

Factors Influencing the Divergence of Precious Metals Prices: The Case of Gold in 2024

Monika BURGHAUSEROVÁ^{1*}, Yelyzaveta APANOVYCH^{2,3} and Jindřiška VITVAROVÁ⁴

Authors' affiliations and addresses:

¹Institute of Technology and Business in České Budějovice, Okružní 517/10, 37001 České Budějovice, Czech Republic
e-mail: 27011@mail.vstecb.cz

²Institute of Technology and Business in České Budějovice, Okružní 517/10, 37001 České Budějovice, Czech Republic
e-mail: 31377@mail.vstecb.cz

³Pan-European University in Bratislava, Faculty of Economics and Business, Tomášikova 20, 821 02 Bratislava, Slovak Republic
e-mail: 31377@mail.vstecb.cz

⁴Pan-European University in Bratislava, Faculty of Entrepreneurship and Law, Spálená 76/14, 11000 Prague, Czech Republic
e-mail: 31377@mail.vstecb.cz

*Correspondence:

Monika Burghauserová, Institute of Technology and Business in České Budějovice, Okružní 517/10, 37001 České Budějovice, Czech Republic. tel.: +420 736641032
e-mail: jindriska.vitvarova@peuni.cz

Funding information:

Institute of Technology and Business in České Budějovice

How to cite this article:

Burghauserová, M., Apanovych, Y., Vitvarová, J. (2025), Factors Influencing the Divergence of Precious Metals Prices: The Case of Gold in 2024, *Acta Montanistica Slovaca*, Volume 30 (2), 357-372

DOI:

<https://doi.org/10.46544/AMS.v30i2.07>

Abstract

This study investigates the key factors influencing the divergence of gold prices in 2024. Using content analysis of scientific articles, multilayer perceptron neural networks, and SARIMA modeling, the research identifies economic and geopolitical drivers that shaped gold market trends. The results indicate that changes in interest rates, geopolitical tensions, and inflation expectations significantly contributed to price volatility and record gold prices. A forecast based on historical patterns and macroeconomic variables suggests that gold will continue to serve as a critical safe haven asset amid global uncertainty. The study highlights the complexity of gold price forecasting and suggests directions for future research.

Keywords

Gold price divergence, Precious metals, Economic forecasting, Neural networks, SARIMA model, Content analysis, Macroeconomic indicators



© 2025 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).

Introduction

Negotiated globally and tightly held by investors and central banks (Baur et al., 2020), gold is a precious metal and an invaluable asset (Baur et al., 2023). This rare commodity enjoys popularity in jewelry crafting, technology, investments, and among central banks. The diversity of demand for gold and the self-regulatory nature of the gold market encourage its robust properties as an investment asset (Jianwei et al., 2023). The gold price is the key indicator of global entrepreneurial confidence, assuming overriding importance in international gold reserves. Major currency fluctuations and risky government bonds have aroused market expectations of an increased share in central bank gold reserves, positively influencing their price (Manakhov, 2020).

Gold has significant economic value and serves as a security against inflation during periods of economic upheaval (Areh & Miswan, 2024). Although the gold price scales with inflation rates on a long-term basis, as gold serves as a hedge against inflation, its financial value fluctuates in the short term (Shen et al., 2020). Although the commodity serves as a safe haven and a diversification instrument for Islamic shares in various economic conditions, its effect wears off during a severe economic depression. Gold does not provide security in standard market conditions, but allows portfolio diversification (Rusmita et al., 2024). The gold price is subject to numerous factors, including investors' expectations, economic uncertainty, and a widespread perception of gold as a sought-after sanctuary. Although gold increases in value during financial meltdowns, investors may seek to sell the commodity to find even safer assets or ensure liquidity (Apanovych et al., 2023).

The gold price is liable to various market trends. Oil revenues and the VIX index have a positive influence on gold prices, whereas the American Dollar Index has an adverse effect on gold prices (Chai et al., 2021). Other factors include economic and political uncertainty, exchange and interest rates (Shen et al., 2020). An increased demand for gold reflects the rising market price of the commodity and its widespread use in the electronic industry (Ahmad et al., 2024).

The gold price tends to grow when stagflation and global inflation rise. China is witnessing an increase in gold consumption for jewelry crafting, where demand for the commodity dramatically exceeds supply, driving its price further upward (Liu et al., 2023).

Gold has been used as an instrument for global trading and transactions for a long time, playing an essential role in fiscal, trading, and financial ventures. The commodity is used to scale global and local economies (Baguda & Al-Jahdali, 2021). The gold price reflects national economic soundness (Das et al., 2022), playing a major role in the global economy and finances (Liang et al., 2022).

Financial markets are very sensitive to information flows, which profoundly shape gold prices (Immanuel & Lazar, 2023).

Investing in gold has become increasingly popular, particularly among millennials, as gold prices tend to rise despite economic uncertainty (Ulyah et al., 2021). The commodity is widely regarded as a 'sanctuary' or 'anchor of stability', although its price has recently deviated from historical trends, exhibiting heightened divergence and volatility (Beretta & Peluso, 2022). Investors' needs, expected return rates, the bandwagon effect, fear of financial collapse, increased appreciation, store of value, and liquidity involve key factors determining investments in gold. A crisis like the Covid-19 pandemic sways the market sentiment, offering gold as a shelter during increased financial instability and a security against inflation (Apanovych et al., 2023).

Liable to factors such as pandemics, geopolitical events, and the financial value of other commodities, gold prices are highly volatile, making the commodity trend difficult to predict (Wang & Lin, 2024). An accurate price forecast is essential for economic and foreign exchange markets (Weng et al., 2020), posing a huge intellectual challenge to investors (Yuan et al., 2020). Financial institutions, mining companies, and associated firms need an effective and correct forecast model for analyzing gold price divergence to make the right decisions (Jabeur et al., 2024).

The gold price depends strongly on the confidence in the current market. Recent studies have adopted various methods, including online daily gold forecasts and news analysis, to generate predictors for a prognostic model (Yuan et al., 2020). Although complex, unstable, and extremely hard to predict (Li et al., 2021), understanding the trend in gold prices is vital for global investments and risk management. Gold prices are subject to violent fluctuations, witnessing marked divergence in times of economic meltdowns like the US-China trade war, the armed conflict in Ukraine, and the COVID-19 pandemic (Yang et al., 2024). The COVID-19 pandemic encouraged investments in gold, seeing a considerable price rise (Kovacikova et al., 2024). The gold price soared dramatically during the COVID-19 pandemic, providing a safe refuge against the crisis. Gold will probably maintain its value in the long term, entailing reduced risk compared to other currencies and cryptocurrencies (Kim et al., 2024). More sensitive to loosening than tightening FOMC rates, gold prices reflect monetary policy rather asymmetrically. Their reaction to rate change notifications exceeds five minutes, indicating the short-term ineffectiveness of the market with gold (Awartani et al., 2024). Thus, the following three research questions, i.e., Research Question 1 (RQ1), Research Question 2 (RQ2), and Research Question 3 (RQ3), were formulated:

RQ1: What are the root causes of gold price divergence in 2024?

RQ2: What are the historical patterns of gold price divergence?

RQ3: What is the prognosis of the gold price divergence trend?

Gold is a precious metal with significant economic value, providing security against inflation and serving as a refuge during financial upheavals. Its price depends on many factors, including economic uncertainty, investors' expectations, global events, oil prices, the VIX index, and the American dollar. Gold is essential for international reserves, growing in significance when major currencies are unstable. Gold prices are a key indicator of entrepreneurial confidence and must be correctly forecast. However, the gold value soars during a crisis (the COVID-19 pandemic), and unsteady and volatile markets prevent an accurate prediction. Although its price scales with inflation rates, the commodity is subject to violent short-term fluctuations. Investments in gold are popular among multiple groups, including millennials, who expect the commodity to grow in importance in the global economy.

The presented study aims to identify the key factors influencing gold price divergence and assess their impact on market trends in 2024.

In 2024, gold price divergence is subject to the following key factors: 1) expected changes in interest rates, determining the appeal of gold as an investment; 2) geopolitical tension in the Middle East; and 3) unresolved conflict between Ukraine and Russia. The suggested determinants create economic uncertainty, deflecting investors' attention to gold. Reaching a record high in 2024, market sentiment confirms that the precious commodity is a 'safe haven' during financial upheavals.

Providing security during economic meltdowns or geopolitical crises, gold has always provided a shelter for investors against financial uncertainty. Trying to escape the Great Recession of 2008, investors massively sank money into gold. We might have witnessed similar behaviour during the COVID-19 pandemic.

