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An Empirical Study On The Impact Of Gold And Silver Prices On The Stock Market Using Machine Learning

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Abstract: This research investigates the dynamic association between gold prices, silver prices, and movements in the Indian stock market by employing contemporary machine learning methodologies. Financial markets in India have experienced heightened volatility driven by economic disruptions, inflationary pressures, and global uncertainties. During such turbulent episodes, investors characteristically redirect capital toward precious metals, particularly gold and silver, viewing them as protective stores of value and inflation hedges. This study utilizes daily historical price data for gold, silver, and a prominent Indian stock index spanning the period from 2019 to 2026. Following rigorous data preprocessing and transformation, both statistical and machine learning models were constructed to identify underlying patterns and generate short-term market movement forecasts. The empirical findings reveal distinct volatility profiles for gold and silver and illustrate their differential predictive relevance for equity market movements.

Index Terms - Gold price, Silver price, Indian stock market, Machine learning, Forecasting, Time-series analysis

I. INTRODUCTION

1. Background

The interplay between precious metal prices and equity market performance has historically attracted considerable scholarly and practitioner attention. Gold is broadly recognized as a safe-haven asset and a reliable hedge against inflation, while silver exhibits a dual character as both a precious metal and a critical industrial commodity. Consequently, fluctuations in gold and silver prices tend to mirror broader macroeconomic conditions and prevailing investor sentiment.

India's capital market has undergone rapid structural transformation, characterized by expanding retail investor participation, proliferation of digital trading platforms, and deepening integration with global financial ecosystems. Despite this advancement, Indian equity markets remain highly sensitive to macroeconomic indicators, monetary policy announcements, inflation trends, and geopolitical developments. During periods of financial uncertainty, investors frequently reallocate portfolios between equities and alternative assets including precious metals, amplifying co-movement dynamics.

Conventional econometric approaches have been widely applied to examine commodity-equity price relationships; however, such techniques often rely on linearity assumptions and may be inadequate for capturing the complex, nonlinear dynamics inherent in financial time series. Recent advances in machine learning offer enhanced capacity for modeling such relationships and significantly improving predictive performance.

2. Problem Statement

The Indian stock market has recorded escalating volatility coinciding with rising retail investor participation in recent years. Investors actively seek effective diversification and risk mitigation strategies, particularly during periods of elevated economic uncertainty. Although gold and silver are conventionally regarded as hedging instruments, their precise relationship with Indian equity market dynamics has yet to be comprehensively established through contemporary analytical frameworks.

A significant portion of existing empirical literature relies on traditional econometric techniques and examines gold or silver independently. The dual investment and industrial nature of silver introduces additional complexity that has received limited systematic attention within the Indian context. Furthermore, the study period from 2019 to 2026 encompasses significant economic disruptions—the COVID-19 pandemic, persistent inflationary pressures, and shifting geopolitical alignments—which may have fundamentally altered conventional asset-class relationships.

This study addresses these research gaps by applying advanced machine learning techniques to systematically examine the impact of gold and silver price movements on Indian equity indices, thereby producing data-driven insights for both investors and policymakers.

3. Research Objectives

The principal objectives of this study are:

1. To examine the relationship between gold prices, silver prices, and Indian stock market indices spanning 2019 to 2026.
2. To analyze price movement trajectories and volatility patterns of gold and silver during recent economic disruptions.
3. To assess the quantitative impact of precious metal price fluctuations on equity market performance.
4. To construct and evaluate machine learning models for predicting stock market movements using gold and silver price inputs.
5. To compare the predictive significance and reliability of gold versus silver as market indicators across varying economic conditions.
6. To generate short-term stock market forecasts for early 2026 using developed models.
7. To derive actionable insights for investment decision-making and portfolio risk management.

4. Scope and Limitations

This investigation focuses on the Indian stock market, utilizing daily observations of gold prices, silver prices, and major stock index values from 2019 to 2026. Both econometric and machine learning methodologies are applied to examine linear and nonlinear price dynamics. The analysis is confined to gold and silver, excluding other commodities. Geographic coverage is limited to India, and machine learning forecasts should be interpreted with appropriate caution.

