Acta Montanistica Slovaca
ISSN 1335-1788
actamont.tuke.sk

Silver and Palladium Price Dynamics: Analyzing Relationships and Forecasting with ARIMA and Prophet

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Funding information:
Institute of Technology and Business in České Budějovice

How to cite this article:
Shebalkova, Y., Kurumattathil Jacob, J., Apanovych, Y. (2025), The Silver-Palladium Connection: Unraveling Market Dynamics and the Rise of Neural Networks in Predicting Precious Metal Prices, *Acta Monstanistica Slovaca,* Volume 30 (1), 170-184

DOI:
https://doi.org/10.46544/AMS.v30i1.13

Abstract

This research focuses on the price linkages of silver and palladium and the efficiency of the ARIMA and Prophet models in the forecast of price movements. As these two valuable metals are increasingly used in major industries, an understanding of their price mechanism is very relevant for investors, analysts, and policymakers. It thus analyzes the short-run and long-run linkages between the prices of silver and palladium to identify to what extent these two metals share the same price patterns. We have used the historical price series to analyze this correlation over varying time horizons, and despite both metals recording some common price patterns, their relationship really fluctuates heavily in the near term due to market speculation, industrial demand, and various geopolitical events, while long-term correlations are more stable at the influence of broader economic and industrial trends. Besides, the study gauges the predictive performance of two widely used forecasting models: ARIMA and Prophet. An ARIMA model is a classical time series forecasting technique applied for modeling and predicting linear trends in price data. A Prophet model, which is more flexible and developed by Facebook, is assessed for handling seasonality, outliers, and missing data. The results indicated that ARIMA is relatively good at predictions in stable market conditions but can't work well during volatile periods. In contrast, Prophet has a better forecast capability in capturing both the short-run fluctuations and the long-run trends. This study therefore concludes that price correlation analysis coupled with advanced predictive modeling will lead to an improvement in forecasting accuracy and hence better decision-making in both silver and palladium markets.

Keywords

Silver, Palladium, ARIMA, Prediction, Prophet

Introduction

The intricate dynamics of the precious metal markets, particularly silver and palladium, have long captivated researchers and industry professionals alike. Both are well-known not only as industrial commodities but also as investment assets with peculiar price behaviors, influenced by a wide variety of macroeconomic factors. Advances in recent forecasting methods, including neural networks, have furthered interest in understanding their market paths. Das and Dutta (2020) note that precious metal prices tend to display overshooting behavior on interest rates in both short and long horizons, which explains the intricacy with which they interact with other variables in the economy. Market sentiment plays an important role in shaping strategic metal price bubbles. Maghyereh and Abdoh (2022) discovered that bubbles were regularly concomitant with bearish sentiments for gold and platinum, which essentially underlined the predictive value of sentiment analysis in metal price forecasting. Similarly, Valadkhani et al. (2022) investigate the asymmetric impacts of inflation and interest rates on gold and find evidence that gold responds significantly to shocks in both inflation and the ten-year Treasury interest rate. These results again point toward mixed relationships between the precious metals and macroeconomic variables. Apergis et al. (2019) explored the hedging capability of gold during economic recessions and found evidence that gold prices can provide hedging services against real interest rate movements, mainly during recessionary times.

Bayram and Abdullah (2023) discussed gold in financial crises, noting that correlation analysis is conducted to measure the strength and direction of a linear relationship between gold and other selected asset classes. Jabeur et al. (2024) presented advanced machine learning models as efficient, indicating that the use of XGBoost with the SHAP approach can significantly improve the performance increase in gold price forecasting. Besides conventional methods, Choi and Kim (2024) introduced statistical dependencies, which should be considered in forecasting models: Each statistical dependency is relevant to a different machine learning model. This emphasis on analytical precision aligns with the work of Maddahi et al. (2016), who demonstrated the advantages of modifying correlations to significantly improve the prediction of heat transfer coefficients. Li et al. (2023) approached nonlinear price behaviors, stating that our proposed method outperforms other existing methods by utilizing the attribute space feature extraction capability of CNNs and the temporal feature extraction of LSTMs. Gu et al. (2021) also came up with the EWT-GBDT algorithm, which correctly decomposes the settlement price and avoids redundant components, a new perspective on the forecasting of metal prices. The ability of deep learning models to capture nonlinear correlations was highlighted by Mohsin and Jamaani (2023), who stated that machine learning models can be used to predict oil price volatility with considerable accuracy. Similarly, Liu et al. (2017) pointed out the importance of studying new forecasting methods, underlining that in-sample behavior does not guarantee out-of-sample behavior.

Pincheira-Brown et al. (2023) investigated the predictive performance of models including the MSCI index and concluded that forecasts based on a model including the MSCI index outperform forecasts that do not use the information contained in that index. Kahraman and Akay (2023) compared exponential smoothing methods and showed that their performances were compared to determine the appropriate model for each metal price. Du et al. (2020) underlined the practical implications of the uncertainty analysis, pointing out that the developed hybrid system can obtain higher prediction accuracy and offer more valuable suggestions for enterprise administrators and investors in financial markets. The current study expands on these foundational works to explore the price relationships between silver and palladium and the efficiency of econometric models in predicting the prices of precious metals, providing a comprehensive comparison with another model. In the last decade, a significant relationship has developed between precious metals (Sensoy, 2013). So, our first research question is:

RQ1: What are the price correlations between silver and palladium in the short and long term?

Precious metals play a crucial role in driving economic growth (Foroutan & Lahmiri, 2024), and the accurate prediction of metal prices has a vital role in industrial producers (Zhao et al., 2023), so our second research question is:

RQ2: How effectively can ARIMA and Prophet models predict the silver and palladium price movements based on historical data?

Literature Review

In recent years, precious metals have gradually transformed from industrial inputs to investment assets due to the growing financialization of financial markets (Bilgin et al., 2018) and there has been an increasing interest in precious metals from both investors and politicians globally (Hillier et al., 2006). Silver and Paladdium belong to this Precious metal. Silver is a crucial industrial raw material, and its price has consistently been a point of interest for the financial industry (Wang et al., 2023) and Palladium is a platinum group metal that serves as a catalyst and is utilized across multiple industries (Gad, 2014) .