The gold price will always be liable to global economic conditions. Financial uncertainty or global geopolitical events are likely to push gold prices even higher. If the economy expands or central banks increase interest rates, the interest in investments in gold as a 'safe haven' might flag.

Literature review

An invaluable non-cash asset, gold is vital during economic upheavals in the macroeconomic environment (Li et al., 2021). Stable in unstable conditions, the commodity provides a haven during financial meltdowns. Given the numerous global financial undertakings, the gold price forecast is a vital decision-making tool for investors (Nurhambali et al., 2024). A reliable predictive model is essential for understanding the fluctuations, trends, and dynamics of gold prices, creating opportunities for high incomes (Livieris et al., 2020). The price fluctuations of futures depend on various factors, including macroeconomic conditions, policy changes, and market sentiments. The interaction between these determinants makes the future trends complex and hard to predict (Pan et al., 2024).

We used a DBN model composed of RBM and a controlled BP layer for gold price forecasting, comparing the model performance with traditional methods like BP neural networks, GA-BP, and ARIMA. The results showed the highest predictive accuracy in the DBN model, indicating the lowest error metrics and highest standard statistics compared to other models (Zhang & Ci, 2020). Chai et al. (2021) used STL-ETS models, neural networks, and a Bayesian structural time series model to predict the gold price return rate and compared their performance. Their results showed that oil revenues and VIX generate additional gold profits, while the US Dollar Index reduces the income from the commodity. The STL-ETS model made the most accurate forecasts of gold price fluctuations. Sun et al. (2022) applied LSTM neural networks to explore the dependence of financial time series data and the local correlations between gold and bitcoin. The process involved categorizing the inputs into cycles using integrated empirical data decomposition and RNN and LSTM methods. The results showed that the model had made more accurate predictions for gold than for bitcoin, the latter indicating higher volatility and instability than the former.

Zhou & Mengoni (2020) used financial sentiment analysis to convert textual data to numerical statistics, applying an MLP model (multilayer perceptron) for forecasting gold spot prices. The authors combined financial news information with historical price data to make accurate predictions of gold spot prices. Lee et al. (2021) combined wavelet analysis with ARIMA and LSTM models to predict gold futures prices, demonstrating that the wavelet analysis enhanced the performance of both models. Their study confirmed that the LSTM deep learning model can correctly forecast gold futures prices, not affected by non-stationary time series data. Khan (2024) used ARIMA to analyze historical data on gold prices in the Saudi Arabian market and predict future price movements, disclosing that the autoregression of previous prices is vital for capturing serial correlation in the market. The ARIMA model accurately predicted future price movements. Gbadamosi et al. (2024) applied ARIMA and MLP models for forecasting monthly gold prices in the US market. They optimized the hyperparameters to minimize MSE and MAE errors, revealing better outcomes in the MLP than in the ARIMA model. Jabeur et al. (2024) compared six machine learning models, including XGBoost and CatBoost for gold price predictions, identifying the former as the best model for gold price forecasts compared to other tested tools.

The authors applied a SHAP method to interpret the forecasts and analyze various gold price determinants. Sadorsky (2021) compared several machine learning classifiers (bagging, stochastic gradient boosting, random forests, etc.) with logistic models for predicting gold and silver price trends. He revealed that machine learning models are far more accurate (85-90%) than logistic models (55-60%) over a 20-day period. The portfolio based on random forests surpassed the buy-and-dip strategy for gold and silver. Huang et al. (2022) applied an MR model for predicting gold prices and compared it to GBM and TS tools, using an MCS for a stochastic gold price simulation. Qiu et al. (2024) developed an innovative two-stage deep fusion integration framework, combining feature fusion and residual correlation for a more accurate gold price forecast. The prediction was even more correct using variational mode decomposition for clustering time series data into three classes. Their results are promising for making even more efficient prognostic models. Nurhambali et al. (2024) explored the optimal hyperparameters of the LSTM model for gold price predictions using World Gold Council data from 2003 to 2023, including cross-validation, testing of optimization algorithms (Adam, RMSProp), learning speed, and the number of epochs. The optimization algorithm Adam showed the best results, learning as fast as 0.01 and 100 epochs, and achieving the MAPE of 0.4867%. The predictions indicated a growing trend in gold prices over the past eight years.

Theertagiri & Ruby (2023) forecast prices and assessed SARIMA models, using the Akaike criterion for selecting the optimal relative quality orders. The results of SARIMA are analysed using performance error metrics and Kurtosis, and compared with existing algorithms. SARIMA models predict more accurately, demonstrating a considerably lower mean absolute error by 30 to 59% compared to traditional approaches.

The first research question involves content analysis. The second comprises a multilayer perceptron network (MLP), and the third question includes SARIMA methods.

In addition to the above-mentioned approaches for forecasting and modelling in financial and economic systems, several recent studies have emphasized the integration of fuzzy logic, hybrid decision models, and algorithmic personalization in socio-economic decision-making environments. For instance, Gavurova et al. (2025) introduced a hybrid decision support model to assess the socio-economic impact of digital transformation in tourism, showing the potential of intelligent systems for sector-specific strategic planning. Similarly, decision-making systems tailored for inclusive travel planning using fuzzy set theory were proposed to address uncertainty in personalized services (Gavurova & Polishchuk, 2025). Algorithmic personalization and media content structuring (Moravec et al., 2025; Gavurova et al., 2024; Skare et al., 2023) also illustrate the growing relevance of AI and fuzzy frameworks in modelling complex, data-rich environments. Furthermore, the integration of digital technologies into healthcare management (Smolanka et al., 2024) and patient trust modeling (Gavurova et al., 2024) demonstrates how hybrid intelligent models can improve institutional performance and strategic decision-making. These studies collectively highlight the increasing utility of information-analytical and fuzzy-based systems across different domains, underscoring the importance of adaptive and interpretable models for supporting real-world decisions under uncertainty. This background provides a relevant theoretical foundation for evaluating gold price forecasts and contributes to a broader understanding of AI applications in decision support systems.

Materials and Methods

We used annual secondary data for all monitored variables from 31st December 1980 to 31st December 2024, processing gold price data from 'Gold Prices – 100 Years Historical Chart 2024 in US Dollars per ounce. The same method applies to Brent Oil price movements from 'Average Annual Brent Crude Oil Price from 1976 to 2024' (2024), using data from the 'Consumer Price Index Historical Tables for US'. City Average', 2024, and the 'U.S. Dollar Index' 2025, 'U.S. Dollar Index (DXY) historical data from 1973 to 2025', 2025. The US Dollar Index is a weighted geometric mean of the dollar rate to the selected weighted currencies: Euro (57.6%), Japanese Yen (13.6%), British Pound (11.9%), Canadian Dollar (9.1%), Swedish Crown (4.2%), and Swiss Franc (3.6%). All time series contain annual values up to 31st December of each year from 1980 to 2024.

All the data are in chronological order, compiled in MS Excel. The dataset consists of two columns: the first contains statistics up to 31st December of each year, and the second contains the values of the variables. The resulting data are imported into the Mathematica Wolfram software for further processing and analysis.

To answer the first question, we analyze scholarly articles to identify the main causes of gold price divergence in 2024, focusing on publications indexed in the Web of Science and published in 2024. We search the sources using keywords like 'gold price', or 'gold' AND 'price', exporting bibliographic data from Zotero reference manager in RIS. This standardized tag format uses 'export notes', ensuring a complete export including notes and keywords. VOS viewer specialized software allows us to visualize the relationships between keywords in several steps. First, we click on 'create' and choose 'create a map based on bibliographic data', followed by clicking on 'read data from reference manager files' and opting for our exported file in the RIS format. The next step involves setting 'co-occurrence' analysis and choosing 'keywords' as the analysed unit. We adopt a 'full counting' method for covering all keyword occurrences, setting a minimum number of occurrences of a keyword to 1. The minimum threshold

contains 58 keywords from which we choose the 14 most significant words for our analysis, allowing us to explore and visualize the most important terms. The last step involves finalizing the visualization, which helps us better understand the relations and structures within the subject.

To answer the second research question on the historical trend of gold price divergence, we use multilayer neural networks (MLP), importing the data from xlsx files and processing them in Mathematica Wolfram software. We import five different data time series: gold prices (golddata and golddate), the US dollar index (dxydata and dxydate), Brent oil prices (brentdata and brentdate), consumer price index CPI (cpidata and cpidate), and interest rates (ratedata and ratedate). All the time series cover the period from 31st December 1980 to 31st December 2024, including 45 observations for each timespan. We extract the data from the Excel file sheets by combining the Import, Take, and Flatten functions, and remove unnecessary lines and columns. The dates of all observations are standardized in GMT+1 format, and numerical values are arranged into vectors to analyze the relationships between the gold price and other economic indicators over the monitored period. The next step involves creating new time series using the TimeSeries function for all imported variables, including tsgold for gold prices, tsdxy for the US dollar index, tsbrent for Brent oil prices, tscpi for consumer prices, and tsrate for interest rates. Each time series contains 45 data values covering the period from 31st December 1980 to 31st December 2024.

