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Developing A Conceptual Framework For Addressing The Accuracy Of Forecasting Models In Predicting Platinum Group Metals Prices.

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ABSTRACT.
The volatility and complexity inherent in Platinum Group Metals (PGMSs) markets necessitate robust forecasting models for accurate price prediction, crucial for informed decision-making and risk management. This study proposes a comprehensive conceptual framework aimed at addressing the accuracy of forecasting models in predicting PGMSs prices, leveraging the Autoregressive Integrated Moving Average (ARIMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and Artificial Neural Network (ANN) methodologies.
The framework integrates key stages of model selection, evaluation, and refinement tailored to the unique characteristics of PGMSs price data. It begins with meticulous data collection, incorporating historical price series, macroeconomic indicators, supply-demand dynamics, and geopolitical factors influencing PGMSs markets. Model selection involves the exploration and comparison of ARIMA, GARCH, and ANN models, each offering distinct capabilities in capturing different aspects of price behavior, such as trend, seasonality, and volatility clustering.
Central to the framework is the rigorous evaluation of forecasting models using appropriate statistical metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and forecast error distributions, to assess accuracy and robustness across various market scenarios. Additionally, diagnostic tests and sensitivity analyses are employed to validate model assumptions and identify potential sources of forecasting uncertainty. Furthermore, the framework emphasizes the iterative nature of model refinement, enabling the incorporation of new information and adaptive adjustments to forecasting methodologies in response to changing market dynamics. Expert judgment and qualitative insights are integrated to complement quantitative analysis, enhancing the reliability and interpretability of forecast outcomes.
By offering a structured approach to forecasting model development and evaluation, this conceptual framework provides valuable guidance for stakeholders involved in PGMSs markets analysis, including traders, investors, and policymakers. Future research directions may explore the integration of hybrid models and advanced machine learning techniques to further enhance forecasting accuracy and resilience to market fluctuations.

Keywords: Platinum Group Metals, Price Prediction, Forecasting Models, Conceptual Framework, Model Selection, Model Evaluation and Time Series Models

1. Introduction.

Forecasting has been a crucial component in facilitating informed decision-making for investors, institutions, and asset managers over an extended period. The task of making predictions has grown more difficult because of the growing risks and uncertainties present in both market and socioeconomic contexts, compounded by the intricate nature of many occurrences (Villegas, 2021). Due to the criticality of predictions and models in informing significant decision-making processes, they must exhibit a high degree of precision, even to the decimal point.
The analysis of past and present occurrences anticipates future events (Kourentzes et al., 2019). The decision-making technique described here helps organizations cope with future uncertainty. According to Lopez et al. (2010), the system examines patterns and historical data. For precise prognostications, a crystal ball may unveil forthcoming events (Lopez et al., 2010). The materials are regrettably no longer available. Never a crystal ball when you need one, as stated by Mozes (2003) in the Washington Times, underscores the unpredictability of a recession in the United States. A multitude of concepts elucidates forecasting. The aforementioned concepts include problem formulation, information gathering, technique selection and application, evaluation, and prediction execution. We therefore concentrate on "extrapolation" from available data through methodical prediction. Although numerous extrapolative methods are available, the prediction of the future is challenging for two fundamental reasons (El-Shagi et al., 2016).
The primary issue is the absence of a robust framework for evaluating the accuracy of price forecasting models about Platinum Group Metals. Consequently, stakeholders such as investors, corporations, and governmental entities engaged in the production and trade of platinum group metals (PGM) are prone to making suboptimal judgments due to inaccurate price projections.
Based on this premise, one may argue that the establishment of a comprehensive framework for evaluating forecasting methodologies is warranted, considering many measures of accuracy. This study presents a novel approach that addresses the need for a distinct assessment measure, facilitating the comparison of various categorization methodologies.
This study aimed to develop robust forecasting models for Platinum Group Metals (PGMs) by employing three distinct forecasting techniques (ARIMA, GARCH, and ANN). Additionally, it seeks to establish a systematic framework for selecting the most precise forecasting approach to predict PGMs prices under specific predetermined circumstances.

The significance of PGMs commodity price forecasting models is in their use for the prediction of PGMs prices, facilitation of PGMs trading activities, and the development of techno-economic and valuation models. Furthermore, they may serve as a foundation for conducting analyses on policy effect evaluation, strategy development, and providing recommendations.

2. Literature Review

Petropoulos et al. (2022) asserts that the predominant focus of forecasting research rests on theoretical advancements, with less attention given to empirical investigation and resultant consequences. Makridakis and Hibon (2001) expressed scepticism over the acceptance of concepts without empirical validation via real-world data testing, as opposed to relying only on simulations. The response of theoretical statisticians to critiques, such as the one presented by Clements and Henry (2001), is characterized by a stance that does not entail the outright dismissal of empirical data. According to Moon et al. (2003), forecasting research is characterized by its emphasis on the development of innovative forecasting methodologies, rather than the identification of specific needs. Researchers in the field of forecasting are now seeking error measures that possess the capability to be used across many kinds of series and can be effectively compared to other methodologies (Andrade et al., 2017; Arvan et al., 2019). About the expectations of practitioners, the emphasis is on understanding the error rather than its application in practical settings. Furthermore, the prioritization of features that are easily incorporable into software may have greater significance for software developers than the preferences and needs of practitioners and end users (Wallstrom, 2006).

