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# Evaluating the Geometric Brownian Motion Model for Gold Price Movements (XAU/USD) across Market Conditions

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**Abstract.** This study evaluates the performance of the Geometric Brownian Motion (GBM) model in predicting prices and estimating the risk of XAU/USD under stable and unstable economic conditions. Daily closing price data are divided into in-sample and out-of-sample periods, where return and volatility parameters are estimated from the in-sample data and applied in Monte Carlo simulations. Prediction accuracy is assessed using the Mean Absolute Percentage Error (MAPE), while risk is measured using Value at Risk (VaR) and Expected Shortfall (ES). The results indicate that MAPE values exceed 20% in both economic conditions, suggesting that the predictive accuracy of the GBM model remains moderate. Although the model performs slightly better during stable periods, the difference is not statistically significant. In contrast, risk estimation results show that VaR and ES range between 58% and 59%, with higher values observed during unstable periods. This reflects an increase in market risk driven by higher volatility. Overall, the findings suggest that while GBM is capable of capturing the general movement of gold prices, it has limitations in accurately predicting price levels and capturing extreme market fluctuations, particularly during periods of economic instability.

## Introduction

The foreign exchange (forex) market is widely recognized as the largest and most liquid financial market in the world, with daily transactions reaching USD 7.5 trillion as of April 2022 (CME Group, 2022). Among the various instruments traded, XAU/USD (representing the price of gold per troy ounce in US dollars) plays a significant role, particularly due to gold's function as a safe haven asset during periods of market uncertainty (Novianto & Akbar Wibowo, 2023; Pakpaharan, 2024). Market stability itself reflects the ability of the financial system to effectively allocate resources, distribute risk, and absorb external shocks (Ghassan & Krichene, 2025), whereas instability arises when these mechanisms weaken under economic pressure.

Under normal conditions, gold prices tend to move inversely with the US dollar, as a stronger dollar generally suppresses gold prices (Herley et al., 2024). However, this relationship does not always hold during periods of crisis. In times of severe economic stress, such as the 2008 global financial crisis and the COVID-19 pandemic, gold has consistently acted as a safe haven asset (Cheema et al., 2022; Vieira et al., 2023). In addition, gold price movements are influenced by

various macroeconomic factors, including inflation, interest rates, oil prices, and policy uncertainty, making the behavior of XAU/USD highly dependent on prevailing market conditions.

The increasing accessibility of online trading platforms has also contributed to a surge in retail investor participation, particularly among younger generations. While this trend has expanded investment opportunities, it has also introduced new challenges. Several studies suggest that decisions influenced by financial influencers are often subject to behavioral biases, such as overconfidence and fear of missing out, especially among individuals with lower levels of financial literacy (Jasneet Kaur, 2025; Umakanth et al., 2024). As a result, many investors may engage in trading activities without sufficient analytical support, which can lead to suboptimal outcomes.

This issue is further reflected in the high level of risk associated with forex trading, where approximately 60–83% of retail trader accounts experience losses (Blystone, 2025). Such outcomes are frequently linked to misconceptions about trading as a means of generating quick profits, as well as the absence of structured risk management strategies (Nirun & Asgarli, 2024; Satria, 2026). These conditions highlight the importance of adopting quantitative modeling approaches to better understand price dynamics and assess financial risk in a systematic manner.

Among the available approaches, Geometric Brownian Motion (GBM) has been widely used to model asset price dynamics due to its simplicity and theoretical foundation. Previous studies have reported that GBM performs relatively well in stock markets (Agista et al., 2023). However, its assumptions, particularly constant volatility and lognormal price distribution, limit its ability to capture extreme price movements (Gbolahan et al., 2025). Despite its widespread use, existing studies tend to focus on equity markets and often evaluate predictive accuracy without explicitly considering differences in market regimes. In addition, only limited research has examined prediction performance alongside tail risk estimation within a single framework, especially for highly volatile assets such as XAU/USD. This creates a gap in understanding how GBM performs not only in predicting prices but also in capturing extreme risks under different market conditions.

In this context, Value at Risk (VaR) and Expected Shortfall (ES) are commonly used to measure financial risk, with VaR estimating the maximum potential loss at a given confidence level and ES capturing the average loss beyond that threshold (Burzoni et al., 2022; Syuhada et al., 2023). Combining these measures provides a more comprehensive view of tail risk compared to conventional approaches.