Economic relationships are visualized by five graphs using DateListPlot, allowing a depiction of all monitored time series. The red curve illustrates the gold price movement (tsgold), blue curve the US dollar index (tsdxy), black curve Brent oil prices (tsbrent), brown curve the consumer price index (tscpi), and purple curve the Federal Funds Rate (tsrate). All charts share the same structure involving the boundary, zooming, and captions, including their own headings, captions, and Year-axis. The vertical axis expresses the analysed data in USD, as an index or percentage. We also devised two predictive models based on neural networks. The first design involves only the gold price time series, while the second contains multiple regressive analyzes using all monitored economic indicators. The first model utilizes a dataset that connects temporal data with gold prices using the Thread function. Then, we apply a predictive function based on a neural network method (Method → 'NeuralNetwork'), displaying the results on a graph that illustrates real values (a continuous red line), predicted values (a dashed black line), and residues.

The second model follows a similar pattern, containing a dataset with all economic indicators (DXY index, Brent oil prices, CPI, and interest rates). The results are graphically depicted using a blue-coloured scale. To measure the accuracy of both models, we drew a combined graph of residues with a red curve depicting the first and a blue one depicting the second model's residues. The space between the curves is light brown to see more clearly the differences between the designs. The first reflects basic time series, including the historical movement of gold prices as the only predictor. The second also covers DXY – an index representing the strength of the US dollar, Brent oil prices as a commodity market indicator, the consumer price index, including inflation pressure, and interest rates reflecting monetary policies. The analysis of residues assesses the accuracy of the predictive models by measuring the distance between the residues and the zero value. The residues closest to zero mean the most accurate forecast.

We use Wolfram Mathematica software to answer the third research question on forecasting the future gold price movement, applying a SARIMA model (Seasonal Autoregressive Integrated Moving Average). Extended by seasonality, SARIMA can accurately analyse seasonal time series. The prototype consists of three main components: an autoregressive model (AR), which describes the dependence of current values on previous ones; an integrated part (I), ensuring time series stationarity; and a moving average model (MA), which detects the impact of economic fluctuations. The model reflects the following parametric setting $\{\{3, 1, 2\}, \{0, 3, 0\}13\}$, where the first bracket determines non-seasonal parameters with Period 13 (seasonal AR = 0, seasonal fluctuations = 3, seasonal MA = 0). This model specification considers seasonality and non-seasonality of the time series using autoregressive components, differentiation, and moving averages. The predicted period is set to ten years from 2025 to 2034, using the TimeSeriesModelFit for calculations. Generated predictions blend with the last known observation from 2024 to ensure time series continuity. We compile two diagrams: the first focuses on the predicted period, using red marking to highlight future values; the second illustrates a wider historical context, containing historical data from 1980 to 2024, marked by a full red line, and predicted values from 2025 to 2034, labelled by a dashed red line. Both diagrams include descriptions of time axes, USD rates, relevant captions, glossaries, and additional grids to facilitate clear interpretation.

Results

Our analysis of relationships in the market with gold using VOSviewer revealed the links between key factors influencing the gold price movement.

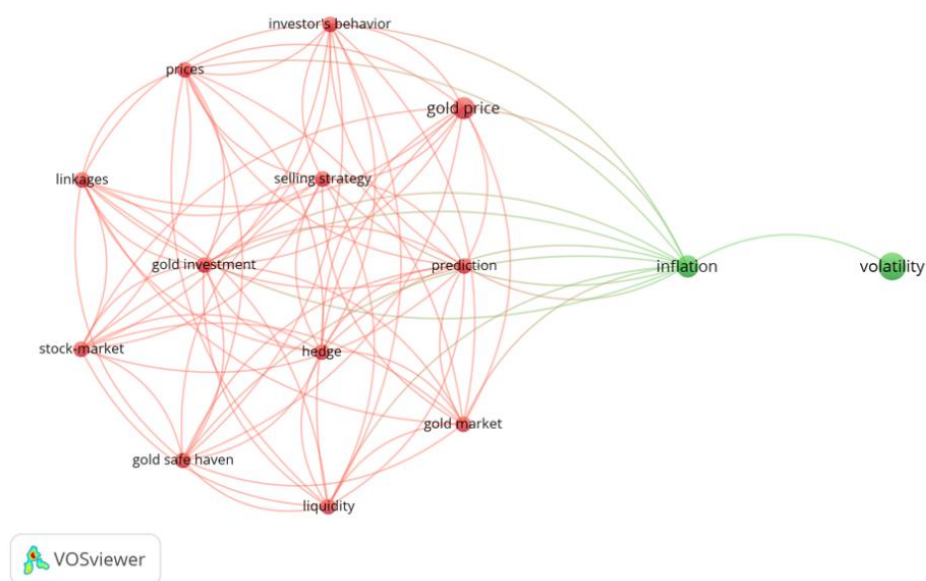


Figure 1: Visualized relationships in the market with gold

Figure 1 suggests nodes (points) representing the keywords like 'gold price', investments in gold, 'inflation', and 'volatility'. The larger in size, the more important these nodes are, as they are interconnected by lines symbolizing the relationships between the words. For better clarity, we classified the terms into two main colourful groups – red represents keywords related to investments in gold, while green shows broader economic factors responsible for gold price movements.

The figure illustrates the gold price as a central node connected to multiple decisive factors that affect the market for gold, which also influence investment decisions in the commodity market.

The gold price depends on many determinants, including investor behavior, investment strategies, and forecasts of future price movements. Perceived as a haven and hedge against inflation and stock market volatility, its price correlates with market liquidity and overall gold market conditions. These keywords are interrelated.

The graphical overview suggests the following decisive factors: investor behavior, Marketing strategies, Investments in gold, Predictions, Inflation, Market volatility, Stock Market, Hedge, Market with gold, Gold as a safe investment, Liquidity, and Relations.

We applied two predictive models based on neural networks to identify the historical movement of gold price divergence. The first design exclusively reflects the historical time series of gold prices, whereas the second prototype explores the relationships between the gold price and other economic indicators, including the US dollar index (DXY), Brent oil prices, the consumer price index (CPI), and Federal Funds Rate interest rates.

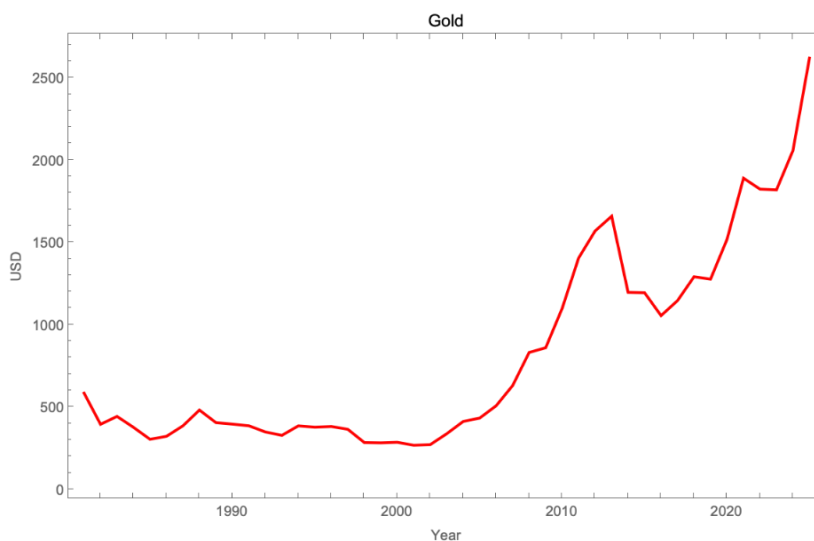


Figure 2: Historical movement of gold prices

As depicted in Figure 2, we created a time series from 31st December 1980 to 31st December 2024.

The gold price movement over the last forty years shows violent fluctuations, marking several critical periods. At the beginning of the monitored period in 1980, the gold value reached 600 USD per ounce, followed by a worldwide price slump. The following decade, the 1980s, was more settled, setting the gold price between 300 and 500 USD per ounce. The 1990s saw prices fall and settle at 300 – 400 USD per ounce. The breaking point of 2000 witnessed a rise in gold rates, considerably accelerating after 2005. The most dramatic growth occurred between 2005 and 2012, marking a massive upsurge to almost 1,700 USD per ounce. The following three-year period, 2013-2013, saw a further increase, culminating in 2024 when gold prices topped 2,700 USD per ounce, a historical maximum.



