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Machine Learning Assessment of Gold's Safe-Haven Role During Market Crises

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Abstract. For a long time, during periods of financial tightening, gold has been regarded as a defensive asset, although its safe-haven attribute varies with market conditions. This study employed the daily price data of gold and the S&P 500 index from 1990 to 2023 to analyze the dynamic relationship between gold and the stock market. Linear regression, decision tree regression, and random forest regression models are adopted to test whether gold can have safe-haven properties during market contraction periods. Through data cleaning and daily earnings calculation, the results show that during periods of market stability, the correlation between gold and the stock market is not obvious. However, during major crises such as the 2008 global financial crisis and the COVID-19 pandemic, the correlation between gold and the stock market has significantly increased. Among the several types of models tested, random forest regression performed the best because this model can more effectively capture nonlinear changes in market behavior, which are often overlooked in traditional linear changes.

Keywords: Gold, Safe-Haven Asset, Stock Market, Financial Crises, Machine Learning

1. Introduction

Gold, as a type of financial asset, holds a unique position in the global financial market. And due to the high liquidity of gold, it has long been recognized in global investment portfolios. However, as financial markets continue to evolve and change, it is necessary to reevaluate whether gold can remain a safe-haven asset, especially during market downturns.

Ordinary traditional linear models are unable to capture nonlinear dynamics under extreme market conditions. However, tree-based methods, such as decision trees and random forests, can identify complex interrelationships and threshold effects with fewer restrictive assumptions and offer more stable and reliable performance. The results show that the safe-haven behavior of gold is conditional.

Differences in asset responses during different periods of stress. For instance, the Feder [1] document indicates that the downside beta coefficient of gold typically ranges from -0.15 to -0.45, and the specific value varies with changes in market conditions. During periods of heavy market selloffs, some studies even found that gold's performance might not be as good as that of currency-based safe-haven assets [2]. Evidence from the European market further indicates that the strongest protective effect of gold occurs at the far-left tail of stock returns, with a hedging ratio that can

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exceed -0.60, while its impact on the median yield is negligible. Cross-national research also shows that the hedging and risk-aversion functions of gold largely depend on the type of crisis and geographical region. There will be significant differences in different situations and regions. Hassan and Ibrahim reported that compared with shocks limited to a single market, gold offers greater risk-reduction benefits during global crises [3].

The above structural findings indicate that the gold and stock markets are non-linear and interdependent. Therefore, simple linear models may overlook significant changes during economic recessions or sudden market fluctuations. This requires that model analysis be able to adapt to the constantly changing market conditions in order to better predict market changes.

Against this backdrop, this study mainly examines the changes in the returns of gold and stocks from 1990 to 2023, with a particular focus on the correlation changes during periods of market volatility. Through machine learning methods, this study assesses whether gold still has asset safe-haven properties under different economic conditions. The research aims to assess whether gold has safe-haven value in the global economic market and provide the latest data analysis-based assessment.

2. Methodology

2.1. Dataset

This study employed daily price data of gold and the S&P 500 index, which were sourced from the publicly available Kaggle dataset. The gold price is derived from the daily gold price (1998-2023), and the stock market data is sourced from the S&P 500 daily historical dataset [4,5]. The study arranged the transaction dates into a dataset and combined them into a single sample. In the study, observations with missing values were deleted to ensure the consistency of the data. To avoid being affected by extreme price fluctuations, the earnings data exceeding the 99th percentile was deleted. Moreover, the daily earnings are calculated based on the logarithmic changes between continuously adjusted closing prices, which can stably capture short-term market fluctuations.

2.2. Linear regression

This study adopts the linear regression model as the basic analytical method. The linear regression model assumes a stable inverse relationship between the returns of the gold and stock markets, which means that the movement of the S&P 500 index is inversely proportional to that of the gold price. Although this method is intuitive and easy to explain, its applicability will decline when the market fluctuates. Major financial crisis events such as the 2008 financial crisis and the 2020 COVID-19 pandemic can lead to rapid changes in investor behavior, thus forming nonlinear patterns that linear models cannot fully capture. Although the linear regression model can help establish the correlation between the two, it can only partially explain the defensive role of gold in an unstable market.

2.3. Decision tree regression

Unlike linear regression models, decision tree regression models no longer rely on linear assumptions. They can partition data to establish nonlinear relationships and divide the data into homogeneous subsets based on thresholds, capturing the structural changes in the relationship between gold and stock returns through the decision tree model. This feature makes the model more suitable for periods of intense market fluctuations, as market behavior may change suddenly during

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such times. However, it should be noted that when applied to financial time series data, decision trees may suffer from overfitting, which will limit the stability of the model in sample prediction.