This paper comprehensively examine, compare, and assess the three predominant forecasting methodologies extensively used in the majority of scholarly works, namely ARIMA, GARCH, and ANNs. The objective was to determine the most precise way among these options and identify the appropriate circumstances in which it should be used instead of the other methods. When using a forecasting methodology, it is important to evaluate the accuracy of the strategy in predicting the intended outcomes. Alizadehsani et al. (2021) asserts that accuracy is the predominant factor contributing to the occurrence of a certain kind of prediction error in the year 2020. Another reason for using a certain prediction error is that the measure of error is easily understandable. The study conducted by Fildes et al. (2009) raised concerns about the limited scope of accuracy as a metric. Mathews and Diamantopoulos (1994) argue that a single kind of error is insufficient to account for all the user-relevant aspects of prediction accuracy. Nevertheless, it should be noted that forecasting software just assesses a single kind of error (Wallstrom, 2006). Typically, errors are seen as distinct entities, with little recognition of the interconnections between different metrics. Regarding erratic demand, none of the examined publications investigated the relationship between incorrect forecasts and the used approaches.

Numerous research studies have included various accuracy assessments as evaluative criteria to improve the effectiveness of forecasting techniques. Numerous prediction accuracy measures have been devised for regression and classification problems, and the academic literature has a wealth of commentary and recommendations for their use. These accuracy metrics provide decision-makers with crucial information for fine-tuning and enhancing the model to enhance the precision of the outcomes. According to scholarly research, there is a lack of consensus about the definitive method for determining the most precise forecasting methodology (Mozes, 2003). The accuracy of forecasting algorithms might vary significantly based on the chosen statistic. Empirical evidence from real-world data evaluations indicates that some procedures exhibit superior performance when error-based metrics are used, whilst others provide enhanced performance when several metrics are utilized with the same data set (Pierdzioch et al., 2013).

The assessment of a mining project's economic viability heavily relies on mineral commodity prices, which are considered to be a crucial criterion. The impact of these factors on the company's financial gains is significant, hence exerting a large influence on the strategic decisions made by the board. In addition, mining companies have less agency in determining mineral prices since they operate as price takers, relying significantly on the fluctuations of mineral commodity prices to shape their strategy. Mineral price forecasting is a tough task due to the volatility of commodity markets, despite the reliance on mining commodity price estimates and the implementation of various solutions to tackle this issue. The phenomenon of globalization has resulted in increased susceptibility of many regions to economic, commercial, ecological, and political crises. Numerous global commodities exchanges exist. Considerable effort has been dedicated to the development and enhancement of methodologies aimed at predicting forthcoming mineral prices (Fildes et al., 2009).

Supply and demand are the primary determinants of mineral commodity price, exerting significant influence on this economic phenomenon. According to Rodrguez and De La Torre (2013) and Tapia et al. (2018), some conventional forecasting techniques use historical data on supply and demand, together with mathematical methodologies, to anticipate both short-term and long-term mineral prices.

Comprehending the precision and significance of these forecasting methodologies, it is essential to do a case study. The mineral resources include a diverse array of metallic elements. The selection of the platinum group metals (PGM), namely Platinum, Rhodium, and Palladium, for this investigation, was based on their significant role as essential resources and their profound impact on both the mining sector and the South African economy.

According to Mehdiyev (2016), the selection of an optimal forecasting methodology is a complex undertaking that requires a comprehensive analysis of empirical evidence. The performance evaluation of forecasting models is contingent upon the use of accuracy metrics, as shown by current research findings. Certain algorithms demonstrate superior performance when error-based metrics are used; whereas others show superior performance when precision values are utilized as accuracy measures. The use of a specific set of accuracy measures by researchers to evaluate the performance of forecasting models necessitates the consideration of several aspects of accuracy to assure the reliability and validity of the evaluation.

Nevertheless, the findings of several studies suggest that there is not a universally accepted, optimal measure of accuracy that may serve as a singular criterion for determining the appropriate forecasting method. The use of forecasting tools may provide significantly divergent outcomes based on the statistical methods employed. Empirical evaluations indicate that some methodologies exhibit superior performance when error-based measures are used, whereas others provide superior performance when alternative metrics are applied to the same dataset.

3. RESEARCH METHODS.

The research used a post positivist philosophical perspective, often referred to as the scientific method. According to Creswell (2014), the post positivist perspective encompassed many key elements, including determination, reductionism, and empirical observation and measurement, and theory verification. This research employed the logical method. The deductive research method involved examining the connection between theories, hypotheses, and concepts derived from existing literature (Bryman & Bell, 2015). Quinlan et al. (2015) assert that the deductive viewpoint serves as a rational framework, drawing conclusions from a universally accepted premise that is known to be true.