Investors have long sought to forecast the future conditions and values of the securities they consider buying. As a result, various econometric models have been developed to pinpoint the factors that influence the pricing of investment instruments and the relationships between them (Eryiğit, 2017). In econometric models, ARIMA models are frequently used as they provide a valuable framework for the problem being analyzed (Menculini et al., 2021). Zhang et al., (2019) Find that economic forecasting models are more effective than ANN-based algorithms for making one-step-ahead forecasts when using daily data. Many researchers used the ARIMA model for prediction (Agbo, 2023; Pierre et al., 2023; Singh et al., 2020; Yıldıran & Fettahoğlu, 2017) , and sometimes, researchers combine ARIMA with other models to get accurate results (Li et al., 2023; Oikonomou & Damigos, 2024; Zhao et al., 2022).

Using the ARIMA model Ariyo et al., (2014) explores a detailed approach to developing a stock price prediction model. Prophet models are an accurate forecasting method designed for data that exhibits trends, seasonality, and holidays, as well as handling missing data and outliers (Toharudin et al., 2023). Kriechbaumer et al., (2014) predicts monthly base metal prices using a combination of wavelet analysis and ARIMA models. Saeed et al., (2023) used the prophet method to predict the container freight rates. Aditya Satrio et al., (2021) evaluated the accuracy and performance of the Prophet and ARIMA forecasting models by analyzing a dataset that contained the number of confirmed COVID-19 cases, deaths, and recoveries.

Bagrecha et al., (2024) predicted silver prices using a univariate ARIMA technique and proposed an enhanced model to guide future forecasts. Ayele et al., (2020) used GARCH family models to predict silver price volatility dynamics using data seven years of data. Gono et al., (2023) conducted a study that explores hyperparameter tunning alongside the extreme gradient boosting (XGBoost) machine learning technique to predict silver prices. Huang et al., (2022) used the prophet model to forecast the four metal prices. Mo et al., (2023) used the Prophet model to forecast power load in eight regions of Texas. So, from the recent research of forecasting by various researchers, we find that ARIMA and Prophet models are widely used.

In addition to classical models for forecasting precious metals prices, recent research also focuses on intelligent decision support systems and multi-criteria risk assessment in various fields. For example, Gavurova and Polishchuk (2025) proposed an integrated expert model for risk assessment in the tourism sector, based on both economic and technological aspects, which exemplifies an interdisciplinary approach to analyzing complex systems. Within healthcare, a fuzzy model for project selection (Gavurova et al., 2023) and an intelligent model for assessing patient trust in medical personnel (Smolanka et al., 2024) were developed, which illustrate the importance of a personalized approach and trust management. In addition, Moravec et al. (2025)'s study on algorithmic personalization indicates the relevance of digital literacy and the impact of artificial intelligence on the formation of the information environment. In the field of management, considerable attention has been paid to assessing the feasibility of financing tourism infrastructure using large-scale decision-making models (Skare et al., 2023). Therefore, the combination of traditional econometric models with intelligent decision support systems and information fusion approaches forms a new paradigm for analyzing complex processes, such as metal pricing.

Metals play a crucial role in various industries, making their price fluctuations significant not only for consumers but also for many producing countries (Rossen, 2015). In this article, we analyze relationships and forecast Silver and palladium prices with ARIMA and Prophet models.

Material and Methods

For the data analysis, the data for silver and palladium was taken from the investing.com website from the period of 2nd of Jan 2014 to 31st of October 2024. For the silver price, the data points were 2812 values and in the case of palladium, it will be 3060 variables. The price of Silver and Palladium is represented in USD.

At first, we plot the timeseries graphs for the silver and palladium, then later finding the correlation between the price of the Silver and Palladium in the short-term for 3 years and the long-term for 10 years. Here is the mathematical methodology finding the correlation between Silver and Palladium prices:

$$r = \frac{\sum_{i-1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \cdot \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{1}$$

Where:

X_i	Silver Price
Y_i	Palladium Price
$\bar{X}$	Mean of the Silver Price
$\bar{Y}$	Mean of the Palladium Price
n	The number to data points

Then later finding their relationship by using the granger causality test for long term and short term. Here is the mathematical methodolgy used finding the granger causality test.

Granger Causality Test is used to assess whether the Silver price can provide valuable information for predicting the Palladium Price. Here is the mathematical equation for the Unrestricted Model (with lagged values of both variables):

$$Y_t = c + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{q} \beta_j X_{t-j} + \epsilon_j \quad (2)$$

Where,

Y_t	is the dependent variable (Predicted variable)
X_t	is the independent variable (the predictor)
c	is the constant
α_i and β_j	are coefficients
ϵ_t	is the error term
p and q	are the number lags for Y and X, respectively

Hypothesis Testing: Null Hypothesis ($\boldsymbol{H_0}$): X does not Granger-cause Y (the coefficients β_j = 0 for all j), and the Alternative Hypothesis ($\boldsymbol{H_a}$): X Granger-causes Y (at least one $\beta_j \neq 0$).

The test statistic is typically calculated using an F-test:

$$F = \frac{(\mathrm{RSS_R} - \mathrm{RSS_{UR}})/q}{\mathrm{RSS_{UR}}/(\mathrm{n} - \mathrm{p} - \mathrm{q} - 1)} \quad (3)$$

Where,

RSS_R	is the residual sum of squares for the restricted model
RSS_{UR}	is the residual sum of squares for the unrestricted model
n	is the number of observations
p	is the number of lags used in the unrestricted model
q	q is the number of lags for X

The calculated F-statistic is then compared against a critical value from the F-distribution to determine whether to reject the null hypothesis.