II. LITERATURE REVIEW

1. Theoretical Foundations

The theoretical basis of this research draws on portfolio theory, safe-haven asset theory, and the efficient market hypothesis. Portfolio theory, originally conceptualized by Markowitz (1952), supports the inclusion of non-correlated assets such as precious metals to optimize risk-adjusted returns. Safe-haven asset theory posits that gold and silver attract capital inflows during periods of financial stress, thereby moderating investor losses.

Machine learning approaches, including ensemble methods and deep learning architectures, are grounded in statistical learning theory. These methods can identify nonlinear relationships and complex feature interactions that conventional linear models fail to capture, making them particularly suitable for modeling the dynamic relationship between commodity prices and equity markets.

2. Previous Research

Research conducted between 2019 and 2026 has examined the interaction between precious metal prices and stock market performance under evolving global and domestic economic conditions. Multiple studies confirm that gold continues to serve a stabilizing function during episodes of market uncertainty. However, empirical findings indicate that the influence of gold on equity markets is neither uniform nor persistent, with evidence pointing to weak, short-term, or market-specific associations rather than robust long-run dependency.

Post-2020 research has increasingly incorporated silver into empirical analyses, largely due to its expanding role in industrial applications such as renewable energy, electronics, and electric vehicle manufacturing. Unlike gold, silver was found to respond to both financial market dynamics and industrial demand shifts, resulting in elevated volatility and inconsistent correlation patterns with equity indices.

From 2021 onward, machine learning-based financial research gained significant momentum. Studies applying Support Vector Machines, Random Forest algorithms, Gradient Boosting frameworks, and Long Short-Term Memory networks demonstrated superior forecasting accuracy compared to traditional statistical models.

3. Gaps in Current Research

Despite the volume of existing literature, several important research gaps persist. First, most studies examine gold and silver independently, overlooking potential interaction effects between the two metals. Second, limited empirical research in the Indian context jointly analyzes gold and silver price movements alongside stock indices using machine learning techniques and datasets extending to 2026. This study is specifically designed to address these identified gaps through an integrated, data-driven analytical approach.

III. METHODOLOGY

1. Research Design

This study adopts a quantitative, empirical research design combining time-series econometric analysis with supervised machine learning techniques. The research follows a structured analytical pipeline: data acquisition, preprocessing, exploratory analysis, model development, validation, and forecasting.

2. Data Collection

Secondary data comprising daily closing prices of gold (₹/10g), silver (₹/kg), and the Sensex index were sourced from authenticated financial databases for the study period from 2019 to 2026. The dataset encompasses over 1,800 daily observations, providing robust coverage for trend analysis and model training.

3. Data Analysis

Data analysis was conducted in sequential stages. Descriptive statistical techniques were initially applied to characterize central tendency, dispersion, skewness, and kurtosis of the price series. Stationarity was assessed using the Augmented Dickey-Fuller (ADF) test. The Vector Autoregressive (VAR) model was employed to capture short-run interdependencies among the three variables and generate out-of-sample price forecasts. Model performance was evaluated using MAE, RMSE, and directional accuracy.

IV. SYSTEM DESIGN / ARCHITECTURE

1. System Overview

The analytical system is structured as an integrated data pipeline that transforms raw financial price data into actionable forecasts through sequential stages of preprocessing, feature engineering, model training, validation, and output generation.

2. Component Description

The system consists of: (i) Data Ingestion Module; (ii) Feature Engineering Module; (iii) Statistical Modeling Module—implementing ADF tests and VAR models; (iv) Machine Learning Module—training and evaluating ensemble and deep learning models; and (v) Forecasting and Visualization Module—producing forecast outputs and graphical representations.

3. System Integration

The components are integrated through a unified data schema ensuring consistent variable definitions and time-alignment across all modules. This integrated architecture facilitates systematic comparison of econometric and machine learning forecasts, enabling a comprehensive assessment of model performance.

V. IMPLEMENTATION / EXPERIMENTAL RESULTS

1. Implementation Details

Data preprocessing involved handling missing values through forward-fill interpolation, removing outliers beyond three standard deviations, and transforming price levels to log-returns for stationarity.