Therefore, this study aims to address the identified gap by integrating GBM-based price simulation with risk measurement using VaR and ES, while explicitly comparing model performance across stable and unstable economic conditions. By simultaneously evaluating prediction accuracy and extreme risk behavior, this research seeks to provide a more comprehensive understanding of GBM performance in the XAU/USD market. From an actuarial perspective, the findings contribute to the application of probabilistic methods in risk modeling, particularly in the context of highly dynamic and volatile financial environments.

## Method

This study employs a quantitative approach to evaluate the predictive accuracy of the Geometric Brownian Motion (GBM) model in forecasting XAU/USD prices and to measure potential losses using Value at Risk (VaR) and Expected Shortfall (ES). The methodology integrates stochastic modeling based on GBM with Monte Carlo simulation to generate the probability distribution of future price returns. To capture differences in market behavior, the analysis is conducted under two distinct market regimes, namely stable and unstable economic conditions, allowing for a comparative assessment of how volatility characteristics influence both prediction accuracy and extreme risk estimation.

This study was conducted between October 2025 and January 2026 using historical daily closing prices of XAU/USD obtained from TradingView, with OANDA as the data provider. The observations span from January 1, 2018, to October 31, 2025, and are used to evaluate the performance of the Geometric Brownian Motion (GBM) model in predicting price movements and estimating financial risk using Value at Risk (VaR) and Expected Shortfall (ES). The time series is divided into three periods to reflect different market conditions. The first period (2018–2019) represents relatively stable conditions prior to the COVID-19 pandemic and is used for in-sample parameter estimation. The second period (2020–2022) captures a phase of heightened volatility during the pandemic and serves as the in-sample data for the unstable regime. The final period (2023–2025) is used as out-of-sample data to evaluate the predictive performance of the model based on the estimated parameters.

**Geometric Brownian Motion Model**

Geometric Brownian Motion (GBM) is one of the most widely used stochastic models to represent the dynamics of asset prices over time (Black & Scholes, 1973; Hull, 2018). In this study, GBM is employed to simulate future price paths of financial assets, including commodities such as gold, as the model explicitly incorporates two key components in price formation, namely the average growth rate (return) and volatility, which represents random price fluctuations (Black & Scholes, 1973; Hull, 2018). Mathematically, GBM is defined as a stochastic differential equation as proposed by Brigo et al., (2008), as follows

$$dS_t = \mu S_t dt + \sigma S_t dW_t$$

where $S_t$ denotes the asset price at time $t$, $W_t$ represents a standard Brownian motion process, $\sigma$ is the volatility, and $\mu$is the expected return. In empirical applications, this continuous-time formulation cannot be observed directly; therefore, a discrete-time solution is required for simulation and numerical analysis. Accordingly, the closed-form solution of the Geometric Brownian Motion model, as commonly presented in financial literature (Hull, 2018), is used to generate price paths, expressed as:

$$S_{t+\Delta t} = S_t \exp\left[(\mu - \frac{1}{2}\sigma^2)\Delta t + \sigma\sqrt{\Delta t} Z_t\right]$$

where $S_0$ is the initial price and $Z_t$ is a standard normal random variable. This formulation enables the generation of simulated price trajectories consistent with the GBM assumptions.

**Monte Carlo Simulation**

To extend the GBM framework and explore the range of possible future price movements, this study employs Monte Carlo simulation as a supporting method. Monte Carlo simulation is a computational technique based on random sampling, widely used to address problems involving uncertainty and multiple random variables (Mohamed et al., 2020). In financial applications, this approach has been applied in portfolio optimization and asset price modeling to evaluate return distributions and risk characteristics under uncertain market conditions (Masbratha et al., 2026).

The core idea of this method is to generate random samples from a specified probability distribution and use them to estimate the statistical properties of a function or parameter. In this study, Monte Carlo simulation is utilized to generate multiple possible price paths based on the GBM model, thereby constructing a distribution of potential returns. The general form of the Monte Carlo estimator is given by (Mohamed et al., 2020).

$$E[f(X)] \approx \frac{1}{N}\sum_{n=1}^{N} f(x_n)$$

where $x_n$ represents random samples drawn from the probability distribution, $N$ is the number of simulations, and $f(x_n)$ is the function evaluated at each sample. This approach enables the estimation of expected values and the construction of return distributions under uncertainty.