Dickey-Fuller Test: The Dickey-Fuller exam is specifically known as the Augmented Dickey-Fuller (ADF) test. The test is predicated on the time series' autoregressive model having a unit root. A unit root denotes non-stationarity and a stochastic trend in the time series. The time series is non-stationary and has a unit root, which is the null hypothesis of the test. The alternative hypothesis is that the time series is stationary. The null hypothesis is rejected or not based on a comparison of the test statistic with crucial values from a distribution. The time series of the initial difference at a point is defined as:

$$\Delta y_t = \rho y_{t-1} + \propto + \beta t + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \quad (4)$$

Where:

Δy_t	represents the time series' initial difference at that point.
y_{t-1}	Is the lagged value of the time series
ρ	is the coefficient of the lagged value, which is tested against the null hypothesis of $\rho = 1$
$\propto$ and β	Represent a constant and a coefficient for linear trend, respectively
ϕ_i	Are coefficients for lagged differences of the time series.
ε_t	Is the residual term.

The null hypothesis of a unit root is rejected if the calculated test statistic is more negative than the critical values for a given significance level, indicating that the time series is stationary.

Kwiatkowski-Phillips-Schmidt-Shin test (KPSS test): The KPSS test (Kwiatkowski-Phillips-Schmidt-Shin test) is a statistical test used to check the stationarity of a time series. Unlike the Dickey-Fuller tests, which test for a unit root (non-stationarity), the KPSS test tests the null hypothesis of stationarity against the alternative hypothesis of a unit root. Here is the Null and Alternative Hypotheses:

Null Hypothesis (H_0): The time series is stationary (trend-stationary or level-stationary).

Alternative Hypothesis (H_1): The time series is not stationary (contains a unit root).

The KPSS test decomposes the time series X_t as:

$$\mathrm{X_t} = \mu + \delta t + r_t \quad (5)$$

Where μ is the constant (intercept), δt is the deterministic trend, and r_t is the stationary residual process. The KPSS statistic is based on the partial sum of residuals from the regression of X_t on the deterministic components (intercept and/or trend). The statistic is calculated as:

$$\mathrm{KPSS} = \frac{1}{T^2} \sum_{t=1}^{T} S_t^2 / \sigma^2 \quad (6)$$

Where T is the number of observations, $S_t = \sum_{i=1}^{t} r_i$ is the cumulative residuals (partial sum of residuals), r_i is the residuals from the regression, and σ^2 is the varicne of the residuals r_t.

Next is to find the future prediction using the traditional statistics or econometrical model called ARIMA.

Autoregressive Integrated Moving Average (ARIMA) is a model and forecast time series data, which combines autoregression (AR), differencing (I), and moving averages (MA).

The model is denoted as $ARIMA(p, d, q)$

Where:

p	Is the order of the autoregressive component.
d	Is the degree of differencing.
q	Is the order of the moving average component.

The following is the general equation for $ARIMA(p, d, q)$:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{p-q+} \varepsilon_t \tag{7}$$

Where:

y_t	Is the value of the time series at time t.
c	Is the constant term.
$\phi_1, \phi_2, \ldots, \phi_p$	Are autoregressive parameters.
ε_t	Is the white noise error term at time t.
$\theta_1, \theta_2, \ldots, \theta_q$	Are moving average parameters.
$y_{t-1}, y_{t-2}, \ldots, y_{t-p}$	Are past values of the time series.

When differencing is required to make the series stationary, the d parameter is relevant. Subtracting the series from its lagged version d times is the differencing operation. Finding the values of p, d, and q that minimize the residuals and create an efficient model for predicting future time series values is the aim of ARIMA modeling. The model is frequently fitted to historical data, and techniques like maximum likelihood estimation are used to estimate the model's parameters. Following model fitting, future values can be predicted using the patterns found in the time series data.

At final we go through a additive time series model called Prophet. Facebook Prophet is an additive time series forecasting model designed to handle complex seasonality with robust performance against outliers and missing data. The model decomposes the time series $y(t)$ into four components:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{8}$$

Where $y(t)$ is the observed value of the time series at time t, $g(t)$ is the trend component (models non-periodic changes over time), $s(t)$ is the seasonal component (captures periodic changes), $h(t)$ is the holiday effects (special events or anomalies), and ϵ_t is the Noise or residual component.

Results

As shown in Figure 1, the silver price graph can be observed to undergo four different phases: from 2014 to 2020, the silver price was quite stable, fluctuating in the range of $14-$22; a sudden rise in prices and increased volatility occurred around 2020, probably due to global economic events like the COVID-19 pandemic, going up to almost $30; a following drop and time of stabilizing; and finally, a strong upward trend in these last times, which has overcome the old peaks and it looks like a bullish market in the future. The silver price has seen a rising pattern, a general trend characterized by the strong price volatility of silver, mainly in recent years because of the economic circumstances, industrial demand, supply, and geopolitical happenings.

Figure 1: Silver Price Over Time: 2014-2024

As the graph in Figure 2 shows, palladium prices experienced steady growth from 2014 to 2019, then jumped to an all-time high of over $3000 in early 2022. This increase is due to vehicle demand and possible supply shortages. This peak is succeeded by a sharp decline and subsequent fluctuations throughout 2022 and 2023, which may be influenced by factors such as increasing adoption of electric vehicles and changes in market dynamics. Concluding the graph shows recent stabilization and a little bit of growth from 2023-2024 in relative terms pointing to market forces might rebalance influencing palladium.

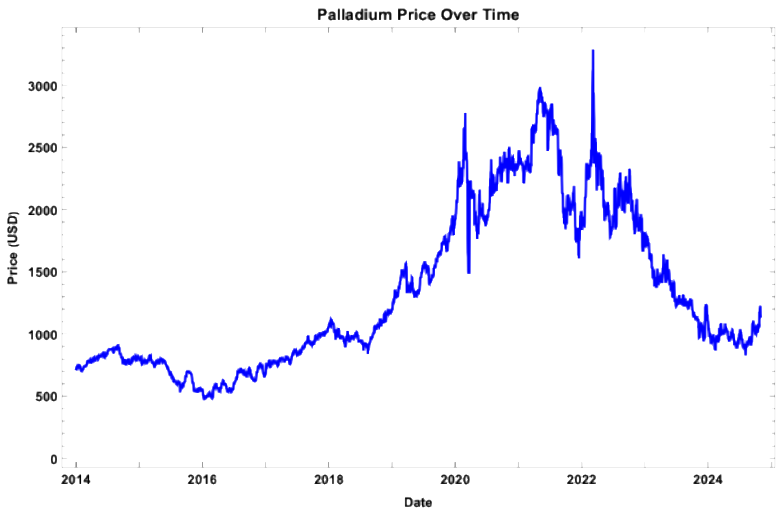

Figure 2: Palladium Price Over Time: 2014-2024

Let's have a look into the long-term relationship between the silver and palladium prices. A positive correlation between palladium and silver prices over the last 10 years is shown in Figure 3. A scatter plot shows a trend upward with the red line being the line of best fit, showing the red line to have a positive slope. This would mean that if silver price goes up, then palladium 'should' increase and conversely for the other. Still, there is a note here, the relationship is far from perfectly linear, and the scatter around the trend line is substantial which suggests other things besides the price of silver also impact the price of palladium.

