379,567	2.6381
24 Nov 2024	1,421,420	1,342,761	5.5339
29 Dec 2024	1,390,606	1,398,780	0.5878

The predicted prices generally followed the actual price trend during the testing period. The model successfully captured the direction of price movements in both upward and downward phases. Complete accuracy evaluation results are presented in Table VI.

TABLE VI
ACCURACY EVALUATION OF ARMA(2,2)-GARCH(1,1)

Accuracy Measure	Value
MAPE (%)	1.8141
MSE	841,933,253.56
RMSE (IDR)	29,016.09
MAPE Interpretation	**Highly Accurate**

A MAPE value of 1.8141% indicates that the average forecasting error is relatively small compared to the actual digital gold prices. The model also produced an MSE value of 841,933,253.56 and an RMSE value of IDR 29,016.09. The RMSE value indicates that the average prediction error remains relatively small compared with the scale of the observed digital gold prices during the testing period. These results further support the robustness of the ARMA(2,2)-GARCH(1,1) model in forecasting digital gold prices. According to the classification proposed by Lewis [16], this result falls into the "highly accurate" category, confirming the strong forecasting performance of the proposed model. Nonetheless, it should be noted that the accuracy classification proposed by Lewis [16] was developed for general forecasting contexts and may not fully capture the characteristics of high-volatility financial data; this classification is therefore interpreted as indicative rather than definitive, and should be considered alongside the RMSE and MSE values reported in Table VI. These findings are consistent with Sanusi et al. [7] and Sari et al. [8], who also demonstrated that GARCH models produce strong predictive accuracy for gold prices in Indonesia. The ARMA(2,2)-GARCH(1,1) model demonstrated good forecasting performance in modeling the volatility of digital gold prices. Therefore, the model can serve as a useful reference for price forecasting on the Indogold platform; however, this evaluation is based solely on price prediction accuracy and does not account for investment return, risk, or trading strategy performance, which would require further validation through backtesting.

IV. CONCLUSION

This study identified ARMA(2,2)-GARCH(1,1) as the most appropriate model for forecasting digital gold prices on the Indogold platform. The estimated conditional variance equation, $\sigma_t^2 = 0.000073 + 0.405334\varepsilon_{t-1}^2 + 0.476482\sigma_{t-1}^2$, satisfies the stationarity condition with $\alpha_1 + \beta_1 = 0.881816 < 1$, indicating stable volatility dynamics. Diagnostic testing confirmed that the model adequately captured both autocorrelation and conditional heteroskedasticity present in the data.

Forecast evaluation on the test dataset yielded a MAPE of 1.8141%, which falls within the “highly accurate” category according to Lewis [12]. These results demonstrate that the ARMA(2,2)-GARCH(1,1) model effectively captures volatility clustering and time-varying variance characteristics in digital gold prices. Therefore, the model can serve as a reliable price forecasting tool on the Indogold platform and a useful reference for future studies on financial time-series forecasting; nevertheless, its application to actual investment decision-making would require further evaluation of return, risk, and trading strategy performance beyond price accuracy alone.

This study has several limitations. First, the analysis is based solely on digital gold price data from the Indogold platform; therefore, the findings may not be fully generalizable to other digital gold platforms because each platform may apply different pricing mechanisms, transaction fees, and market liquidity conditions. Second, the proposed model relies exclusively on historical price data and does not incorporate external variables such as international gold prices, exchange rates, inflation, or interest rates. Third, this study did not compare the proposed GARCH model with other forecasting approaches, such as ARIMA, Exponential Smoothing, Prophet, or machine learning models, so the findings demonstrate the effectiveness of the proposed model within the scope of this study rather than its superiority over alternative forecasting methods. Fourth, this study only considered the symmetric GARCH(1,1) specification and did not examine asymmetric volatility models such as EGARCH, TGARCH, APARCH, or GJR-GARCH, which may better capture potential leverage effects or asymmetric responses to positive and negative price shocks in the digital gold market. Fifth, this study did not examine potential structural breaks or regime shifts in the digital gold price series during the 2020–2024 observation period, such as those potentially induced by the COVID-19 pandemic or subsequent global economic conditions, which may affect the stability of the estimated model parameters over time. Sixth, this study relied on weekly price data to reduce short-term noise; however, this choice may also smooth out finer volatility dynamics, and a higher data frequency such as daily observations could capture short-term volatility patterns more precisely and yield different modeling outcomes. Finally, this study did not evaluate the stability of the estimated model parameters using rolling window analysis or different observation periods.