**Mean Absolute Percentage Error (MAPE)**

The accuracy of the GBM model in predicting XAU/USD prices is evaluated using the Mean Absolute Percentage Error (MAPE). According to Hyndman & Koehler (2006), MAPE is defined as follows

$$MAPE = \frac{1}{n} \sum_{p=1}^{n} \left| \frac{Y_p - F_p}{Y_p} \right| \times 100\%$$

where $Y_p$ represents the actual value at time $p$, $F_p$ denotes the predicted value, and $n$ is the number of observations. MAPE provides a relative measure of prediction error, allowing for interpretation based on predefined accuracy levels. Values below 10% indicate very high accuracy, 11%–20% indicate good accuracy, 21%–50% indicate moderate accuracy, and values above 50% indicate poor predictive performance (Nabillah & Ranggadara, 2020).

**Value at Risk (VaR)**

Value at Risk (VaR) is a statistical measure used to estimate the maximum potential loss of an asset or portfolio over a specified time horizon at a given confidence level (Trimono et al., 2021). VaR has become a fundamental tool in financial risk management due to its ability to quantify extreme loss exposure (Likitratcharoen et al., 2023). The mathematical formulation of VaR at confidence level $(1-\alpha)$over a holding period of $r$ days is expressed as follows (Trimono et al., 2021)

$$VaR_{(1-\alpha)}(r) = W_0 \cdot R^* \cdot \sqrt{r}$$

where $W_0$ is the initial investment value, $R^*$ is the $\alpha$-quantile of the return distribution, and $r$ represents the time horizon. The resulting VaR value indicates the maximum expected loss under normal market conditions.

**Expected Shortfall (ES)**

Expected Shortfall (ES) is a risk measure designed to capture extreme losses by focusing on the tail of the loss distribution (Wang & Zitikis, 2021). Unlike VaR, which only provides a threshold value, ES measures the average loss when the realized loss exceeds the VaR level, thus offering a more comprehensive assessment of tail risk. In modern financial regulation, ES has replaced VaR as a preferred risk metric due to its ability to better capture extreme risk scenarios (Wang & Zitikis, 2021). The mathematical formulation of ES is given by

$$ES_\alpha(Y) = \frac{1}{\alpha} \int_0^\alpha Va\, R_\tau(Y)\, d\tau$$

where $\alpha$ is the confidence level, $VaR_\tau(Y)$ represents the Value at Risk at level $\tau$, and $Y$ denotes the loss variable. ES provides a more informative measure of risk severity, particularly under volatile market conditions, as it accounts for the magnitude of losses beyond the VaR threshold (Wang & Zitikis, 2021).

Furthermore, ES has a strong theoretical foundation as it considers the behavior of losses in the tail distribution, ensuring that portfolios with concentrated extreme risks are not misleadingly

perceived as safe. This characteristic makes ES particularly relevant for assessing risk in highly volatile markets such as XAU/USD.

## Results and Discussion

### Estimation Results of GBM Model Parameters in the XAU/USD Market

Table 1 presents the estimated parameters of XAU/USD returns under stable and unstable market conditions.

**Table 1.** XAU/USD Parameters

| Parameter | Stable Period (2018–2019) | Unstable Period (2020–2022) |
|---|---|---|
| Minimum return | -0.0215796 | -0.0570435 |
| Maximum return | 0.0248117 | 0.0480259 |
| Median | 0.0002271 | 0.0007999 |
| Mean | 0.0002953 | 0.000278 |
| Volatility | 0.006655659 | 0.01002166 |

During the stable period (2018–2019), the minimum return of –0.0216 and maximum return of 0.0248 indicate relatively low daily price fluctuations, with movements ranging approximately between 2% and 3% per day. The mean return of 0.00030 suggests a marginal positive average growth in gold prices, reflecting a relatively calm market environment. In addition, the volatility level of 0.00666 indicates a low degree of uncertainty, consistent with stable economic conditions.

In contrast, during the unstable period (2020–2022), the minimum return decreases significantly to –0.0570, while the maximum return increases to 0.0480, implying a substantially wider range of price movements. This reflects heightened market turbulence, corresponding to the COVID-19 pandemic and global economic uncertainty. Although the mean return remains positive at 0.00028, the volatility increases markedly to 0.01002, indicating a substantial rise in market risk and uncertainty compared to the stable period.