Figure 3: Historical movement of the US dollar index

The US dollar index DXY, i.e. the strength of the currency compared to six major world currencies, is the weighted geometric average of the USD value to the selected currencies with the weights as follows: Eur (57.6%), JPY (13.6%), GBP (11.9%), CAD (9.1%), SEK (4.2%) and CHF (3.6%).

In 1980, the index started at 90, witnessing a dramatic increase, peaking at 150 in 1984, indicating a historical maximum over the monitored period. Following a considerable decline, the index oscillated between 85 and 100 in the second half of the 1980s and during the 1990s. The beginning of the millennium saw the dollar rise to over 110, followed by intermittent decreases and increases, ranging around 80. After 2014, the dollar strengthened, staying over 90 despite periodic fluctuations. The period between 2022 and 2024 saw a massive rise in the currency, oscillating between 101 and 110.

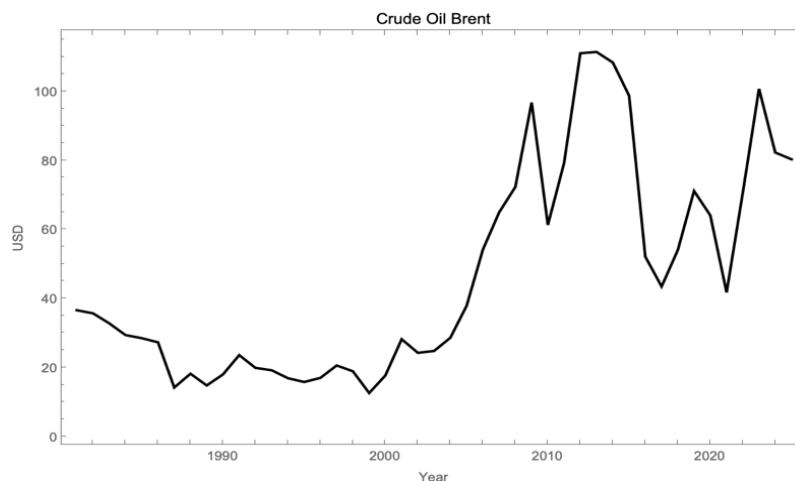


Figure 4: Brent oil price historical movement

At the beginning of the monitored period in 1980, the price reached almost 40 dollars per barrel, witnessing a gradual decline to approximately 15 dollars per barrel. The 1990s brought lower prices, ranging between 15 and 20 dollars per barrel. The period after 2000 saw a massive upsurge in oil prices. This growing trend initially accelerated but later took a downward direction. The values topped 110 dollars per barrel between 2011 and 2013, witnessing a fall to 45 dollars between 2014 and 2016. Although the price partially recovered, the onset of the

COVID-19 pandemic in 2020 slashed the value to 40 dollars. The following years marked a tremendous economic reinvigoration, peaking at 100 dollars per barrel in 2022 and settling at 80 dollars between 2023 and 2024.

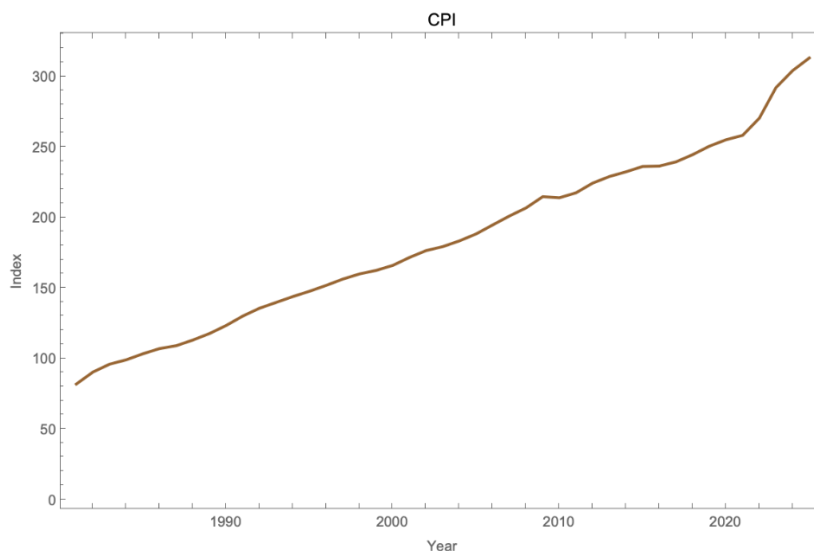


Figure 5: Historical movement of CPI

Figure 5 illustrates the movement of the Consumer Price Index over several decades. The graph suggests that CPI values show a long-term growing trend.

The beginning of the monitored period saw the index below 100 points. It gradually grew at an uneven pace over the following years. The index topped 300 at the end of the monitored period.

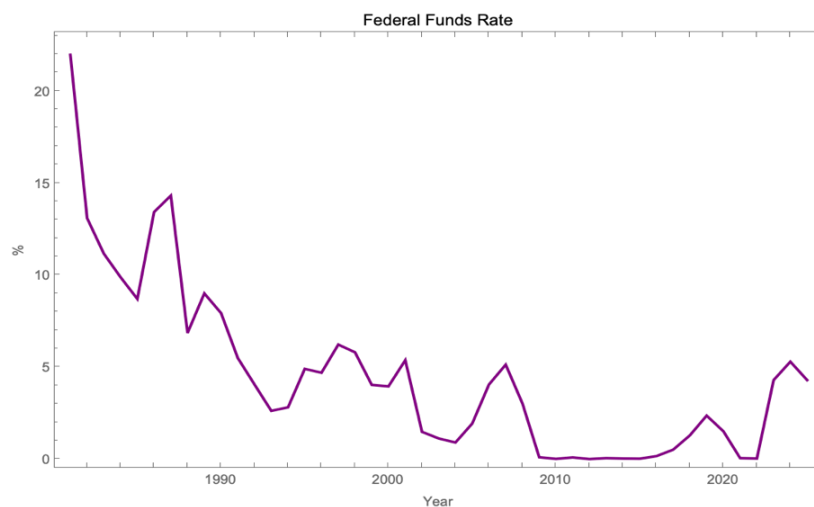


Figure 6: Historical movement of the interest rate index

Figure 6 suggests the movement of the federal funds rate over several decades, radically affecting the US monetary policy.

At the beginning of the monitored period, the federal funds rate was very high, exceeding 20%. Then, they started to decrease and fluctuate. The 1990s witnessed fluctuations oscillating around 5%. The following years were marked by low interest rates, interrupted by short-term fluctuations.

The Fed has recently been trying to increase the interest rate to over 5%.

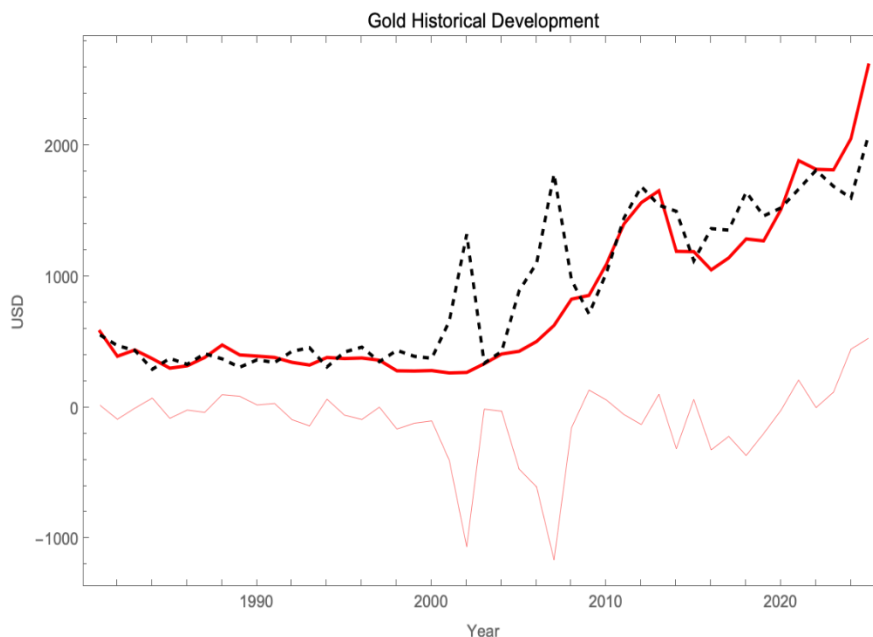


Figure 7: Predicting gold price movements by neural networks based on historical data

We developed a predictive model (Fig. 7) that illustrates the prediction of gold prices based on time series analysis.