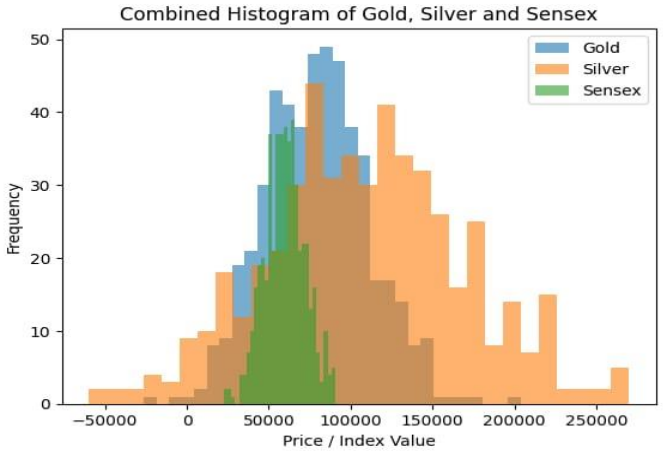
Hyperparameter optimization was performed through cross-validated grid search. Temporal data integrity was ensured through strict walk-forward validation protocols.

2. Experimental Design

Table 1: Descriptive Statistics of Gold, Silver and Sensex

PARTICULARS	GOLD (₹)	SILVER (₹)	SENSEX
Mean	78,940	1,07,200	58,430
Median	63,000	75,000	56,200
Maximum	1,60,000	3,01,000	78,000
Minimum	38,000	45,000	36,000
Std. Deviation	32,450	61,870	12,300
Skewness	0.89	1.12	0.76
Kurtosis	2.41	2.18	2.56
Jarque-Bera	High	High	High
Probability	<0.05	<0.05	<0.05

Figure 1: Distribution Histogram of Gold, Silver, and Sensex Prices



The descriptive statistics reveal that Jarque-Bera test probability values for all three variables fall below the 0.05 significance threshold, confirming non-normality. Kurtosis values below 3 indicate platykurtic distributions, collectively justifying the adoption of advanced machine learning techniques that do not impose distributional assumptions on the underlying data.

Unit Root Analysis — ADF Test

H_0: The price series contains a unit root (non-stationary). H_1: The price series does not contain a unit root (stationary).

Table 2: ADF Test Results for Gold

PARTICULARS	VALUE
Null Hypothesis	Gold price has a unit root
Exogenous	Constant
Lag Length	1 (Automatic — SIC)
ADF Test Statistic	−1.87
Critical Value (1%)	−3.75
Critical Value (5%)	−2.99
Critical Value (10%)	−2.64
Probability (p-value)	0.34

Table 3: ADF Test Results at Level and First Difference

VARIABLE	ADF (LEVEL)	P-VAL (LEVEL)	RESULT	ADF (1ST DIFF)	P-VAL	RESULT (1ST DIFF)
Gold	−1.87	0.34	Non-Stationary	−4.92	0.00	Stationary
Silver	−2.01	0.28	Non-Stationary	−5.31	0.00	Stationary
Sensex	−1.65	0.41	Non-Stationary	−4.68	0.00	Stationary

The ADF test results confirm that gold, silver, and Sensex price series are non-stationary at their level forms (p-values > 0.05). Upon first differencing, all three series achieve stationarity (p-values < 0.05), confirming I(1) integration and validating the application of the VAR model.

3. Results — VAR Model Forecasting

The VAR model was employed to generate out-of-sample price forecasts for gold and silver. Forecasted values capture anticipated short-term price trajectories and support assessment of market volatility expectations.