The research used a quantitative research technique, quantitative techniques use deductive reasoning to examine theory by formulating hypothesised linkages and suggesting outcomes for investigation based on pre-existing information. According to Bryman and Bell (2015), quantitative research used quantitative data and quantitative methodologies in data collection. For quantitative research methods, using objective measures and statistical, mathematical, or numerical analysis to look at data from polls, questionnaires, surveys, or changing existing statistical data using computers is the most important thing. The quantitative method allowed the researcher to assess the precision of the formulated forecasting models by using metrics that quantified prediction accuracy.

The use of the case study technique proved to be very advantageous in situations where there was a need to get a comprehensive understanding of a specific topic, event, or phenomenon within its authentic real-world setting. The research employed a case study approach in this instance, utilising data gathered or assessed over an extended period of time (Cooper & Schindler, 2014).

PGMs consisted of six elements, namely platinum, palladium, rhodium, ruthenium, iridium, and osmium. This research specifically examined the prices of platinum, palladium, and rhodium. The research employed time-series data, which involved the systematic monitoring and collection of data on variable changes over a specified period (Leedy & Ormrod, 2015).

The research obtained the historical monthly commodity pricing data for PGMs from the McGregor BFA and I-Net Bridge (INET BFA) data sources, as well as the databases of the International Monetary Fund (IMF) and the World Bank. We constructed the commodity price database using historical price data from PGMs (commodity price forecasting models) spanning 26 years (1995–2021). The research used the processed data to produce the commodity price forecasting models. The PPI commodity data, which encompasses all commodities without seasonal adjustments and spans from 1995 to 2021, supplemented the PGMs data. This additional dataset served as a deflator for commodity prices. A deflator is a statistical tool that standardizes pricing data by measuring it against a selected base period, which could be any reference period.

The decision to use a dataset including 323 data points, encompassing the historical price data of platinum, palladium, and rhodium (PGM) over 26 years (1995–2021) at a monthly granularity, was made to facilitate the application of this dataset in the training and testing of models. The collected data will be used for the creation of a comprehensive commodity price database. Subsequently, the processed data will be employed to produce accurate commodity price forecasting models. The PGM data was supplemented with the PPI commodity data spanning from 1995 to 2021 to serve as a proxy for the commodity price. The data was not seasonally adjusted. A deflator is a statistical tool that enables the measurement of pricing data at various periods relative to a chosen base period (Edvinsson & Söderberg, 2011). The monthly historical data about the pricing of PGM's was obtained from many sources, including INET BFA, the IMF database, and the World Bank database.

The research used statistical methods to examine the stationarity of the time series. Qualities of a stationary time series remained constant, irrespective of the specific time point under examination. Therefore, time series data that exhibited patterns or seasonality were considered non-stationary. Both the trend and seasonality components, exhibiting varying effects at various points in time, influenced the fluctuation in the value of the time series. In cases when the time series exhibited non-stationarity, it became necessary for the researcher to apply transformations to the time series to attain stationarity. One can use mathematical operations like logarithms to reduce the volatility of a time series. Differentiation enhances the stability of the mean in a time series by removing both trend and seasonality components, thereby eliminating variations in the time series' level (Cooper & Schindler, 2014).

The research used the processed data to develop price-forecasting models for PGMs by implementing the ARIMA, GARCH, and ANN methodologies. We then evaluated the built models using accuracy measures, specifically the forecast error matrix. This matrix included metrics such as R2, MAD, MAPE, and RMSE. The purpose of this evaluation was to assess the forecasting abilities of ARIMA, GARCH, and ANN models in predicting PGMs prices. The study used the identified results and limitations to inform the development of a comprehensive commodity-pricing model. We would build this model on a high-performing strategy that prioritised forecasting accuracy.

Given that this measure did not provide substantial information on the quality of the prediction itself, it was necessary to compare each of the metric values with one another to ascertain the model that exhibited the highest level of accuracy. The analysis examined the comparison among several models in separate intervals of 12, 18, and 24 months. The goal was to determine the most appropriate model for different forecasting phases and investigate the underlying causes of this phenomenon.

4. FORECASTING.

4.1. Autoregressive Integrated Moving Average.

The ARIMA model is a forecasting model that uses a linear combination of random errors and past observations to predict future values. It can be explained by three parameters: the auto-regressive component (p), the moving average component (q), and the trend component (d).

The auto-regressive component refers to the use of past values in the regression, whereas the moving average component represents the model's error as a combination of previous random shocks or error terms. The trend component refers to the number of differences needed among pairs of observations for a non-stationary series to be stationary. Stationarity is a key property of ARIMA models, as it allows for modelling any type of data, both stationary and non-stationary ones.