The graph compares real gold price movements with the values predicted by the neural model. The full red line represents the historical gold price movement, while the dashed black line illustrates the values predicted by the model.

We can observe a long-term upward trend in gold prices, as reflected in both real data and model forecasts.

Both the real and predicted values exhibit a similar long-term trend, indicating that the model can accurately detect the general tendency of the gold price movement over the monitored period.

The graph suggests that the neural prototype fails to forecast short-term gold price fluctuations accurately. Both lines often intersect, indicating that the model either overestimates or underestimates short-term changes.

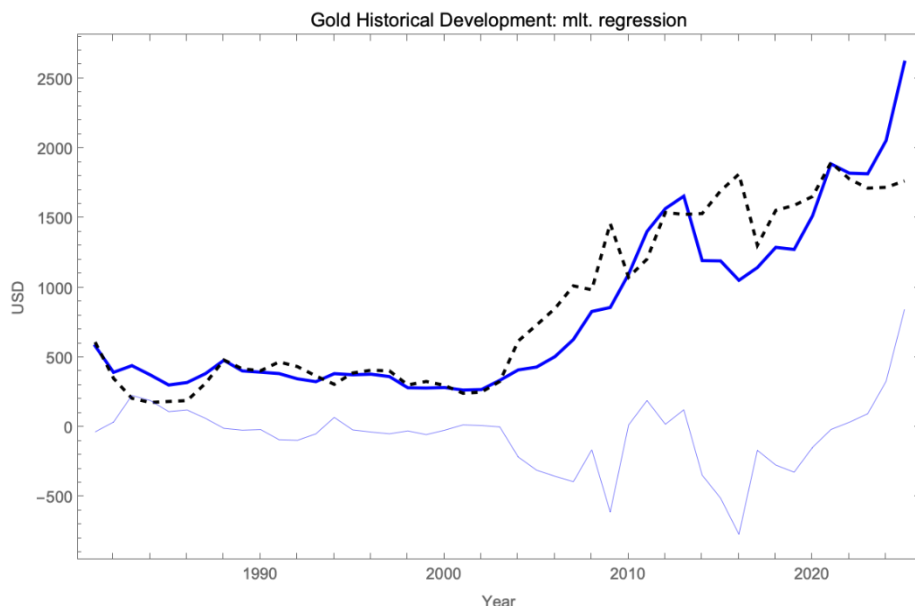


Figure 8: Gold price forecast using neural networks, including macroeconomic indicators

The second model (Fig. 8) includes gold prices and other economic indicators, such as the DXY index, Brent oil prices, CPI, and interest rates, which may significantly influence the gold value. The graph suggests that the blue curve, representing the model predictions, is closer to the real gold price than the forecasts of the first design. This phenomenon indicates that including more economic indicators may improve the model's accuracy.

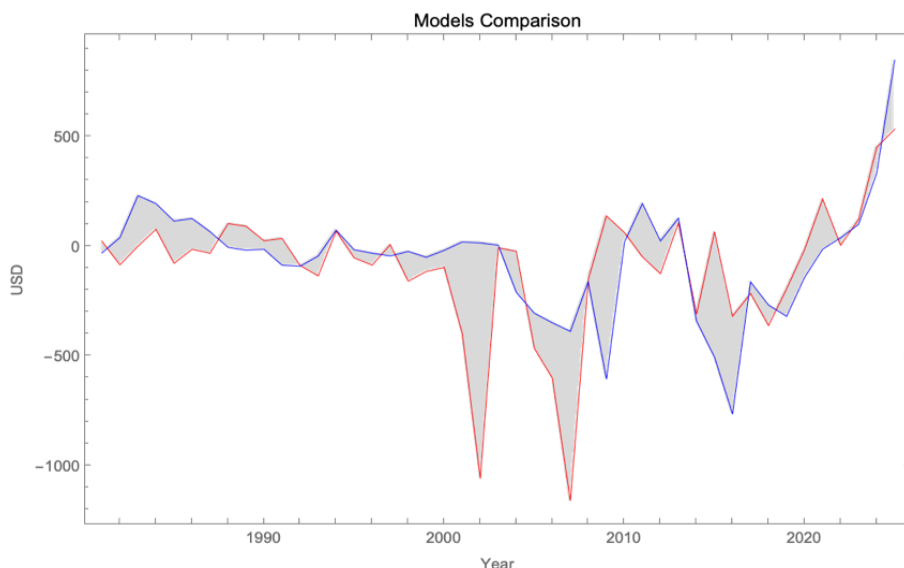


Figure 9: Comparing the accuracy of the basic and extended model using residues

The graph (Fig. 9) compares the accuracies of two predictive models, using residues to mark the differences between real and predicted values. The red curve represents the residues of the model based solely on time series, whereas the blue one depicts the prototype involving other macroeconomic factors. The space between the two curves is grey, allowing for a better visual understanding of the degree of deviation between the models.

Comparing both predictive models shows that the extended version has better outcomes than its counterpart based solely on historical time series. While both designs precisely detected a long-term gold price trend, the extended prototype demonstrates substantially more accurate forecasts, marking less dramatic departures from real values. This improvement reflects a frequent convergence between predicted and real data and close-to-zero residual values. This phenomenon points to a better predictive ability of the extended model. The results show that accurate gold price forecasts should involve a dataset extended by economic factors that may influence its movement, rather than relying solely on the analysis of historical price trends.

We use a SARIMA (Seasonal Autoregressive Integrated Moving Average) model to predict the future gold price movement, including parameters $\{\{3, 1, 2\}, \{0, 3, 0\}13\}$ for 2025 – 2034. The predicted values reflect the observations from 2024 to ensure the time series continuity.

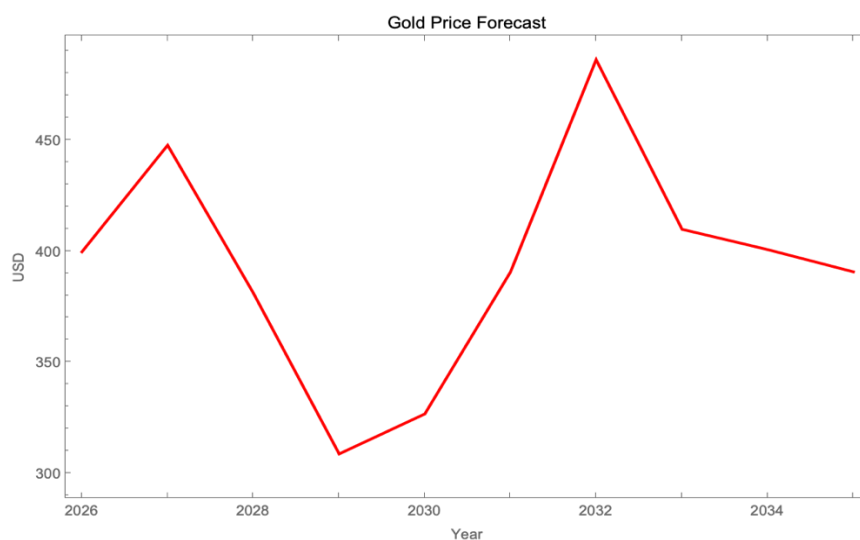


Figure 10: Gold price forecast

The gold price forecast for 2025-2034 exhibits substantial volatility, featuring several notable trends and price reversals. The predictive model analysis indicates a complex price movement, growing as of 2025 and followed by a slump. In 2029, the value will peak at 300 USD per ounce.

The following period demonstrates a gradual appreciation in the gold price, topping 450 USD in 2032.

Although the final phase of the forecast (2032-2034) indicates a price slump, its magnitude is considerably lower than in 2029.



Figure 11: Historical movement and gold price forecasting

Figure 11 depicts the historical movement of gold prices in dollars per ounce from 1960 and their prediction until 2030. While historical data suggests the real gold price movement over the last few decades, the predicted values indicate a potential future trend based on modeled assumptions.

Discussion

RQ1: What are the root causes of gold price divergence in 2024?

The gold price divergence in 2024 is subject to various factors, including investor behavior, inflation pressures, geopolitical events, and changing monetary policies. In times of economic uncertainty, investors tend to tie the capital up in safe assets, including gold. This transition from risk properties, such as shares or currencies, boosts demand and increases gold prices.

Investors invest in gold in various ways – tangible gold, ETF, or futures, which reflect the market volatility. While tangible gold is long-term stable, financial derivatives are liable to short-term speculation.

Inflation acts as a powerful stimulus to push up gold prices. Declining real values make investors turn their attention to gold as a store of value. Price volatility and economic uncertainty in stock markets make gold extremely appealing as a security instrument. As stock markets and gold are inversely proportional, shares plummet when the value of gold rises.