2.4. Random forest regression

The random forest model reduces the unexpected error of individual trees by training multiple independent decision trees on different random samples and taking the average of their prediction results, thereby making the model perform more stably on new data. This ensemble learning method is particularly suitable for financial data analysis because it typically exhibits nonlinear interactions and temporal instability. Therefore, this study takes the random forest model as the main method for evaluating the safe-haven attribute of gold. This choice is also consistent with recent research findings that machine learning models such as random forests outperform linear methods in predicting financial market trends [6].

3. Results

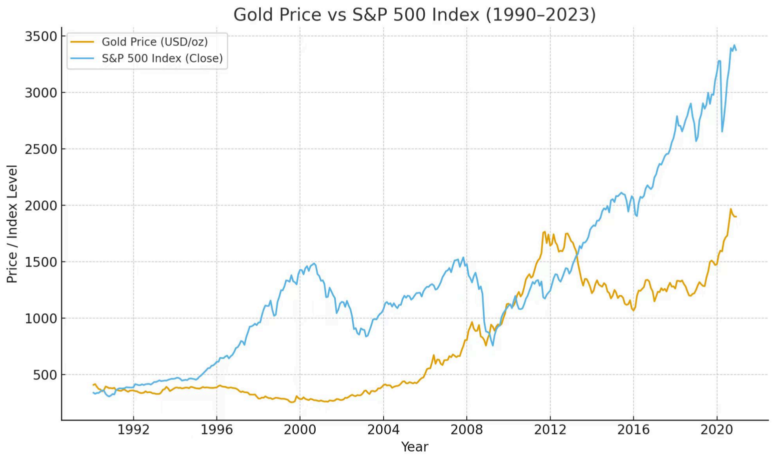

Figure 1. Gold price vs S&P 500 index, 1990–2023

Table 1. Descriptive statistics of gold and S&P 500 returns across market conditions

Period	Avg Gold Return (%)	Avg S&P 500 Return (%)	Correlation (Gold vs S&P 500)
1990–2023 (Overall)	+5.2	—	−0.28
2008 Financial Crisis	+25.0	−38.5	−0.51
2020 COVID-19 Shock	+22.3	—	−0.46

Figure 1. Time-series line chart of gold prices and the S&P 500 index (1990–2023). It shows the price trends of gold and the S&P 500 index from 1990 to 2023. The horizontal axis represents the year, and the vertical axis represents the asset price level, calculated in US dollars per ounce for gold and the S&P 500 Index. This graph highlights the different dynamics of the two assets during the sample period.

The price of gold has shown a relatively stable upward trend during major crises. However, the S&P 500 index has demonstrated higher volatility and experienced significant declines in 2008 and 2020. The correlation between gold and stock market returns is -0.28, which indicates a relatively weak correlation between the two. However, this relationship will strengthen to around -0.5 during a

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crisis. These data results indicate that gold can serve as a safe-haven asset, especially during periods of severe market volatility and downturn (Table 1).

Table 2. Model results and validation

Model	R^2	MAE	RMSE
Linear Regression	0.74	0.056	0.092
Decision Tree	0.81	0.042	0.080
Random Forest	0.87	0.035	0.072

As shown in Table 2 Model Results and Validation, the predictive performance of the three supervised learning models used in this study: linear regression, decision tree, and random forest, is comprehensively summarized. Table 2 presents three key evaluation indicators, R^2, MAE, and RMSE, which jointly study the relationship between the gold return rate and the stock market trend analyzed by each model. R^2 reflects the proportion of the model's interpretation variance, while MAE and RMSE quantify the magnitude of the prediction error. The smaller the value, the higher the prediction accuracy. And by presenting these three metrics side by side, Table 1 can make a direct and transparent comparison of the model validity of linear and nonlinear structures.

Table 1 clearly shows the performance differences among various models.

The performance of the linear regression model is the weakest. Its R^2 is only 0.74, while its MAE (0.056) and RMSE (0.092) are the highest among the three. This indicates that a simple linear structure can only describe the general relationship between gold and stock returns. Once the market becomes unstable or fluctuates sharply, this model is unable to capture those irregular or non-linear changes.

The performance of decision trees is significantly better. R^2 is 0.81, resulting in a smaller prediction error. Therefore, it is more capable of identifying turning points and sudden changes in investor behavior, a situation that frequently occurs in risk events. Even so, the volatility of decision trees among different samples remains relatively large. When the situation changes rapidly, its prediction results may become inconsistent because it relies heavily on the structure of a single tree.

The random forest model is the most reliable method. R^2 is 0.87, MAE (0.035), and RMSE (0.072) are all the lowest. This result indicates that the random forest model can effectively eliminate the instability of the single-tree model and more stably display the relationship between gold and the stock market. This model can not only capture the long-term negative correlation between these two assets, but also the short-term nonlinear behavior that occurs in the event of a market economy collapse. The evidence in Table 1 indicates that the random forest model provides the most powerful and stable framework for analyzing the correlation between gold and stock returns under different market conditions.