Real-world applications like business, engineering, mathematics, finance, and economics, where data lacks defined patterns and non-stationary processes better represent it, have proven the importance of ARIMA models. Checking whether a time series has the property of being stationary can include a variety of procedures, ranging from a simple inspection of the series graph to more sophisticated computational tests. The simplest method to check for stationary is to inspect a time series graph, draw an imaginary line representing the means, and assess whether the different upward and downward fluctuations vary around it, offsetting one another over the selected period. The Augmented Dickey-Fuller (ADF) test is another procedure that checks the null hypothesis that the time series is non-stationary. The ADF test uses a t-examination to check the hypothesis, which can provide different insights if a careful look is taken at each one of their components.

By computing the differences between consecutive observations, the method of differencing makes a non-stationary time series stationary. This helps stabilise the mean of a time series by removing changes in the level of the series and eliminating trend and seasonality. Transformations, such as logarithms, can also help stabilise the variance of a time series.

The autocorrelation function (ACF) plot is another way to identify the number of differences a time series needs to be stationary. For a stationary time series, the ACF will drop to zero relatively quickly, while the ACF of non-stationary data decreases slowly.

To identify essential parameters for any ARIMA model, it is important to analyse the ACF and Partial Autocorrelation Function (PACF). We compute both functions on a series of sequential lags, defined as the periods between two different points of a time series.

The ACF formula can be simplified to:

$$1 \sum N-(Yt-\bar{Y})(Yt-k-\bar{Y}) \qquad (1).$$

where N is the number of observations on the whole series, k is the lag, $\bar{Y}$ is the mean of the whole series, and $\bar{Y} = 1 \sum N\hat{}Y$.

The partial autocorrelation function (PACF) is a conditional correlation between two variables when the value of another one or a set of them is considered to be known. In linear regression, the partial autocorrelation function can be expressed as a regression between xt and $xt-k$, conditional on $xt-1$, $xt-2$, …, $xt-k+1$.

4.2. Generalized Autoregressive Conditional Heteroskedasticity.

While ARMA and ARIMA processes have historically dominated financial forecasting, their linear nature has limitations. Researchers sought a model capable of capturing nuanced features like volatility clustering, where periods of high volatility tend to cluster together, a phenomenon often overlooked by traditional models (Lama, 2015; Tully & Lucey, 2007).

Consider a financial asset's price at time t, denoted as Pt, with Zt representing the log return of traditional ARIMA processes assume that the conditional variance will remain constant over time. However, real-world financial data frequently displays non-stationary behavior. Kingsley and Peter (2019) address this; they developed ARCH and GARCH models, which incorporate past observations of squared returns to model volatility.

In ARCH models, the conditional variance ht depends solely on past squared returns:

$$ht = a0 + \sum p \ ai \ Z2 \qquad (2).$$

Here, p represents the number of past observations considered, $a0$ is a constant greater than zero, and ai coefficients can be non-negative.

GARCH models extend this by including past conditional variances:

$$ht = a0 + \sum p \ ai \ Z2 + \sum q \ bi \ ht-1 \qquad (3).$$

In equation 3, q determines the number of past conditional variances included, and bi coefficients are non-negative. This comprehensive approach allows GARCH models to capture intricate patterns in financial data.

4.3. Artificial Neural Network.

An ANN model processes information like the brain's complex neuron network. Neural networks establish complex interactions between and within data items. Indeed, ANNs are machine-learning forecasting methods that allow for complex non-linear relationships between predictions and forecasts. This is their benefit over time-series linear methods (Zhang, 2003).

Like a network of neurons, the neural network has layers. A single neuron is the neural network's architectural pivot. A single-layer perceptron artificial neural network has two layers: an input layer that receives external information and an output or forecast layer that solves the problem (Panella et al., 2012). Some refer to the input layer neurones as predictors and the output layer neurones as predictions. This setup involves one neuron receiving input and calculating output. We assign weights (wj) to inputs based on their relative importance (Panella et al., 2012).

The most complex artificial neural networks have a hidden layer and hidden neurons, unlike linear regressions (Mombein & Yazdani-Chamzini, 2015). The double-layer neural network, or single neurone, does not exhibit nonlinearity because it behaves as a linear or multilinear linear regression, depending on the number of inputs. Artificial neural networks' non-linear gain is largely due to their hidden layer, which improves prediction accuracy and representativeness (Mombein & Yazdani-Chamzini, 2015).

The multilayer feed-forward network has an intriguing topology where each input layer neuron feeds the hidden layer and undergoes a weighted linear modification (Kristjanpoller & Minutolo, 2015). A non-linear transformation of the hidden layer outputs. Example: Aggregating inputs to a buried neuron "j" yields:

$$Zj = aj + \sum wjYj \qquad (4).$$

aj is the bias factor, while Zj is the linear combination of input neurons (Yj) and their weights (wj) for the hidden layer.
The parameters aj and wj are determined by data learning, where the network simulates with random starting points (Tsay, 201Observed data and expected values guide the random selection and update of both values in the first stage. When these new values are estimated, they are immediately added to the observed data. Usually, the decay parameter limits the coefficients to 0.1. .1. According to Tsay (2012), training the network multiple times, using random starting points and averaging the results is common.