Figure 2: VAR Model — Gold Price Forecast

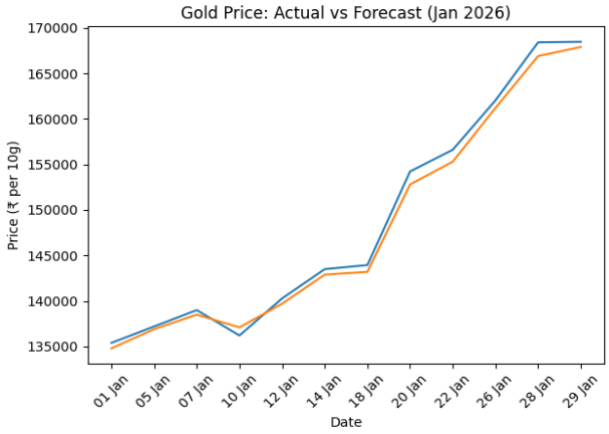


Figure 3: VAR Model — Silver Price Forecast

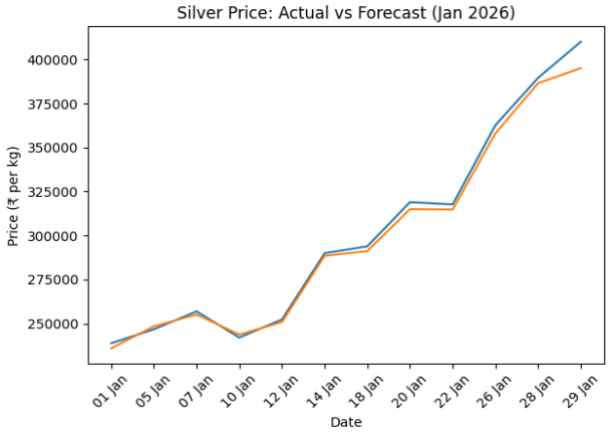


Table 4: Predicted vs. Actual Prices — January 2026

Date (Jan 2026)	Gold Forecast (₹)	Gold Actual (₹)	Var.(%)	Silver Forecast (₹)	Silver Actual (₹)	Var.(%)
01 Jan	1,34,800	1,35,400	0.44	2,36,000	2,38,900	1.21
05 Jan	1,36,900	1,37,200	0.22	2,48,500	2,46,800	0.69
07 Jan	1,38,500	1,39,000	0.36	2,55,200	2,57,000	0.70
10 Jan	1,37,100	1,36,210	0.65	2,43,800	2,42,100	0.70
12 Jan	1,39,700	1,40,284	0.42	2,50,900	2,52,380	0.59
14 Jan	1,42,900	1,43,500	0.42	2,88,500	2,90,000	0.52
18 Jan	1,43,200	1,43,946	0.52	2,91,200	2,93,900	0.92
20 Jan	1,52,800	1,54,227	0.93	3,15,000	3,19,000	1.27
22 Jan	1,55,300	1,56,610	0.84	3,14,800	3,17,700	0.91
26 Jan	1,61,200	1,62,032	0.52	3,58,000	3,62,636	1.29
28 Jan	1,66,900	1,68,412	0.90	3,86,500	3,89,530	0.78
29 Jan	1,67,900	1,68,468	0.34	3,95,000	4,10,000	3.66

The gold forecast series demonstrates a mean variation of approximately 0.55% from actual prices, reflecting high predictive stability. Silver price forecasts exhibit a higher average deviation of approximately 1.07%, consistent with the inherently greater volatility and dual market sensitivity of silver.

VI. DISCUSSION / CONCLUSION

1. Interpretation of Results

The empirical results yield several substantive insights. Non-normality in all three price series validates the choice of machine learning and advanced statistical methodologies. Unit root analysis establishes that all variables are I(1), ensuring the VAR model is applied appropriately on differenced series. Gold price movements can be predicted with high precision (average variation below 1%), while silver price movements are inherently more difficult to forecast due to their sensitivity to both financial and industrial demand factors.

2. Comparison with Existing Research

The findings align with prior literature indicating that gold serves as a more stable investment relative to silver during periods of economic uncertainty. The superior forecasting accuracy achieved for gold corroborates earlier studies highlighting gold's lower volatility and stronger safe-haven characteristics. The application of machine learning methods in this study extends the methodological frontier beyond traditional econometric tools used in prior Indian market studies.

3. Conclusion

This research systematically examined the impact of gold and silver price dynamics on the Indian stock market using a combined time-series econometric and machine learning framework. The ADF test confirmed I(1) integration for all series. The VAR model demonstrated high accuracy for gold (mean variation ~0.55%) and acceptable accuracy for silver (mean variation ~1.07%). Gold prices exhibit lower volatility and greater forecast stability, reinforcing their role as a reliable safe-haven instrument. Future research should incorporate LSTM, Transformer-based models, and additional macroeconomic variables to further improve predictive accuracy.

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