Short-term price fluctuations significantly affect the marketing strategies of investors, who can either profit from inflation or, afraid of financial uncertainty, sell off their assets. The market supply depends strongly on extraction and industrial demand (such as jewellery and technologies), which ensures a supply-demand equilibrium.

Gold has always shown high liquidity, allowing fast capital flows, which is convenient for investing individuals and legal entities. During crises like in 2024, the growing geopolitical tension, galloping inflation, and financial instability cause exorbitant price hikes.

Chai et al. (2021) revealed that oil price revenues and volatility index VIX favour gold price incomes, while the US dollar index has the opposite effect. Jabeur et al. (2024) used the SHAP method to analyze various factors that precipitate gold prices. Pan et al. (2024) argue that price fluctuations reflect macroeconomic conditions, policy changes, and market sentiment, making the future trend indiscernible and hard to predict. Li et al. (2021) suggest taking gold as security against economic upheavals in the macroeconomic environment.

RQ2: What are the historical patterns of gold price divergence?

Historically, gold price fluctuations have been tied to macroeconomic indicators such as the US dollar index (DXY), Brent oil prices, the consumer price index (CPI), and Federal Reserve interest rates. DXY typically moves inversely to gold, while oil and gold respond similarly to economic disruptions. The CPI reflects inflation, and interest rates influence the investment appeal of gold.

The 1980s saw gold prices initially rise due to high inflation and economic uncertainty, leading to capital outflow into safer assets like gold, a response to stagflation. This was followed by a decline and stability as the economy recovered. In the 1990s, gold prices remained low, reflecting healthy economic development and a shift towards riskier assets by investors. Gold's appeal as a hedge diminished during this period of controlled inflation and stable markets.

The new millennium brought a rise in gold prices, spurred by the dot-com bubble burst and geopolitical tensions. Investors turned to gold as a hedge against financial risks. Following 2005, gold prices continued to rise, driven by demand from the Chinese and Indian economies and concerns about the US dollar's devaluation. The 2008 financial crisis further propelled gold prices to historical highs by 2012, as investors sought a safe haven amid financial meltdowns and inflation fears.

From 2013 to 2015, gold prices declined as the US economy strengthened and interest rate hikes were speculated, making gold less attractive. A new price hike followed, driven by global economic concerns, growing public debt, and trade wars. The COVID-19 pandemic in 2020 amplified financial uncertainty, leading to unprecedented monetary stimulus and a significant increase in gold prices, which reached a historical maximum in 2024, also reflecting rising geopolitical tensions.

The US dollar's value (DXY) has fluctuated significantly. It appreciated in the early 1980s due to the Fed's restrictive monetary policy against inflation, then depreciated in the latter half of the decade due to agreements like the Plaza Accord. The 1990s saw greater dollar stability, while after 2000, it initially appreciated before a prolonged downward trend was caused by events such as the dot-com bubble burst and 9/11, leading to expansionary monetary policy. The 2008 financial crisis introduced further volatility, with the Fed employing aggressive stimulus. Following 2014, the dollar appreciated again as the Fed normalized its policy, while other central banks maintained accommodative measures. A recent surge (2022-2024) is attributed to the Fed's sharp interest rate hikes to combat inflation.

Fed interest rates were very high in the early 1980s (exceeding 20%) to combat high inflation, falling by the mid-1980s. In the 1990s, rates fluctuated around 5% amidst stable growth. After 2000, rates were very low due to events like the dot-com bubble and the 2008 crisis, prompting expansionary policy. From 2014, the Fed gradually normalized its policy and increased rates, a process that continued into 2022-2024, reaching over 5% in response to post-COVID-19 inflation and supply chain disruptions. This contributed to dollar appreciation and aimed to restore price stability.

The CPI in the early 1980s was below 100, rising due to the oil crisis and fiscal policy, which culminated in stagflation. The Fed's high interest rates curbed this. Post-1980s, CPI rose gradually. After 2000 and the 2008 crisis, CPI continued to rise, though below the Fed's target for a while. In recent years, particularly after the COVID-19 pandemic, we have seen a sharp increase in the CPI to around 300 points, driven by supply chain disruptions and increased demand.

Oil prices in the early 1980s were high due to the 1970s oil crisis, then gradually declined. The 1990s brought stability. After 2000, global economic growth, especially in emerging economies, led to a significant rise, peaking in 2007-2008, followed by a decrease due to the financial crisis. Prices stabilized but remained elevated until 2014, when a sharp decline occurred due to slower global growth and OPEC's increased production. Prices fell below \$45/barrel by 2016. The market stabilized in subsequent years; however, the COVID-19 pandemic in 2020 led to an unprecedented collapse. Prices rebounded sharply in 2021-2022, then stabilized around \$80/barrel in 2023-2024.

A gold price model incorporating macroeconomic factors (DXY, Brent oil, CPI, interest rates) showed significantly better predictions than one based solely on historical gold prices. This is because gold prices are strongly influenced by the broader economic context. For example, a weaker US dollar directly increases gold prices. Oil prices affect inflation and mining costs, while CPI and interest rates reflect economic conditions that drive demand for gold as a safe-haven asset. Therefore, forecasting gold prices requires considering a broader range of factors beyond historical data alone, as macroeconomic indicators enhance predictive accuracy by capturing short-term dynamics.

Zhou & Mengoni (2020) employed an MLP model combined with financial sentiment analysis and historical price data to forecast the spot price of gold. Gbadamosi et al. (2024) applied the MLP model to predict monthly gold prices in the US market and demonstrated that MLP outperformed the ARIMA model in terms of predictive accuracy. Nurhambali et al. (2024) used an LSTM model to analyse historical data from the period 2003-2023, providing valuable insights into the long-term development of gold prices. Chai et al. (2021) identified the factors influencing historical gold price returns (the impact of oil prices, the VIX index, and the US dollar), which help to explain patterns of divergence over time.

RQ3: What is the prognosis of the gold price divergence trend?

The prediction of gold prices for the period 2025–2034 suggests considerable volatility, with several pronounced trend reversals. At the beginning of the period, in 2025, the price of gold is expected to rise, which

may be attributed to anticipated economic or geopolitical developments that could increase demand for gold as a safe-haven asset. However, this upward trend is projected to reverse by 2029, when the price may drop to around USD 300 per ounce. This decline could be driven by adverse macroeconomic developments, such as shifts in monetary policy, reduced investor demand for gold, or the stabilisation of global markets, which may decrease interest in assets traditionally seen as stores of value.

Following this decline, a gradual appreciation of the gold price is expected, peaking in 2032, when the price is projected to exceed USD 450 per ounce. This increase may be driven by economic crises, rising inflation, or continued erosion of confidence in traditional financial assets, which would increase the demand for gold as a safe haven. Although a decline is forecast for the final phase of the period (2032–2034), it is expected to be considerably less severe than in 2029. The decline may result from improved global economy, stabilized markets, or shifts in geopolitical dynamics that restore investor confidence in conventional financial instruments and reduce the appeal of holding gold.

Nurhambali et al. (2024) used the LSTM model with the Adam optimizer, achieving an MAPE of 0.4867% and predicted the upward trend of gold prices for the upcoming 8 years. Khan (2024) applied the ARIMA model to the Saudi Arabian market, demonstrating high predictive accuracy and highlighting the model's ability to capture the autoregressive properties of historical data. Jabeur et al. (2024) compared six machine learning models and found that XGBoost was the most effective for forecasting gold prices. Qiu et al. (2024) developed a two-stage hybrid framework combining feature extraction with residual correction techniques, laying the groundwork for more precise forecasting models. Lee et al. (2021) combined wavelet analysis with ARIMA and LSTM, which is particularly suitable for forecasting gold futures due to its robustness to non-stationary time series data. Sadorsky (2021) achieved 85-90% accuracy in predicting the direction of gold prices over a 20-day horizon using machine learning models, significantly outperforming traditional logistic regression models. Chai et al. (2021) used STL-ETS models, which proved highly accurate in forecasting gold price fluctuations and in identifying key factors influencing future developments. Theerthagiri & Ruby (2023) applied SARIMA models and evaluated performance using Akaike's information criterion and error metrics. Their results showed that the SARIMA model achieved higher predictive accuracy, with a 30–59% reduction in mean absolute error compared to other algorithms.

Conclusions

The objective of this paper was to identify and evaluate the key factors influencing the divergence of gold prices and assess their importance for the development of the gold market in 2024.