This multilayer network propagates information straight forward without interconnecting neurons across layers, unlike recurrent neural networks. According to Kristjanpoller and Minutolo (2015), input values from one layer, such as the input layer, do not reverse to form a cyclical pattern.

The diagram illustrates the basic neural network with an intermediate or hidden layer.
The activation function transforms the outputs of the hidden layer into the inputs of the output layer, ultimately producing the desired outcome. According to Wongsathan and Seedadan (2016), the activation function is the main cause of model non-linearity. The setup's activation function is crucial since real-world time series are non-linear.

Activation functions turn a single input value into a real number regardless of the formula (Panella et al., 2012). The most common activation function is the sigmoid function, which turns a value from 0 to 1 into a positive real number (4). The sigmoid function ranges from 0 to 1, regardless of domain value.

Formula: $\sigma(x) = 1/1 + \exp(-x)$ (5).

The role Tanh accepts a value and uses Equation (5) to convert it to a real number between -1 and 1.

$$\tanh(x) = \exp(x) - \exp(-x)/(x + -x) \quad (6)$$

5. OUTCOMES.

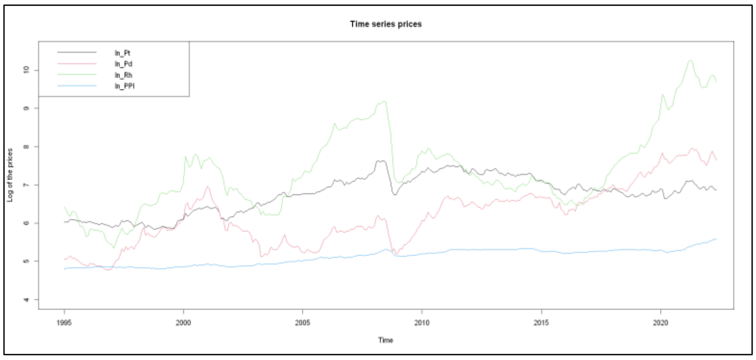

Figure 1: Natural logarithm closing prices.

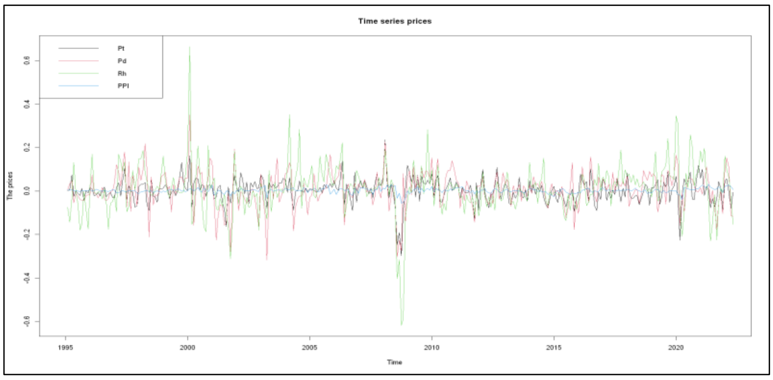

Figure 2: Natural logarithm returns.

rpd	rrh	rppi
0.62	0.52	0.4
1.99	0.57	0.2
0.57	1.00	0.3
0.29	0.36	1.0

Table 1: The Pearson correlation of returns for PGM.

The correlations between the variables are reported in Table 1 As expected, rpt and rpd have the highest positive correlation, reflecting their monetary elements. The latter are followed by Rhodium and Palladium with a positive correlation of 57%. Among all precious metals, platinum has the highest positive correlation with rpd, expressing their importance in industrial uses. Rh has a low positive linear association with platinum. Thus, making it a good possible diversification hedge in the short run.

Autoregressive Integrated Moving Average Forecast:

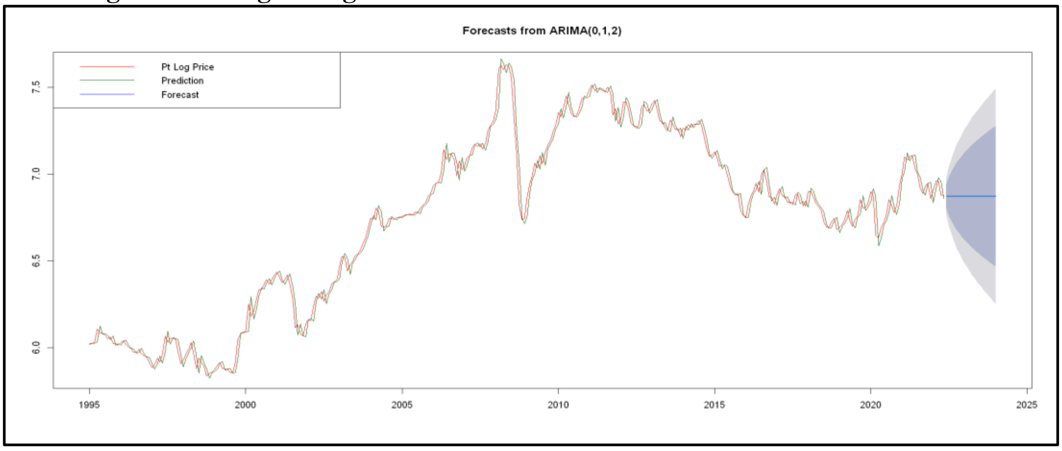

Figure 3: Platinum Arima Forecast.