Therefore, future studies are encouraged to compare multiple digital gold platforms and international benchmark gold prices, incorporate relevant macroeconomic variables, evaluate alternative forecasting methods including asymmetric GARCH variants, examine structural breaks across different market regimes, explore alternative data frequencies, and assess parameter stability using rolling window or other time-varying validation approaches to improve the generalizability and robustness of the forecasting model.

BIBLIOGRAPHY

[1] Bank Indonesia, “Laporan Kelembagaan Bank In Donesia,” 2023.

[2] Bappebti, “Volume Perdagangan Fisik Emas Digital Naik Signifikan di 2024,” Badan Pengawas Perdagangan Berjangka Komoditi. Accessed: Mar. 02, 2026. [Online]. Available: https://news.ddtc.co.id/berita/nasional/1808475/volume-perdagangan-fisik-emas-digital-naik-signifikan-di-2024

[3] Pegadaian, “Perkiraan Harga Emas 2025, Akankah Mengalami Kenaikan?,” Sahabat Pegadaian. Accessed: Mar. 02, 2026. [Online]. Available: https://sahabat.pegadaian.co.id/artikel/emas/perkiraan-harga-emas-2025

[4] W. S. C. M. V. E. Makridakis, “Forecasting-Methods-and-Applications-2nd-Edition-Wile,” 1983.

[5] D. G. Baur and B. M. Lucey, “Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold,” 2010. [Online]. Available: http://www.merriam-webster.com/.

[6] F. Capie, T. C. Mills, and G. Wood, “Gold as a hedge against the dollar,” *Journal of International Financial Markets, Institutions and Money*, vol. 15, no. 4, pp. 343–352, Oct. 2005, doi: 10.1016/j.intfin.2004.07.002.

[7] W. Sanusi, R. Syam, and Y. Sari, “Analysis of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model in Forecasting Antam Gold Prices in Indonesia,” *Journal of Mathematics, Computations and Statistics*, vol. 8, no. 1, pp. 49–58, Mar. 2025, doi: 10.35580/jmathcos.v8i1.6760.

[8] H. R. Sari, S. Wahyuningsih, and M. Siringoringo, “Indonesia Gold Price Forecasting Using ARIMA Model (0,1,1) - GARCH (1,0),” *EKSPONENSIAL*, vol. 15, no. 1, p. 1, May 2024, doi: 10.30872/eksponensial.v15i1.1265.

[9] R. S. Tsay, “Analysis of Financial Time Series, Third Edition (Wiley Series in Probability and Statistics),” 2010.

[10] T. Bollerslev, “Generalized Autoregressive Conditional Heteroskedasticity,” 1986.

[11] O. C. Chuang, R. Gupta, C. Pierdzioch, and B. Shu, “Financial Uncertainty and Gold Market Volatility: Evidence from a Generalized Autoregressive Conditional Heteroskedasticity Variant of the Mixed-Data Sampling (GARCH-MIDAS) Approach with Variable Selection,” *Econometrics*, vol. 12, no. 4, Dec. 2024, doi: 10.3390/econometrics12040038.

[12] Indogold, “IndoGold Resmi Mendapatkan Izin BAPPEBTI Sebagai Pedagang Fisik Emas Digital,” Blog IndoGold. Accessed: Mar. 02, 2026. [Online]. Available: https://blog.indogold.id/indogold-resmi-mendapatkan-izin-bappebti-sebagai-pedagang-fisik-emas-digital/

[13] Indogold, “Tentang Kami,” PT Indogold Makmur Sejahtera. Accessed: Mar. 02, 2026. [Online]. Available: indogold.id/about

[14] R. F. Engle, “Autoregressive Conditional Heteroskedasticity with Estimate of the Variance of United Kingdom Inflation,” 1982.

[15] R. V. Hogg, J. W. McKean, and A. T. Craig, *Introduction to mathematical statistics*. Pearson Education, 2014.

[16] C. R. Lewis. (1982). Industrial and Business Forecasting Methods. London: Butterworths.