These findings highlight that the primary distinction between the two market regimes lies not in the average return, which remains relatively similar, but in the level of volatility. This suggests that market instability is mainly characterized by increased uncertainty and larger price fluctuations rather than significant changes in expected returns. From a modeling perspective, this difference is crucial, as higher volatility directly affects the dispersion of simulated price paths in the GBM framework and may lead to greater prediction uncertainty as well as higher estimated tail risk.

### Normality Test of Returns

Table 2 presents the results of the normality test for daily returns of XAU/USD under both stable and unstable market conditions. While Image 1 illustrates the distribution of actual returns using a bell-shaped diagram.

**Table 2.** Normality Test Results

| Return Period | Statistic (D) | P-value | Conclusion |
|---|---|---|---|
| Stable | 0.052463 | 0.001742 | Not normal |
| Unstable | 0.075193 | 3.56E-11 | Not normal |

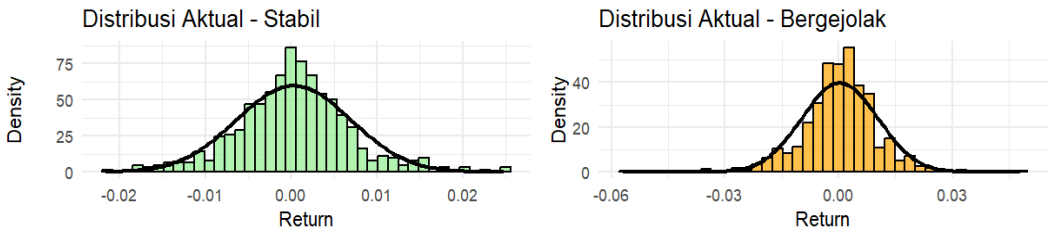



**Image 1.** Bell-Shaped Distribution of Actual XAU/USD Returns

Based on the test results, the p-values for both periods are below 0.05, indicating that the null hypothesis of normality is rejected. This implies that the daily returns of XAU/USD are not normally distributed in both stable and unstable periods. This finding is consistent with the stylized facts of financial markets, particularly in forex and commodity markets, which are often characterized by fat tails, volatility clustering, and excess kurtosis.

The deviation from normality becomes more pronounced during the unstable period, as indicated by the higher test statistic and extremely small p-value. This suggests a greater likelihood of extreme price movements, reinforcing the presence of higher tail risk during periods of economic uncertainty. Such behavior reflects the impact of external shocks, including the COVID-19 pandemic and global macroeconomic instability, which amplify market fluctuations beyond what is predicted by a normal distribution.

Despite the non-normality of empirical returns, the application of the Geometric Brownian Motion (GBM) model remains theoretically valid. This is because the normality assumption in GBM is imposed on the stochastic process of log-returns rather than directly on observed returns, leading to a lognormal distribution of prices. In practice, however, empirical financial returns frequently deviate from normality due to high volatility and the presence of extreme events.

Therefore, the observed non-normality does not invalidate the use of GBM but instead provides an important basis for evaluating its limitations. In particular, the inability of GBM to fully capture fat tails and extreme movements may contribute to reduced predictive accuracy and potential underestimation or misrepresentation of risk in highly volatile markets such as XAU/USD.

From a modeling perspective, this finding highlights the importance of interpreting GBM results with caution, especially under unstable market conditions. It also suggests that while GBM can serve as a useful baseline model, more advanced approaches that incorporate time-varying volatility or heavy-tailed distributions may be required to better capture the true behavior of financial returns.

### GBM Model Results and Prediction Accuracy

Table 3 presents the prediction results of the GBM model under stable and unstable economic conditions, along with the corresponding parameter values and accuracy levels.

**Table 3.** Prediction Results and Accuracy

| Economic Condition | Return | Volatility | MAPE (%) | Accuracy Category |
|---|---|---|---|---|
| Stable | 0.000295324 | 0.006655659 | 22.1846 | Moderate |
| Unstable | 0.00027801 | 0.01002166 | 22.1945 | Moderate |

The estimated return parameter during the stable period is 0.000295, while during the unstable period it is 0.000278, indicating that the average daily growth rate of gold prices remains relatively small and nearly identical across both periods. In contrast, volatility exhibits a substantial difference, increasing from 0.00666 in the stable period to 0.01002 in the unstable period. This finding confirms that the primary distinction between the two market regimes lies not in the expected return, but in the magnitude of price fluctuations.