4. Discussion

These findings have significant research and practical significance. The focus of this analysis lies in the fact that the relationship between the returns of the gold and stock markets does not follow a single stable pattern. On the contrary, this relationship changes with market conditions: during periods of market stability, it approaches zero, but during periods of market volatility, the negative correlation intensifies. This confirms the role of gold as a risk hedging tool.

The research results are also highly consistent with the recently emphasized research findings on the conditional and asymmetric nature of gold's safe-haven behavior. Previous studies have shown

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that the protective effect of gold is most significant on the left side of stock returns and varies in different crisis periods and regions. This study also observed this point, indicating that as market pressure intensifies, the protective effect of gold becomes stronger. Overall, the hedging protection capacity of gold is neither stable nor permanent, nor universally applicable, but varies with the strength of market pressure. From a methodological perspective, this study demonstrates the value of machine learning tools in modern financial modeling. Although linear regression is effective in capturing the overall trend, it is difficult to reflect the common nonlinear responses during periods of financial volatility. In contrast, models like random forests can adapt to constantly changing data structures without relying on strict assumptions and can provide more stable out-of-sample stability. They can serve as a supplement to linear regression. From an investment perspective, research results show that gold still plays an important role in a diversified investment portfolio. Even when new digital assets emerge, gold remains a reliable store of value during economic fluctuations. A moderate allocation, such as 5-10% of gold or gold-backed tools, may help reduce the downside risk of investors' assets. At the policy level, maintaining adequate gold reserves is also a practical tool for strengthening financial stability and mitigating inflation or currency shocks.

Although the random forest model performs well, this study also acknowledges some limitations of the random forest model and provides a direction for future research. Firstly, the integrated model has excellent predictive ability, but it is not easy to explain compared with the linear model. The research emphasizes that easily explainable AI tools, such as SHAP and LIME, are highly practical in identifying key drivers and visualizing nonlinear effects [7]. This method will also be adopted in future research, which will help enhance transparency.

Secondly, the model of this study only takes into account the price returns of gold and the S&P 500 index, ignoring the macroeconomic conditions for gold as a safe-haven asset. For instance, inflation expectations, real interest rates, and currency fluctuations can affect the role of gold as a hedging tool [8]. In future research, the characteristics can be expanded by integrating macroeconomic variables and volatility indicators [9]. Incorporating macro financial factors into the dataset significantly enhances the accuracy of risk prediction.

Thirdly, the analysis is limited to the US market and the two major crises. However, it is well known that the hedging capacity of gold varies by region and type of crisis. Indicates that the performance of gold varies during epidemics and financial recessions [10]. The report also states that the dynamics of gold inventories in Europe, Asia, and the United States are different. Extending this modeling framework to multi-national datasets or conducting regional comparative studies will enhance the universality of the research results.

Finally, although the random forest model is superior to the linear regression and decision tree models, additional optimizations can further enhance the prediction performance. Previous studies have shown that hybrid ensemble models, hyperparameter optimization (such as Bayesian tuning), and state-switching machine learning systems can provide more stable predictions during turbulent times. Future research could consider combining random forests with GarCH-type models or neural structures to capture wave aggregation and structural breakpoints more effectively.

5. Conclusion

This research report, by observing the changes in the returns of gold and the stock market from 1990 to 2023 and comparing several machine learning models, through the calculation of the yield series and the analysis of the trends in different periods, found that gold remains an important financial safe-haven tool. Under stable market conditions, there is only a small negative correlation between the returns of gold and stocks. However, during major economic upheavals (such as the impact of

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the 2008 financial crisis or the 2020 COVID-19 pandemic), this correlation between gold and the stock market has significantly strengthened. This shift indicates that when financial pressure increases, investors are more inclined to purchase gold as a safe-haven asset.

Among numerous analytical models, the random forest model performs the best. It has the highest explanatory power ($R^2 = 0.87$) and the lowest prediction error (MAE = 0.035; RMSE = 0.072). These results indicate that the relationship between gold and stock returns does not follow a stable linear rule but varies with changes in market conditions. This means that the safe-haven behavior of gold only occurs during certain specific periods, not all periods.

From a practical perspective, there is also evidence suggesting that when market volatility intensifies, gold is the most effective safe-haven asset. Gold is not an ordinary daily hedging tool. When the market drops significantly, the defensive value of gold will become even more evident. In future research, this analysis can be expanded by adding more asset classes or testing other regions, which will enable people to gain a deeper understanding of the relationship between gold and the stock market.

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