The gold market was examined using three main tools. VOSviewer was used to map the relationships between the factors influencing gold price divergence in 2024, where investor behaviour in response to economic uncertainty and financial market volatility was particularly pronounced. Multilayer neural networks (MLPs) were utilized to predict gold prices, combining historical price series with macroeconomic indicators such as the US Dollar Index (DXY), the Brent crude oil price, the Consumer Price Index (CPI), and interest rates, resulting in more accurate predictions than models based solely on historical data. The SARIMA statistical model with parameters $\{3, 1, 2\}$, $\{0, 3, 0\}$ applied to a 10-year period predicted price fluctuations between 2025 and 2034, including a rise in 2025, a fall to USD 300 per ounce in 2029, and a subsequent rise above USD 450 per ounce in 2032.

The objective of the paper was achieved, as the application of combined analytical methods enabled identifying and in-depth analysis of the key factors influencing the price divergence of gold in 2024. The use of the VOSviewer tool facilitated a detailed exploration of the interrelationships among various factors within the gold market, while the implementation of multilayer perceptron (MLP) neural networks contributed to a more accurate prediction of price movements by incorporating macroeconomic indicators. The application of the statistical model SARIMA provided a robust foundation for long-term forecasting of the gold price movement over the next decade. The research has demonstrated that gold price dynamics result from the complex interplay of numerous variables, ranging from market expectations and geopolitical developments to macroeconomic conditions. This multilayered interaction shapes the specific market environment that influences the price movements of this precious metal. These findings offer valuable insights into the functioning of the gold market and may serve as a basis for future research, as well as for the practical development of informed investment strategies.

The findings on gold price divergence open new perspectives on the functioning of financial markets and investment decision-making. The demonstrated link between gold price movements and macroeconomic factors, such as interest rates, inflation, and exchange rates, provides investors with a comprehensive tool for strategic portfolio planning. Particularly noteworthy is the strong influence of geopolitical events on gold price dynamics, which confirms gold's enduring role as a safe haven asset in periods of increased market uncertainty.

The practical implications of these insights are relevant for both individual investors and large financial institutions. The enhanced ability to forecast gold price trends, enabled by a combination of neural network models

and statistical methods, facilitates more efficient risk management and portfolio optimisation. For institutional investors, such insights serve as key inputs for long-term strategy development and asset allocation. For small-scale investors, they provide a clearer understanding of market behavior and offer tools to better safeguard savings against volatility.

In the context of monetary policy and financial regulation, the findings provide valuable insights for central banks and financial authorities. Understanding the relationships between monetary policy instruments and gold market dynamics can inform more effective policy design and contribute to mitigating systemic risks. In times of rising inflation and monetary instability, such insights are crucial for maintaining financial system stability.

The current trend of financial market digitalisation and the proliferation of alternative investment instruments casts the role of gold in a new light. The study confirms that, despite the emergence of cryptocurrencies and other digital assets, gold continues to serve as a vital diversification asset. This has important implications for the evolution of investment strategies and the structure of global financial markets.

On a broader economic level, the results contribute to a deeper understanding of the role of gold within the modern financial system. The confirmation of its stabilising role in turbulent times highlights its continued relevance in global reserve structures and the international monetary order. In an era marked by geopolitical tensions and economic transformation, these insights support strategic decision-making by governments and supranational institutions alike.

In summary, the findings on gold price divergence represent a significant contribution to understanding the dynamics of contemporary financial markets. The knowledge gained, encompassing both traditional and emerging aspects of the gold market, including the impact of digitalisation, provides a solid foundation for strategic decision-making across the financial sector. These insights are not only crucial for current market participants but also for future generations of investors and policymakers. At a time of growing global uncertainty and fundamental change in financial systems, a deeper understanding of the role of gold and the factors driving its price is essential for maintaining economic stability and promoting sustainable global growth.

References

- Ahmad, M., Naik, M. u.-d., Tariq, M. R., Khan, I., Zhang, L., & Zhang, B. (2024). Advances in natural polysaccharides for gold recovery from e-waste: Recent developments in preparation with structural features. *International Journal Of Biological Macromolecules*, 261(1). <http://doi.org/10.1016/j.ijbiomac.2024.129688>
- Apanovych, Y., Liskova-Dvorakova, Z., Burghauserova, M., & Kovac, V. (2023). Insights into gold investing: Exploring investor behavior. *Acta Montanistica Slovaca*, 28(4). <http://doi.org/10.46544/AMS.v28i4.02>
- Areh, S. O., & Miswan, N. H. (2024). ARIMA models for Kijang Emas price forecasting: Pre- and post-COVID analysis. *Malaysian Journal Of Mathematical Sciences*, 18(1). <http://doi.org/10.47836/mjms.18.1.08>
- Awartani, B., Hussain, S. M., & Virk, N. (2024). How do the gold intra-day returns and volatility react to monetary policy shocks? *International Review Of Financial Analysis*, 95(B). <http://doi.org/10.1016/j.irfa.2024.103486>
- Baguda, Y. S., & Al-Jahdali, H. M. (2021). An intelligent gold price prediction based on automated machine and k-fold cross validation. *International Journal Of Computer Science And Network Security*, 21(4). <http://doi.org/10.22937/IJCSNS.2021.21.4.10>
- Baur, D. G., Beckmann, J., & Czudaj, R. L. (2020). The relative valuation of gold. *Macroeconomic Dynamics*, 24(6). <http://doi.org/10.1017/S1365100518000895>
- Baur, D. G., Trench, A., & Ulrich, S. (2023). Green gold. *Journal Of Sustainable Finance & Investment*, 13(3). <http://doi.org/10.1080/20430795.2021.1974242>
- Beretta, E., & Peluso, S. (2022). Gold and bubbles: An impossible binomial? A review of historical and current evidence. *Applied Economics Letters*, 29(3). <http://doi.org/10.1080/13504851.2021.1897070>
- Bureau of Labor Statistics. (2023). Historical consumer price index for all urban consumers (CPI-U): US city average, all items, by month. US Department Of Labor. <https://www.bls.gov/cpi/tables/supplemental-files/historical-cpi-u-202302.pdf>
- Bureau of Labor Statistics. (n.d.). Consumer price index historical tables for US city average. US Department Of Labor. https://www.bls.gov/regions/midatlantic/data/consumerpriceindexhistorical_us_table.htm
- Das, S., Sahu, T. P., & Janghel, R. R. (2022). Oil and gold price prediction using optimized fuzzy inference system based extreme learning machine. *Resources Policy*, 79. <http://doi.org/10.1016/j.resourpol.2022.103109>
- Gavurova, B., & Polishchuk, V. (2025). Decision-making support system for travel planning for people with disabilities based on fuzzy set theory. *Oeconomia Copernicana*, 16, 417–462. <https://doi.org/10.24136/oc.3503>
- Gavurova, B., Polishchuk, V., Mikeska, M., & Polishchuk, I. (2025). A socio-economic impact of digital transformation in tourism: A hybrid decision support model. *Economics and Sociology*, 18(2), 305–319. <http://doi.org/10.14254/2071-789X.2025/18-2/16>