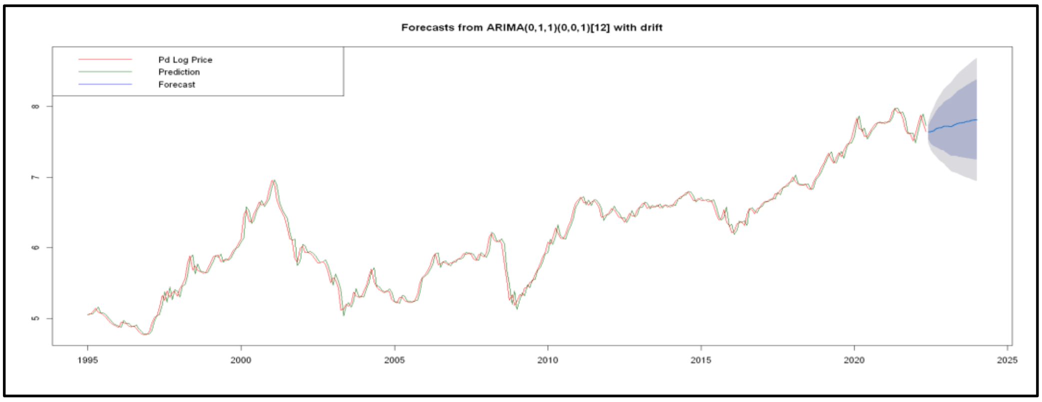

Figure 4: Palladium Arima Forecast.

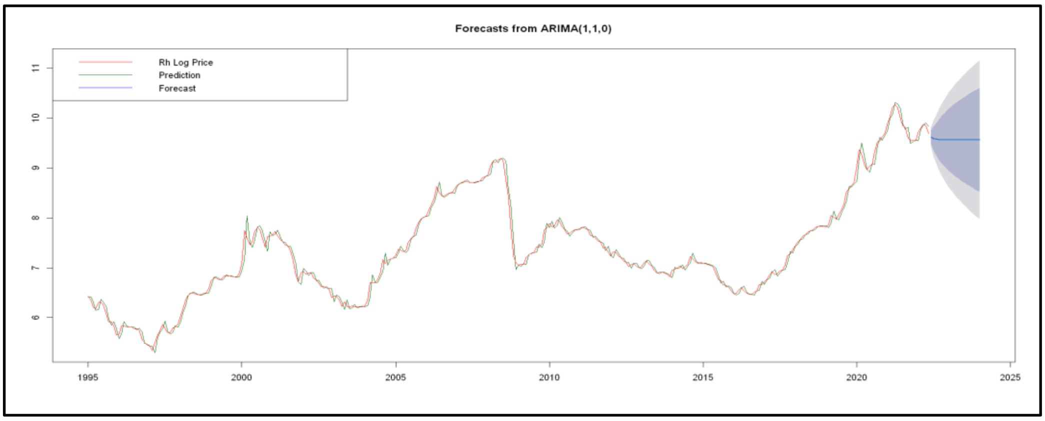

Figure 5: Rhodium Arima Forecast.