The MAPE values of 22.18% for the stable period and 22.19% for the unstable period indicate that the GBM-based predictions exhibit a noticeable deviation from actual prices. According to standard accuracy classification, these values fall within the moderate range, suggesting that the model provides a reasonable but not highly precise level of prediction accuracy. This implies that while GBM is capable of capturing the general direction and overall pattern of gold price movements, it lacks precision in replicating exact price levels.

Interestingly, the similarity of MAPE values across both periods suggests that increased volatility does not significantly deteriorate prediction accuracy in relative terms. However, this does not imply that the model performs equally well in both conditions. Instead, it reflects the inherent limitation of GBM in adapting to changing market dynamics, particularly under high volatility. The assumption of constant volatility in GBM may restrict its ability to respond to sudden market shocks, resulting in persistent prediction errors across different regimes.

Furthermore, the relatively high MAPE values can be linked to the non-normality of returns identified in the previous section. Since GBM relies on the assumption of normally distributed log-returns, deviations from this assumption, such as fat tails and extreme movements, can lead to discrepancies between simulated and actual prices. This limitation becomes particularly relevant in the XAU/USD market, where volatility and extreme events play a significant role in price formation.

Overall, these findings suggest that GBM serves as a useful baseline model for capturing general price dynamics but has limited capability in achieving high predictive accuracy, especially in markets characterized by high volatility and non-normal return distributions. Overall, these findings suggest that GBM serves as a useful baseline model for capturing general price dynamics but has limited capability in achieving high predictive accuracy, especially in markets characterized by high volatility and non-normal return distributions. This finding is consistent with previous studies, which highlight that while GBM performs well under relatively stable conditions, its accuracy tends to decline in highly volatile markets due to its assumption of constant volatility and inability to capture extreme price movements (Gbolahan et al., 2025).

**Normality Test of Predicted Returns**

Table 4 presents the results of the normality test for the predicted returns generated by the GBM model under both stable and unstable market conditions.

**Table 4.** Normality Test of Predicted Returns

| Predicted Return Period | Statistic (D) | P-value | Conclusion |
|---|---|---|---|
| Stable | 0.0075724 | 0.696 | Normal |
| Unstable | 0.0076819 | 0.6748 | Normal |

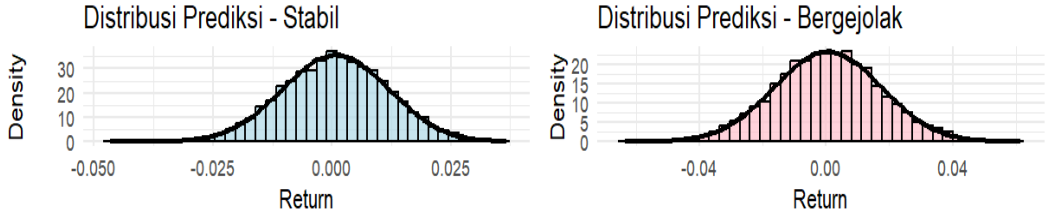



**Image 2.** Distribution of Predicted Returns of XAU/USD

The results indicate that the predicted returns are normally distributed in both stable and unstable periods, as reflected by p-values greater than 0.05. This finding is consistent with the

theoretical assumptions of the Geometric Brownian Motion (GBM) model, where log-returns are assumed to follow a normal distribution, leading to a lognormal distribution of prices.

The observed normality in predicted returns is therefore not merely an empirical outcome but a direct consequence of the mathematical structure of the GBM model. This confirms that the simulation process successfully generates return patterns that conform to the underlying theoretical assumptions. As a result, the simulated data provide a valid basis for subsequent analyses, including prediction accuracy evaluation using MAPE and risk estimation using Value at Risk (VaR) and Expected Shortfall (ES).

However, when compared with the results of the normality test on actual returns, a clear discrepancy emerges. While empirical returns exhibit non-normal behavior characterized by fat tails and extreme values, the simulated returns remain normally distributed. This gap highlights an inherent limitation of the GBM model, namely its inability to fully capture the heavy-tailed nature of real financial data. Consequently, although the model is theoretically consistent, it may oversimplify the underlying return distribution, particularly in volatile markets such as XAU/USD.