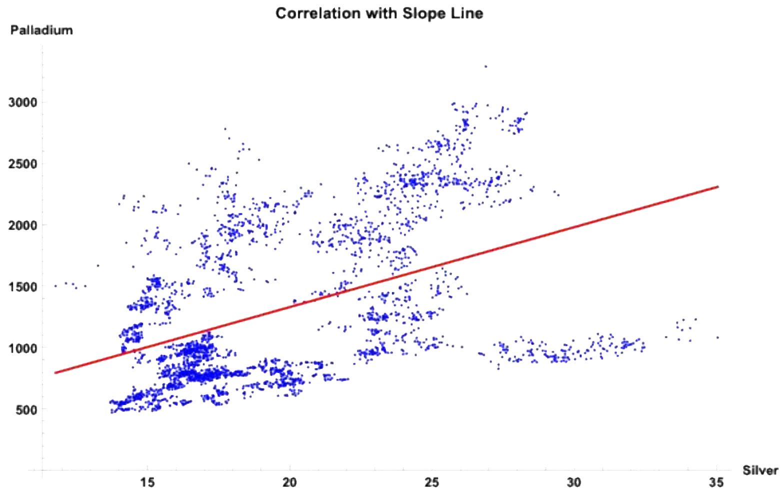

Figure 3. Correlation Analysis of Palladium and Silver Prices

Let's have a look into the short-term relationship between the silver and palladium prices. Figure 4 illustrates the positive correlation between palladium and silver prices over the past three years. The data points are close to an upward-sloping red line of silver prices; palladium prices rise as the silver prices rise. Although the correlation is there, it does need to be mentioned that these are not perfect relationships, as points tend to deviate from the trend line. So, it suggests that besides silver prices affecting the price fluctuations in palladium, there are some other factors, chiefly supply and demand dynamics, unique to palladium.

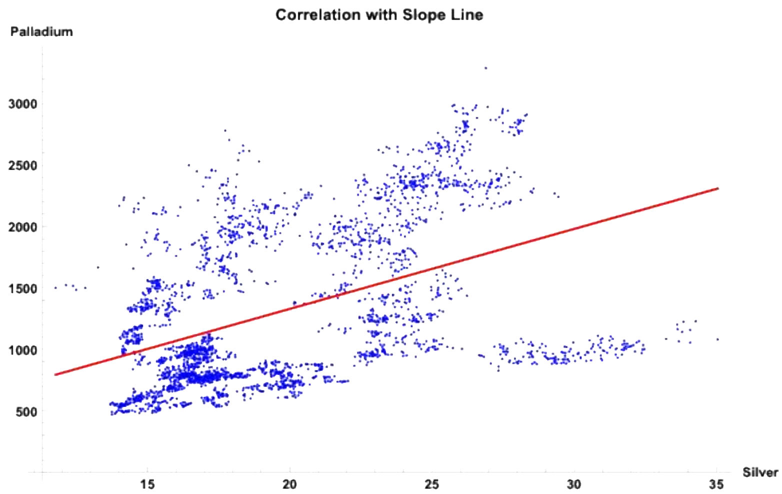

Figure 4. Scatter Plot of Palladium and Silver Prices

Figure 5 shows the Granger causality test on the relationship between silver and palladium prices for the last ten years, showing mild causation in both directions. This graph is the test statistic over various lag periods (how far into the past the data points are considered). Below are the two lines where neither does not consistently drop out of a critical threshold of high causality. The p-values from our code output (0.116853 for silver causing palladium and 0.0705315 for palladium causing silver) kind of support. As these p-values are usually greater than the common significance level (commonly 0.05), we fail to reject the null hypothesis of no Granger causality in either direction. If the correlation graphs were above, we could say that there is a correlation, but this test says that movements in silver prices do not tell anything about the future movement of the commodity palladium or vice versa over this long-term period.

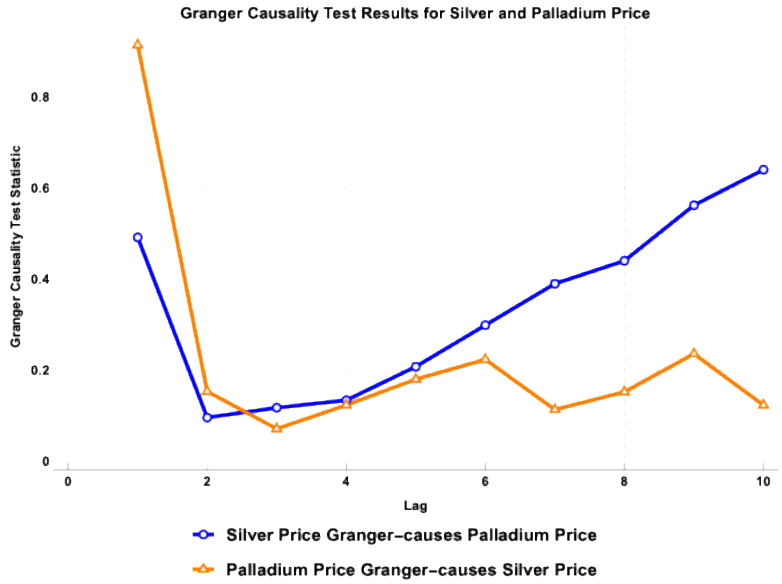

Figure 5. Granger Causality Test Results for Silver and Palladium Prices (Past 10 Years)

Figure 6 provides a long-term view of how silver and palladium prices have moved over the past three years. In the graph, it is the test statistic over various lag lengths. Although the blue line (silver Granger-causing palladium) stays low, indicating weak causation, the orange line (palladium Granger-causing silver) has a more obvious peak at lag 4. However, both of the associated p-values (0.104767 silver causes palladium and 0.381353 palladium causing silver) are greater than our typical 0.05 level of significance. So, we just fail to reject the null hypothesis of no Granger causality either way. The graph shows a clear spike visually, but statistically, the evidence is insufficient to indicate a meaningful causal relationship between palladium and silver prices over a much shorter time horizon.