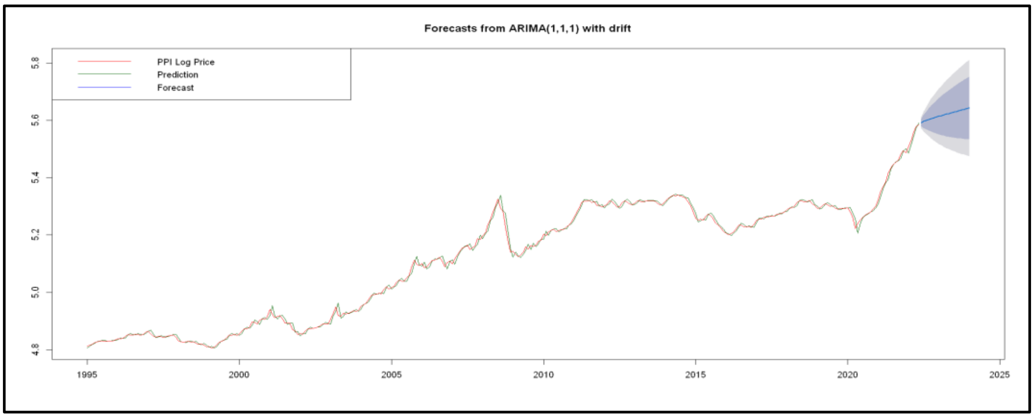

Figure 6: PPI ARIMA Forecast

GARCH Forecasting

The best two results produced by different GGARCH type models were chosen and presented below.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model              : sGARCH(1,1)
Mean Model          : ARFIMA(0,0,1)
Distribution   : snorm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ma1     0.217435    0.058785   3.6988 0.000217
omega   0.000397    0.000177   2.2463 0.024684
alpha1  0.223834    0.098239   2.2785 0.022699
beta1   0.662001    0.090940   7.2795 0.000000
skew    0.954544    0.060831  15.6918 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
ma1     0.217435    0.053889   4.0349 0.000055
omega   0.000397    0.000271   1.4679 0.142144
alpha1  0.223834    0.149167   1.5006 0.133469
beta1   0.662001    0.090993   7.2753 0.000000
skew    0.954544    0.085552  11.1575 0.000000

LogLikelihood : 493.5499

Information Criteria
------------------------------------

Akaike       -3.0921
Bayes        -3.0327
Shibata      -3.0926
Hannan-Quinn -3.0683
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model              : sGARCH(1,1)
Mean Model          : ARFIMA(0,0,1)
Distribution   : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ma1     0.155325    0.058534   2.6536 0.007964
omega   0.000334    0.000188   1.7831 0.074575
alpha1  0.172365    0.085009   2.0276 0.042599
beta1   0.727071    0.105421   6.8968 0.000000
shape   4.948731    1.365337   3.6246 0.000289

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
ma1     0.155325    0.054784   2.8352 0.004579
omega   0.000334    0.000177   1.8850 0.059429
alpha1  0.172365    0.089025   1.9361 0.052850
beta1   0.727071    0.083129   8.7463 0.000000
shape   4.948731    1.413681   3.5006 0.000464

LogLikelihood : 506.8111

Information Criteria
------------------------------------

Akaike       -3.1760
Bayes        -3.1166
Shibata      -3.1765
Hannan-Quinn -3.1523
```

Table 2: Estimation of the platinum GARCH Models with different distributions.

```
---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model              : sGARCH(1,1)
Mean Model : ARFIMA(0,0,1)
Distribution   : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ma1     0.278314    0.057379   4.8505 0.000001
omega   0.000877    0.000519   1.6899 0.091046
alpha1  0.269886    0.121073   2.2291 0.025806
beta1   0.633981    0.144263   4.3946 0.000011
shape   5.321177    1.566928   3.3959 0.000684

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
ma1     0.278314    0.054496   5.1071 0.000000
omega   0.000877    0.000589   1.4877 0.136823
alpha1  0.269886    0.120614   2.2376 0.025247
beta1   0.633981    0.169175   3.7475 0.000179
shape   5.321177    1.542801   3.4490 0.000563

LogLikelihood : 376.8805

Information Criteria
------------------------------------

Akaike       -2.3537
Bayes        -2.2942
Shibata      -2.3542
Hannan-Quinn -2.3299
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model              : sGARCH(1,1)
Mean Model : ARFIMA(0,0,1)
Distribution   : sged

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ma1     0.272126    0.055891   4.8689 0.000001
omega   0.000885    0.000438   2.0210 0.043284
alpha1  0.238092    0.098046   2.4284 0.015166
beta1   0.660539    0.112444   5.8744 0.000000
skew    0.888392    0.046787  18.9881 0.000000
shape   1.239884    0.127929   9.6920 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
ma1     0.272126    0.059100   4.6045 0.000004
omega   0.000885    0.000406   2.1792 0.029317
alpha1  0.238092    0.077167   3.0854 0.002033
beta1   0.660539    0.096889   6.8175 0.000000
skew    0.888392    0.049938  17.7900 0.000000
shape   1.239884    0.144795   8.5630 0.000000