This discrepancy has important implications for both prediction accuracy and risk estimation. Since GBM assumes normally distributed log-returns with constant volatility, it tends to smooth extreme fluctuations and underrepresent the frequency and magnitude of large price movements observed in real markets. As a result, the model may fail to accurately replicate actual price dynamics, leading to relatively high prediction errors as reflected in the MAPE results. At the same time, this limitation may also affect the reliability of risk estimates, as the inability to fully capture tail events could lead to potential underestimation or misrepresentation of extreme risk.

Therefore, while GBM remains useful as a baseline model for understanding general price behavior, its simplifying assumptions restrict its effectiveness in capturing the complex and dynamic nature of financial markets, particularly under conditions of heightened volatility and economic uncertainty.

**Risk Estimation Using Value at Risk (VaR) and Expected Shortfall (ES)**

Table 5 presents the results of risk estimation based on the simulated returns generated by the GBM model under both stable and unstable economic conditions.

**Table 5.** Risk Estimation Results

| Economic Condition | VaR 95% | ES 95% | VaR 99% | ES 99% |
|---|---|---|---|---|
| Stable | 58.50% | 58.71% | 58.83% | 59.01% |
| Unstable | 58.92% | 59.21% | 59.36% | 59.62% |

During the stable period, the estimated VaR values are 58.50% at the 95% confidence level and 58.83% at the 99% confidence level, indicating that the maximum potential loss within one day is not expected to exceed these values under normal market conditions. The corresponding ES values of 58.71% and 59.01% represent the average losses when the VaR threshold is exceeded, providing a more comprehensive measure of tail risk.

In the unstable period, both VaR and ES values increase, with VaR reaching 58.92% (95%) and 59.36% (99%), and ES reaching 59.21% and 59.62%, respectively. This indicates that under volatile market conditions, the potential for extreme losses becomes significantly higher. The increase in both VaR and ES reflects the impact of heightened volatility, which amplifies the dispersion of simulated returns and leads to greater downside risk.

These findings are consistent with the earlier results showing higher volatility during the unstable period, confirming that volatility plays a critical role in driving market risk. Moreover, the relatively close values between VaR and ES suggest that extreme losses are not only more likely but also more severe, reinforcing the presence of substantial tail risk in the XAU/USD market.

Nevertheless, it is important to interpret these results with caution. Since the risk estimates are derived from GBM-based simulations that assume normally distributed returns, they may underestimate the true extent of extreme risk observed in real markets, which are characterized by fat tails and non-normal behavior. Therefore, while VaR and ES derived from GBM provide useful benchmarks, they may not fully capture the severity of tail events, particularly during periods of economic instability.

**Comparison of Prediction Accuracy and Risk Across Economic Conditions**

The results indicate that the predictive capability of the Geometric Brownian Motion (GBM) model in forecasting XAU/USD prices remains limited in numerical terms. This is evidenced by MAPE values exceeding 20% in both observed periods, suggesting a considerable deviation between simulated and actual prices. These findings imply that although GBM is able to capture the general trend and directional movement of gold prices, it lacks precision in reproducing daily price levels.

In contrast, risk estimation using Value at Risk (VaR) and Expected Shortfall (ES) yields relatively high values, particularly during the unstable economic period. This divergence highlights that prediction accuracy and risk measures capture different dimensions of market behavior. While MAPE reflects average prediction error and is less sensitive to extreme fluctuations, VaR and ES explicitly focus on tail risk, which is highly relevant in the XAU/USD market due to its elevated volatility and frequent extreme price movements.

When comparing across economic conditions, the GBM model demonstrates more consistent performance during the stable period. Under these conditions, lower volatility leads to a narrower gap between simulated and actual prices, resulting in more controlled prediction errors. Conversely, during the unstable period, heightened volatility amplifies the discrepancy between simulated and realized prices. This is reflected not only in slightly higher MAPE values but also in increased VaR and ES estimates, indicating that the model becomes more sensitive to market shocks. In other words, the effectiveness of GBM tends to decline under conditions of high volatility and extreme price dynamics.

In comparison with previous studies, the findings of this research reveal a relatively lower level of predictive accuracy. Prior studies have shown that the Geometric Brownian Motion (GBM) model can perform well in relatively stable market environments, particularly in stock markets with lower volatility (Agista et al., 2023; Gbolahan et al., 2025). In contrast, this study records MAPE values of approximately 22% under both economic conditions. This discrepancy suggests that the performance of GBM in the forex market, particularly for XAU/USD, is relatively weaker compared to its application in stock markets.