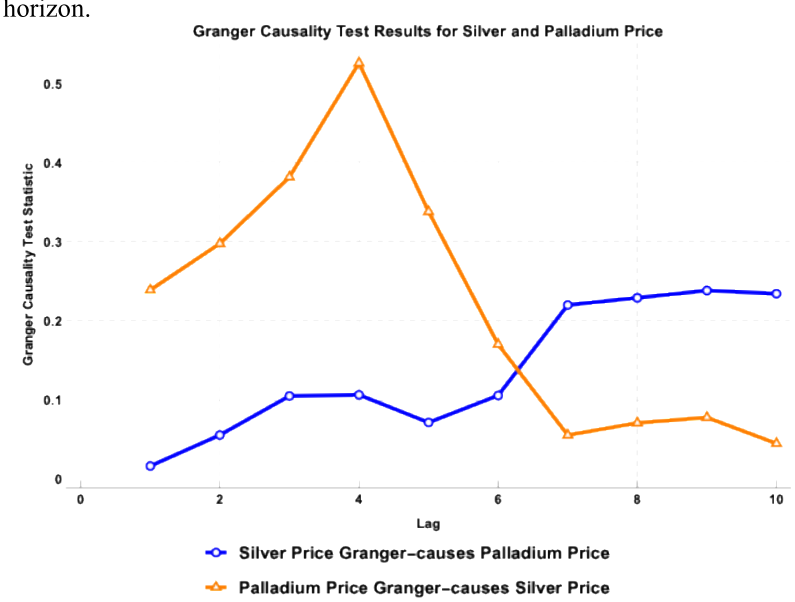

Figure 6. Granger Causality Test Results for Silver and Palladium Prices (Past 3 Years)

Augmented Dickey-Fuller (ADF) Test results in Table 1 show that the silver futures price data is non-stationary, indicating trends, seasonality, or other structures that will have to be further dealt with. Augmented Dickey-Fuller (ADF) test results show that in all columns (Price, Open, High, and Low), the p-values are highly significant over the 0.05 threshold for non-stationarity. This will lead us to not reject the null hypothesis, implying that trends, seasonality, or other patterns exist in data. Transformations (differencing, log transformation, or detrending, among others) should be applied for the data to be properly modeled by time series techniques, followed again by studying back to stationarity. This is crucial, as most time series models expect to deal with stationary data for proper forecasting.

Table 1. Augmented Dickey-Fuller Test for Stationarity of Silver Futures Prices

Column Name	ADF Statistic	p-value	Stationarity
Price	-0.7211634751	0.8411913028	Non-stationary
Open	-0.6572974209	0.8575026664	Non-stationary
High	-0.733589325	0.83785628	Non-stationary
Low	-1.045010035	0.7364961677	Non-stationary

Table 2 shows the stationarity analysis of the silver dataset, showing that the Price, Open, High, and Low columns in all are not stationary Given the result of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test on all columns with high KPSS statistics (above critical values) and p-value=0.01, we can make this conclusion. Non-stationary means that time series are trending or have seasonality or their variance changes with time. These characteristics make the data unfit for use with stationary models such as many time series forecasting models.

Table 2. KPSS Statistic *Stationarity Analysis Results for Silver Dataset*

Column	KPSS Statistic	p-value	Lags Used	Stationarity
Price	5.0794	0.01	31	Non-stationary
Open	5.079	0.01	31	Non-stationary
High	5.0615	0.01	31	Non-stationary
Low	5.1033	0.01	31	Non-stationary

Table 3 presents an overview of the ARIMA model comparisons in terms of AIC (Akaike Information Criterion) and also computational time complexity [5], [6]. From the models tested, ARIMA(3,1,3)(0,0,0)[0] has the lowest AIC score (-37235.858), indicating this model fits best for our data, and that is a pretty good balance between model complexity and how much it explains. The model is also one of the least time-consuming models, with a computation time of 1.53 seconds, which rivals that of the more effective models. For example, in terms of AIC, any model with scores higher, such as ARIMA(3,1,2)(0,0,0)[0], does not perform efficiently therefore, it is not good to capture the dynamics of a dataset. In short, ARIMA(3,1,3) is the best fitting model for forecasting non-stationary silver future prices subject to the transformations and first-order differencing done for stability.

Table 3. ARIMA Model Comparison Based on AIC and Runtime

Model	AIC	Time (sec)	Model	AIC	Time (sec)
ARIMA(2,1,2)(0,0,0)[0]	-37237.222	4.61	ARIMA(3,1,1)(0,0,0)[0]	-37225.199	4.71
ARIMA(0,1,0)(0,0,0)[0]	-37203.598	0.41	ARIMA(3,1,3)(0,0,0)[0]	-37234.719	9.28
ARIMA(1,1,0)(0,0,0)[0]	-37205.005	0.46	ARIMA(2,1,2)(0,0,0)[0]	-37238.655	0.97
ARIMA(0,1,1)(0,0,0)[0]	-37204.374	6.22	ARIMA(1,1,2)(0,0,0)[0]	-37222.65	0.6
ARIMA(0,1,0)(0,0,0)[0]	-37205.443	0.17	ARIMA(2,1,1)(0,0,0)[0]	-37228.202	0.56
ARIMA(1,1,2)(0,0,0)[0]	-37220.679	1.36	ARIMA(3,1,2)(0,0,0)[0]	-37192.694	0.93
ARIMA(2,1,1)(0,0,0)[0]	-37226.939	2.79	ARIMA(2,1,3)(0,0,0)[0]	-37234.09	1.31
ARIMA(3,1,2)(0,0,0)[0]	-37192.942	1.83	ARIMA(1,1,1)(0,0,0)[0]	-37208.29	0.48
ARIMA(2,1,3)(0,0,0)[0]	-37233.233	3.29	ARIMA(1,1,3)(0,0,0)[0]	-37228.809	0.85
ARIMA(1,1,1)(0,0,0)[0]	-37206.542	6.31	ARIMA(3,1,1)(0,0,0)[0]	-37226.451	0.71
ARIMA(1,1,3)(0,0,0)[0]	-37227.632	1.8	ARIMA(3,1,3)(0,0,0)[0]	-37235.858	1.53