- Gavurova, B., Skare, M., Hynek, N., Moravec, V., & Polishchuk, V. (2024). An information-analytical system for assessing the level of automated news content according to the population structure – A platform for media literacy system development. *Technological Forecasting and Social Change*, 200, 123161. <https://doi.org/10.1016/j.techfore.2023.123161>
- Gavurova, B., Smolanka, V., & Polishchuk, V. (2024). Intellectual model for analyzing and managing patient trust in medical staff of primary healthcare institution. *Polish Journal of Management Studies*, 30(1), 98–115. <https://doi.org/10.17512/pjms.2024.30.1.06>
- Gbadamosi, S. L., Nwulu, N. I., & Akinola, S. O. (2024). Exploring the effectiveness of a multilayer neural network model for gold price prediction. *Przegląd Elektrotechniczny*, 100(3). <http://doi.org/10.15199/48.2024.03.28>
- Huang, S., Ma, Z., Jin, F., & Zhang, Y. (2022). Prediction of mineral product price based on mean reversion model. *Gospodarka Surowcami Mineralnymi – Mineral Resources Management*, 38(2). <http://doi.org/10.24425/gsm.2022.141665>
- Chai, J., Zhao, C., Hu, Y., & Zhang, Z. G. (2021). Structural analysis and forecast of gold price returns. *Journal Of Management Science And Engineering*, 6(2). <http://doi.org/10.1016/j.jmse.2021.02.011>
- Immanuvel, S. M., & Lazar, D. (2023). Does information spillover and leverage effect exist in world gold markets? *Global Business Review*, 24(3). <http://doi.org/10.1177/0972150919885472>
- Jabeur, S. B., Mefteh-Wali, S., & Viviani, J.-L. (2024). Forecasting gold price with the XGBoost algorithm and SHAP interaction values. *Annals Of Operations Research*, 334. <http://doi.org/10.1007/s10479-021-04187-w>
- Jianwei, E., He, K., Liu, H., & Ji, Q. (2023). A novel separation-ensemble analyzing and forecasting method for the gold price forecasting based on RLS-type independent component analysis. *Expert Systems With Applications*, 232. <http://doi.org/10.1016/j.eswa.2023.120852>
- Khan, R. (2024). Fluctuation and forecasting of gold prices in Saudi Arabia's market. *Kybernetes*, 54(7). <http://doi.org/10.1108/K-09-2023-1725>
- Kim, Y., Topal, E., Ghosh, A. K., & Asad, M. W. A. (2024). Investor behavior in gold, US dollars and cryptocurrency during global pandemics. *Economies*, 12(3). <http://doi.org/10.3390/economies12030064>
- Kovacikova, N., Kovac, V., & Janek, S. (2024). Price dynamics of gold and silver in the period 2015–2023. *AD ALTA: Journal Of Interdisciplinary Research*, 13(2).
- Lee, D. H., Kim, D. H., & Yoon, J. H. (2021). Prediction of US gold futures prices using wavelet analysis; a study on deep learning models. *Journal Of Applied Mathematics And Informatics*, 39(1–2). <http://doi.org/10.14317/jami.2021.239>
- Li, Y., Wang, S., Wei, Y., & Zhu, Q. (2021). A new hybrid VMD-ICSS-BiGRU approach for gold futures price forecasting and algorithmic trading. *IEEE Transactions On Computational Social Systems*, 8(6). <http://doi.org/10.1109/TCSS.2021.3084847>
- Liang, Y., Lin, Y., & Lu, Q. (2022). Forecasting gold price using a novel hybrid model with ICEEMDAN and LSTM-CNN-CBAM. *Expert Systems With Applications*, 206. <http://doi.org/10.1016/j.eswa.2022.117847>
- Liu, S., Geng, Y., Gao, Z., Li, J., & Xiao, S. (2023). Uncovering the key features of gold flows and stocks in China. *Resources Policy*, 82. <http://doi.org/10.1016/j.resourpol.2023.103584>
- Livieris, I. E., Pintelas, E., & Pintelas, P. (2020). A CNN-LSTM model for gold price time-series forecasting. *Neural Computing And Applications*, 32. <http://doi.org/10.1007/s00521-020-04867-x>
- Macrotrends. (n.d.). Federal funds rate – 62 year historical chart. Macrotrends. <https://www.macrotrends.net/2015/fed-funds-rate-historical-chart>
- Macrotrends. (n.d.). Gold prices – 100 year historical chart. Macrotrends. <https://www.macrotrends.net/1333/historical-gold-prices-100-year-chart>
- Manakhov, B. M. (2020). The new institutionalization of monetary gold: Theories and prospects for the revival of the gold standard. *Turismo*, 5.
- Moravec, V., Hynek, N., Skare, M., Gavurova, B., & Polishchuk, V. (2025). Algorithmic personalization: A study of knowledge gaps and digital media literacy. *Humanities and Social Sciences Communications*, 12, 341. <https://doi.org/10.1057/s41599-025-04593-6>
- Nurhambali, M. R., Angraini, Y., & Fitrianto, A. (2024). Implementation of long short-term memory for gold prices forecasting. *Malaysian Journal Of Mathematical Sciences*, 18(2). <http://doi.org/10.47836/mjms.18.2.11>
- Pan, H., Tang, Y., & Wang, G. (2024). A stock index futures price prediction approach based on the MULTI-GARCH-LSTM mixed model. *Mathematics*, 12(11). <http://doi.org/10.3390/math12111677>
- Qiu, C., Zhang, Y., Qian, X., Wu, C., Lou, J., Chen, Y., Xi, Y., Zhang, W., & Gong, Z. (2024). A two-stage deep fusion integration framework based on feature fusion and residual correction for gold price forecasting. *IEEE Access*, 12. <http://doi.org/10.1109/ACCESS.2024.3408837>
- Rusmita, S. A., Filianti, D., Mayasani, E. N., & Abd Samad, K. (2024). Gold characteristics as safe haven and assets diversification for Sharia stocks in Indonesia. *Journal Of Islamic Accounting And Business Research*. <http://doi.org/10.1108/JIABR-11-2021-0302>

- Sadorsky, P. (2021). Predicting gold and silver price direction using tree-based classifiers. *Journal Of Risk And Financial Management*, 14(5). <http://doi.org/10.3390/jrfm14050198>
- Shen, L., Shen, K., Yi, C., & Chen, Y. (2020). Regression and hidden Markov models for gold price prediction. In X. Wu et al. (Eds.), 2020 IEEE International Conference On Big Data (Big Data). <http://doi.org/10.1109/BigData50022.2020.9378468>
- Skare, M., Gavurova, B., & Polishchuk, V. (2023). A large-scale decision-making model for the expediency of funding the development of tourism infrastructure in regions. *Expert Systems*, 2023, 13443. <https://doi.org/10.1111/exsy.13443>
- Smolanka, V., Gavurova, B., & Polishchuk, V. (2024). Managing and evaluating the integration of information technologies in healthcare institutions. *Polish Journal of Management Studies*, 30(2), 297–313. <https://doi.org/10.17512/pjms.2024.30.2.18>
- Statista. (n.d.). Average annual Brent crude oil price from 1976 to 2024. Statista. <https://www.statista.com/statistics/262860/uk-brent-crude-oil-price-changes-since-1976/>
- Statista. (n.d.). US dollar index (DXY) historical data 1973–2025. Statista. <https://www.statista.com/statistics/1404145/us-dollar-index-historical-chart/>
- Sun, C., Wang, S., Song, Q., Zhu, S., Heng, J., & Lei, L. (2022). Optimal trade strategy based on RNN-LSTM deep learning method. In H. M. Srivastava & C. H. Chen (Eds.), 2nd International Conference On Applied Mathematics, Modeling And Intelligent Computing (CAMMIC 2022). Proceedings Of SPIE, 12259. <http://doi.org/10.1117/12.2638942>
- Theerthagiri, P., & Ruby, A. U. (2023). Seasonal learning based ARIMA algorithm for prediction of Brent oil price trends. *Multimedia Tools And Applications*, 82. <http://doi.org/10.1007/s11042-023-14819-x>
- Ulyah, S. M., Andreas, C., & Rahmayanti, I. A. (2021). Forecasting gold and oil prices considering US-China trade war using vector autoregressive with exogenous input. In C. Alfiniyah, Fatmawati, & Windarto (Eds.), International Conference On Mathematics, Computational Sciences And Statistics 2020. AIP Conference Proceedings, 2329(1). <http://doi.org/10.1063/5.0042362>
- Wang, Y., & Lin, T. (2024). A novel deterministic probabilistic forecasting framework for gold price with a new pandemic index based on quantile regression deep learning and multi-objective optimization. *Mathematics*, 12(1). <http://doi.org/10.3390/math12010029>
- Weng, F., Chen, Y., Wang, Z., Hou, M., Luo, J., & Tian, Z. (2020). Gold price forecasting research based on an improved online extreme learning machine algorithm. *Journal Of Ambient Intelligence And Humanized Computing*, 11. <http://doi.org/10.1007/s12652-020-01682-z>
- Wikipedia. (2025). US dollar index. Wikipedia. https://en.wikipedia.org/wiki/U.S._Dollar_Index
- Yang, M., Wang, R., Zeng, Z., & Li, P. (2024). Improved prediction of global gold prices: An innovative Hurst-reconfiguration-based machine learning approach. *Resources Policy*, 88. <http://doi.org/10.1016/j.resourpol.2023.104430>
- Yuan, F.-C., Lee, C.-H., & Chiu, C. (2020). Using market sentiment analysis and genetic algorithm-based least squares support vector regression to predict gold prices. *International Journal Of Computational Intelligence Systems*, 13. <http://doi.org/10.2991/ijcis.d.200214.002>
- Zhang, P., & Ci, B. (2020). Deep belief network for gold price forecasting. *Resources Policy*, 69. <http://doi.org/10.1016/j.resourpol.2020.101806>
- Zhou, J., & Mengoni, P. (2020). Spot gold price prediction using financial news sentiment analysis. In J. He, H. Purohit, G. Huang, X. Gao, & K. Deng (Eds.), 2020 IEEE/WIC/ACM International Joint Conference On Web Intelligence And Intelligent Agent Technology (WI-IAT 2020). IEEE. <http://doi.org/10.1109/WIIAT50758.2020.00117>