From a risk perspective, prior studies generally report lower VaR estimates, whereas this study finds substantially higher values of VaR and Expected Shortfall, especially during periods of market instability. This difference reflects the inherent characteristics of the gold market, which exhibits higher volatility and more pronounced tail risk compared to individual stocks or stock indices. Therefore, these findings emphasize that the effectiveness of the GBM model is highly dependent on the underlying asset characteristics and prevailing market conditions.

Overall, the results suggest that while GBM can serve as a useful baseline model, its performance is constrained in highly volatile and non-normal market environments. This limitation underscores the need for more advanced modeling approaches that can better capture extreme events and time-varying volatility, particularly for assets such as XAU/USD.

**Practical Implications and Future Research**

Building upon the findings of this study, several practical and research implications can be highlighted. The results indicate that relying solely on the Geometric Brownian Motion (GBM) model for price prediction in highly volatile markets such as XAU/USD may lead to suboptimal decision-making. This limitation arises from the model's inability to fully capture extreme price movements and non-normal return behavior, which are commonly observed in real financial markets. Although GBM remains useful for understanding general price trends and long-term dynamics, it may underestimate the likelihood and magnitude of large losses. Therefore, practitioners are encouraged to complement GBM-based analysis with more robust risk management techniques and alternative modeling approaches that can better account for extreme events.

From a risk management perspective, the relatively high values of Value at Risk (VaR) and Expected Shortfall (ES) highlight the importance of incorporating tail risk into financial decision-making. Models that rely on normality assumptions may fail to reflect the true extent of downside risk, particularly during periods of economic instability. This suggests that additional tools such as stress testing and scenario analysis are necessary to improve the assessment of potential losses under extreme conditions. At the same time, the findings emphasize that volatility plays a central role in shaping market risk, as higher volatility is consistently associated with increased risk exposure.

From a modeling standpoint, the limitations identified in this study suggest the need for more advanced approaches that allow for time-varying volatility and non-normal return distributions. Models such as GARCH, stochastic volatility models, and jump-diffusion processes may provide a more realistic representation of market dynamics, particularly in capturing volatility clustering and extreme price movements. In addition, the relatively lower predictive accuracy of GBM in the XAU/USD market, compared to results reported in stock market studies, indicates that model performance is highly dependent on asset characteristics and market conditions.

Future research may extend this study by conducting comparative analyses between GBM and alternative models across different asset classes and market regimes. Furthermore, integrating macroeconomic variables or combining traditional stochastic models with machine learning techniques may offer promising directions for improving both prediction accuracy and risk estimation.

## Conclusion

This study concludes that the Geometric Brownian Motion (GBM) model provides a moderate level of predictive accuracy in modeling XAU/USD price movements under both stable and unstable economic conditions. Although the simulated price paths are generally able to capture the overall trend and directional movement of gold prices, noticeable deviations persist between simulated and actual values. This suggests that, in practice, GBM is more effective in representing general price behavior rather than delivering precise day-to-day predictions. From a risk perspective, the findings indicate that the estimated values of Value at Risk (VaR) and Expected Shortfall (ES) are relatively high, particularly during periods of economic instability. This reflects the increasing level of market uncertainty and volatility, which significantly amplifies the potential for extreme losses. In this context, the XAU/USD market demonstrates strong tail risk characteristics, especially during periods of global economic stress, where price movements tend to be more abrupt and less predictable. An important insight from this study lies in the discrepancy between prediction accuracy and risk estimation. While the GBM model assumes normally distributed log-returns and produces simulated returns that conform to this assumption, empirical evidence shows that actual market returns often exhibit non-normal behavior, including fat tails and extreme fluctuations. As a result, the model tends to smooth out extreme movements, which

may reduce its ability to fully capture real market dynamics. This limitation helps explain why prediction errors remain relatively high and why the model may not accurately reflect the true magnitude of risk. Overall, these findings suggest that GBM remains useful as a baseline or benchmark model for understanding general price dynamics. However, its simplifying assumptions limit its effectiveness in capturing extreme events and tail risk, particularly in highly volatile markets such as XAU/USD. Therefore, for more accurate prediction and risk assessment, it is important to consider alternative modeling approaches that incorporate time-varying volatility and non-normal return distributions. Such approaches may provide a more realistic representation of financial markets and improve decision-making in environments characterized by uncertainty and rapid price changes.

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