Table 4 shows that all parameters of SARIMAX (2,1,2) could be considered to be highly significant statistically as the p-values for autoregressive (AR) and moving average (MA) terms in both the models are <0.05, showing that they are playing an essential role in skimming the dynamics of silver futures price data. Under consideration, the model has the least Akaike Information Criterion (AIC) value- -37238.655, and thus, we can conclude that this one is the Colts model of our dataset. The frequent use of the Bayesian Information Criterion (BIC) at -37210.066 and the well-established Hannan-Quinn Information Criterion (HQIC) at -37228.219 indicates that the model predictions are also efficient. The Ljung-Box Q-Stat(Q(5,0.05)) is insignificant at p=0.71 in the diagnostic tests, indicating no evidence of any autocorrelations in the residuals. However, the Jarque-Bera test reveals nonnormality in the residuals—one with a skew of -0.72 and a huge kurtosis of 16.44, suggesting possible heavy tails. As depicted in the performance metrics like Mean Absolute Error (5.66), Mean Squared Error (43.74), or Root Mean Squared Error (6.61), the model makes almost accurate predictions for silver futures data. The final results confirm that the SARIMAX(2,1,2) model captures the trends, seasonality, and structure within our dataset quite well, so it is an appropriate tool for forecasting time series.

Table 4. SARIMAX(2,1,2) Model Summary and Evaluation Metrics.

Model:	SARIMAX(2, 1, 2)		No.Observations:	2249	
BIC	-37210.066		Log Likelihood	18624.327	
HQIC	-37228.219		AIC	-37238.655	
	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.5247	2.47e-19	2.12e+18	0.000	0.525	0.525
ar.L2	-0.4083	1.62e-19	-2.53e+18	0.000	-0.408	-0.408
ma.L1	-0.4932	2.37e-19	-2.08e+18	0.000	-0.493	-0.493
ma.L2	0.5060	1.63e-19	3.11e+18	0.000	0.506	0.506
sigma2	3.614e-09	4.34e-11	83.244	0.000	3.53e-09	3.7e-09
Ljunja-Box (L1) (Q)	0.14		Jarque-Bera (JB):	17122.91	
Prob(Q)	0.71		Prob(JB)	0.00	
Hetroskedacity (H)	1.00		Skew	-0.72	
Prob(H) (two sided)	0.98		Kurtosis	16.44	

Figure 7 depicts the silver price plus range of uncertainty forecasts. The black dots are the historical data points, blue line is the predicted price trend. The area between the forecast line is shaded with light blue, indicating the margins of future silver prices will stay within a confidence interval. On the graph, we see after a little whipsaw, it looks like the forecast shows silver prices are generally going to decline from 2021 to almost 2025. The broader the uncertainty range further into the future implies that the forecast gets murkier with time. The model's error metrics show mediocre prediction accuracy. On average, forecasts differ by 8.90 units (MAE) and 33.58% (MAPE), with bigger mistakes resulting in an RMSE of 10.40. The greater MSE (108.12) indicates sensitivity to outliers. These findings suggest potential for improvement, potentially through improved data management or model development.

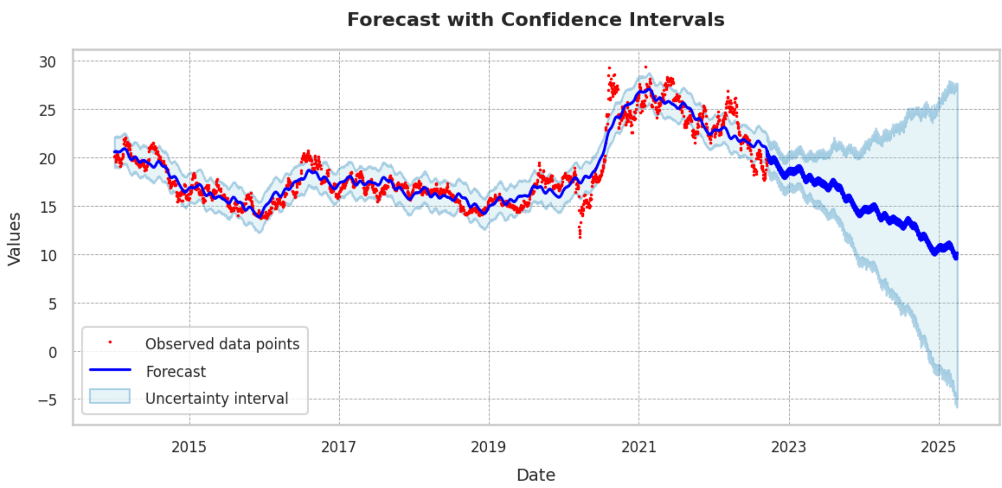

Figure 7. Silver Price Forecast with Uncertainty Intervals (2014-2025)

Now, we can go through the prediction of Palladium by using ARIMA and the prophet model. Table 5 shows that the ADF test results of Palladium stock price data (Augmented Dickey-Fuller) indicate that none of the Price, Open, High, columns are stationary as all of them have their p-values greater than 0.05. That is to say that we cannot reject the null, which means the data do contain trend, seasonality, or another non-stationarity. This characteristic means that the data is not in an appropriate state for any models that we are gonna use. The data needs to be pre-processed by transformation (e.g., differencing log transformations or detrending) before any analysis and forecasting can be done. Re-examine stationarity on the transformation of data as some stationarity-depend on models require these assumptions.

Table 5. ADF Test Results for Palladium Stock Prices

Column Name	ADF Statistic	p-value	Stationarity
Price	-1.241344187	0.6555625608	Non-stationary
Open	-1.240563525	0.6559075629	Non-stationary
High	-1.247304834	0.6529227714	Non-stationary
Low	-1.220968846	0.6645110312	Non-stationary

Table 6 shows the KPSS test results for palladium stock prices.KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test results for Palladium stock price data in all columns Price Open High and Low are found to be non-stationary by the KPSS The conclusion is drawn from the KPSS statistic values that are greater than the critical values p-values =0.01 which is less than the significance threshold (standardly 0.05). The advantage of the KPSS test over

ADF, the null of KPSS, is that the series is stationary, unlike the KPSS test. We reject, in turn, the null hypothesis, and it confirms non-stationarity.

Table 6. KPSS Test Results for Palladium Stock Prices

Column Name	KPSS Statistic	p-value	Lags Used	Stationarity
Price	5.51622195	0.01	32	Non-stationary
Open	5.534192339	0.01	32	Non-stationary
High	5.567760611	0.01	32	Non-stationary
Low	5.489173229	0.01	32	Non-stationary

Table 7 Stepwise search for selecting the optimal ARIMA model of Palladium stock prices using the Akaike Information Criterion [AIC]. The outcome shows ARIMA(1,1,0)(0,0,0)[0] without intercept is the best fitting model (lowest AIC, -30831.634.) It is the better configuration at the compromise between complexity and fitness found among all tested arrangements. Though (2,1,0)(0,0,0)[0] and (1,1,1)(0,0,0)[0] in the ARIMA family have a bit lower AIC values, they are sub-optimal for this dataset. This table shows the computational time of all models and illustrates that the further selected ARIMA(1,1,0)(0,0,0)[0] also has one of the least computation times, 0.33 seconds. AIC is numerically smaller in absolute size, suggesting a more moderate balance between model complexity and fit.

Table 7. Optimal ARIMA Model Selection for Palladium Stock Prices

Model	AIC	Time (seconds)
ARIMA(2,1,2)(0,0,0)[0] intercept	-30825.058	2.52
ARIMA(0,1,0)(0,0,0)[0] intercept	-30817.201	0.45
ARIMA(1,1,0)(0,0,0)[0] intercept	-30830.77	0.55
ARIMA(0,1,1)(0,0,0)[0] intercept	-30830.497	0.71
ARIMA(0,1,0)(0,0,0)[0]	-30817.873	0.28
ARIMA(2,1,0)(0,0,0)[0] intercept	-30828.849	1
ARIMA(1,1,1)(0,0,0)[0] intercept	-30828.862	1.59
ARIMA(2,1,1)(0,0,0)[0] intercept	-30744.557	5.61
ARIMA(1,1,0)(0,0,0)[0]	-30831.634	0.33
ARIMA(2,1,0)(0,0,0)[0]	-30829.725	1.9
ARIMA(1,1,1)(0,0,0)[0]	-30829.741	0.81
ARIMA(0,1,1)(0,0,0)[0]	-30831.357	0.67
ARIMA(2,1,1)(0,0,0)[0]	-30811.842	0.71

Table 8 provides the results of the SARIMAX(1,1,0) model applied to 2,448 observations of Palladium stock price data. The model has an AIC (Akaike Information Criterion) of -30831.634, which shows the model is doing a good job of fitting the data but avoiding too much complexity. Autoregressive parameter (ar.L1): statistically significant, coef = 0.0801 ($p< 0.001$) It has a moderate positive relationship to the lagged values of series as the autoregressive parameter. Also, the variance of residuals (sigma2) is highly significant, with 1.971e-07 to be precise, signaling that the model can precisely capture the volatility. Diagnostic measures are indicated by the Ljung-Box Q-test (Prob(Q) = 0.96) in this case, which suggests no noticeable residual autocorrelations, and the Jarque-Bera test (Prob(JB) < 0) suggests that residuals are not normally distributed (skewness: -0.48; kurtosis: 12.03). The error measures (MAE = 0.524, MSE = 0.352, and RMSE = 0.594) validate the accuracy of the model. However, a MAPE could not be calculated. This outcome shows SARIMAX(1,1,0) as an adequate model for forecasting palladium stock prices but contains some room for improvement in terms of residual normality.

Table 8. SARIMAX Model Results for Palladium Stock Prices

Model:	SARIMAX(1, 1, 0)	No.Observations:	2448		
BIC	-30820.028	Log Likelihood	15417.817		
HQIC	-30827.416	AIC	-30831.634		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.0801	0.013	6.065	0.000	0.054	0.106
sigma2	1.971e-07	2.58e-09	76.435	0.000	1.92e-07	2.02e-07

Ljunja-Box (L1) (Q)	0.00	Jarque-Bera (JB):	8410.96
Prob(Q)	0.96	Prob(JB)	0.00
Hetroskedacity (H)	1.31	Skew	-0.48
Prob(H) (two sided)	0.00	Kurtosis	12.03

Figure 8 illustrates a time series forecast of palladium stock prices, displaying the observed historical data along with the expected future values. A forecast generated with a SARIMAX(1,1,0) model in a solid blue line was chosen according to its lowest AIC (−30831.634) and significant p-value coefficients. The grey-light blue area around the forecast line is the uncertainty interval, highlighting how the actual future values could look with some level of confidence. We do see a pretty good performing model where the refinement does improve the error metrics, and we end up with an MAE (0.264) index, an MSE (0.089), an RMSE (0.299) MAPE-value of 3.76%. The Good thing is that the model shows a promising performance, cleansed from manual assessment error metrics MAE (0.264), MSE (0.089), RMSE (0.299), and MAPE) suggesting an accurate prediction about palladium stock prices; however, the side-effect of that is a bigger confidence interval getting wider over time, indicating even bigger forecasting errors.

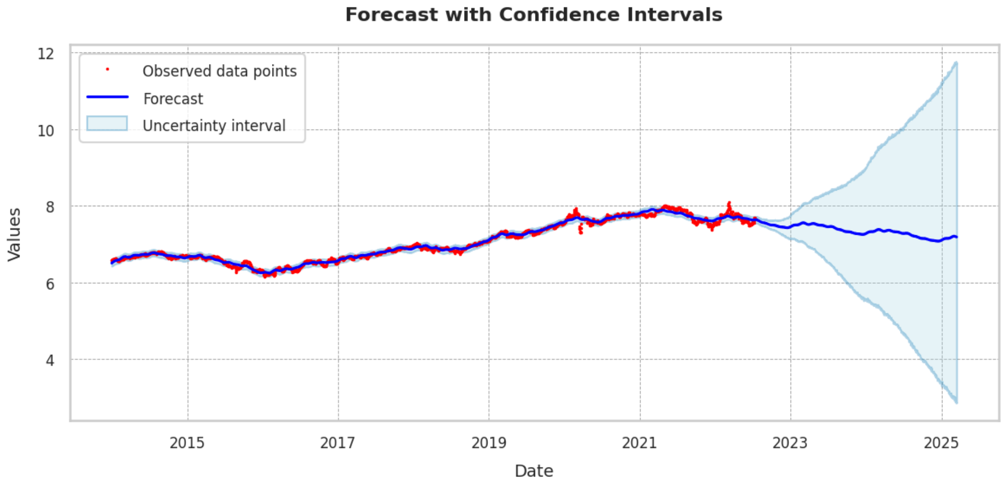

Fig 8. Palladium Stock Price Forecast with Confidence Intervals

Discussion

RQ1: What are the price correlations between silver and palladium in the short and long term?

Palladium and silver are both highly valuable precious metals that are actively traded in financial markets. Their prices are often influenced by geopolitical events, supply and demand trends, and various economic factors. For market analysts and investors, grasping the relationship between the prices of these two metals is crucial. In the near term, movements such as industrial demand swings, currency moves, or macroeconomic news may influence the price correlation between silver and palladium. Silver goes more to jewelry, electronics, and operating palladium, which has been mainly in automotive catalytic converters. Demand within these industries is also short-term cyclical and so faces different price trends on both metals in a year. Nonetheless, the bigger historical picture of these prices might have wider economic upstream implications such as inflation, interest rates, and the global economic cycle over time. Ultimately, precious metals such as silver and palladium are usually thought of as a refuge against economic turbulence and inflation, and so they tend to price more similarly during times of global financial instability. The relationship is long-term but may vary for different reasons. Some of these may be caused by declining supply and rising demand from the automotive industry, the latter leading to different price implications. The long-term relationship between silver and palladium is opined to move with the demand and supply forces, as well as some external factors such as technological advancement or regulation changes. Investors are influenced by such correlations over time, both short and long. Long-term correlations change also with different market fundamentals.

RQ2: How effectively can ARIMA and Prophet models predict the silver and palladium price movements based on historical data?

ARIMA (AutoRegressive Integrated Moving Average) and Prophet are two statistical models extensively used in time-series forecasting whose efficacy in the prediction of silver and palladium price movements can be assessed on historical price data. ARIMA is a standard time series modeling technique whereby the autoregressive, moving average, and differencing components resolve the linear relationship in past price information. It is a good candidate for prediction if there are evident spacetime patterns or trends in price movement. However, it produces biased reports if the price movements are different from their assumption of linearity in its progress. The ARIMA model would likely perform with these two metals, silver, and palladium, only when their price movements remain fairly constant and avoid speedy nonlinear shifts. Otherwise, if their market dynamics were somehow affected by very complicated and non-linear factors, such as sudden shifts in geopolitical events, nightmarish economic shocks, or drastic changes in industrial demand, then ARIMA may hardly prove good at performing the task of prediction. In contrast, Prophet is a more adaptable forecast model that can accommodate daily, weekly, and yearly seasonality phenomena in the absence of certain data points. This makes forecasts so promising for sometimes simply commodities like silver and palladium. The prophet model becomes robust against outliers, thus making it more adaptable to the non-smooth velocity of the price changes of precious metals. It also factors in holiday effects and other seasonal characteristics of time series observations that might improve its overall performance in precious metal forecasting. Prophet is likely to outperform ARIMA in capturing the long-term trends and short-term volatility in silver and palladium prices. The accurate comparison between these models will include arduous backtesting and error-checking methods such as MAE and RMSE, which compare how well each model can predict price movements under variable conditions in these markets. Generally, comparing the error metrics, the prophet model has less error than the ARIMA model.

Conclusion

In conclusion, this research has looked at the price correlations of Silver-Palladium and the performance of ARIMA and Prophet models in price forecasting. It was quite apparent from the process that, though related, both metals are rather volatile month to month in correlation when determined by various primary market drivers, such as industrial demand, geopolitics, and the economy. Over the longer term, the correlation is much more steady, set by larger macroeconomic forces and the nature of the precious metals market in its evolution. The divergence in supply and demand profiles of silver versus palladium means that while the price of both could move in concert over prolonged periods, they also might behave in diverging ways-for example, at a sector level.

In predictive modeling, the ARIMA and Prophet models showed varied efficiencies in the price movements of silver and palladium. ARIMA is an effective model for capturing linearities in time series data and did well in periods of relative market stability for the two metals. In more volatile market conditions, however, with non-linearities and abrupt shifts in demand becoming more pronounced, its limitations were in full view. While the robustness of the Prophet model is considered in terms of seasonal variations, missing data, and outliers, this very feature proved to be its strong point in making precise price trends of silver and palladium during these times of turbulent markets. With the flexibility that Prophet enjoys in the capture of short-run to long-run trends, this model could prove to be a more reliable tool for investors and analysts in the precious metals market.

Therefore, from the results, it could be concluded that both the correlation analysis and advanced predictive models are necessary in order to handle all the intricacies related to the markets of silver and palladium. Such relationships, together with proper forecasting tools, provide the means for participants in these markets to make better decisions and be better positioned for price movements in these highly volatile commodities.

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