LogLikelihood : 376.8922

Information Criteria
------------------------------------

Akaike       -2.3474
Bayes        -2.2761
Shibata      -2.3481
Hannan-Quinn -2.3189
```

Table 3: Estimation of the palladium GARCH Models with different distributions.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model              : sGARCH(1,1)
Mean Model          : ARFIMA(1,0,0)
Distribution   : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ar1     0.409577    0.054792   7.4751 0.000000
omega   0.002462    0.001660   1.4834 0.137969
alpha1  0.443865    0.235496   1.8848 0.059456
beta1   0.467296    0.221308   2.1115 0.034728
shape   3.302321    0.712165   4.6370 0.000004

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
ar1     0.409577    0.053512  7.65399 0.000000
omega   0.002462    0.002610  0.94347 0.345438
alpha1  0.443865    0.330343  1.34365 0.179063
beta1   0.467296    0.351650  1.32887 0.183891
shape   3.302321    0.711497  4.64137 0.000003

LogLikelihood : 324.1779

Information Criteria
------------------------------------

Akaike       -2.0201
Bayes        -1.9607
Shibata      -2.0206
Hannan-Quinn -1.9964
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model              : sGARCH(1,1)
Mean Model          : ARFIMA(1,0,0)
Distribution   : sged

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ar1     0.415863    0.032609  12.7532 0.000000
omega   0.002967    0.000922   3.2186 0.001288
alpha1  0.498488    0.136987   3.6389 0.000274
beta1   0.325663    0.110770   2.9400 0.003282
skew    0.988529    0.021825  45.2928 0.000000
shape   0.935546    0.097602   9.5853 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
ar1     0.415863    0.020839  19.9558 0.000000
omega   0.002967    0.000783   3.7866 0.000153
alpha1  0.498488    0.104549   4.7680 0.000002
beta1   0.325663    0.069919   4.6577 0.000003
skew    0.988529    0.014370  68.7901 0.000000
shape   0.935546    0.108740   8.6035 0.000000

LogLikelihood : 327.4666

Information Criteria
------------------------------------

Akaike       -2.0346
Bayes        -1.9633
Shibata      -2.0353
Hannan-Quinn -2.0061
```

Table 4: Estimation of the rhodium GARCH Models with different distributions.

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model         : sGARCH(1,1)
Mean Model : ARFIMA(1,0,0)
Distribution   : norm

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ar1     0.400340    0.053895   7.4281 0.000000
omega   0.000007    0.000002   3.4308 0.000602
alpha1  0.327124    0.072977   4.4825 0.000007
beta1   0.649777    0.018443  35.2311 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
ar1     0.400340    0.056347   7.1049 0.000000
omega   0.000007    0.000002   3.4024 0.000668
alpha1  0.327124    0.074703   4.3790 0.000012
beta1   0.649777    0.059151  10.9851 0.000000

LogLikelihood : 1051.021

Information Criteria
------------------------------------

Akaike       -6.6267
Bayes        -6.5792
Shibata      -6.6270
Hannan-Quinn -6.6077
```

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model         : sGARCH(1,1)
Mean Model : ARFIMA(1,0,0)
Distribution   : sstd

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
ar1     0.425975    0.055478  7.67833 0.000000
omega   0.000006    0.000009  0.63774 0.523642
alpha1  0.292693    0.085603  3.41918 0.000628
beta1   0.706307    0.137338  5.14283 0.000000
skew    0.812953    0.046751 17.38896 0.000000
shape   5.738366    1.667349  3.44161 0.000578

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
ar1     0.425975    0.059568  7.15102 0.000000
omega   0.000006    0.000030  0.19228 0.847521
alpha1  0.292693    0.123244  2.37490 0.017554
beta1   0.706307    0.517502  1.36484 0.172303
skew    0.812953    0.106516  7.63219 0.000000
shape   5.738366    8.588796  0.66812 0.504056

LogLikelihood : 1059.174

Information Criteria
------------------------------------

Akaike       -6.6657
Bayes        -6.5943
Shibata      -6.6664
Hannan-Quinn -6.6372
```

Table 5: Estimation of the producer price index GARCH Models with different distributions.

Best model is the one with high likelihood estimation given by AR(1) – GARCH (1,1)-SSTD. The returns, volatility and QQplot for normality are given below.

Artificial Neural Network.

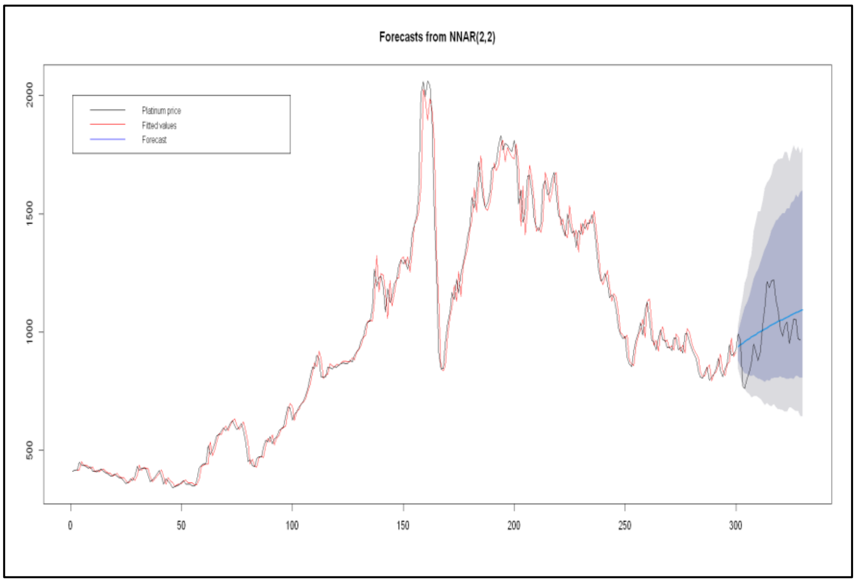

Figure 7 : Platinum ANN Forecast

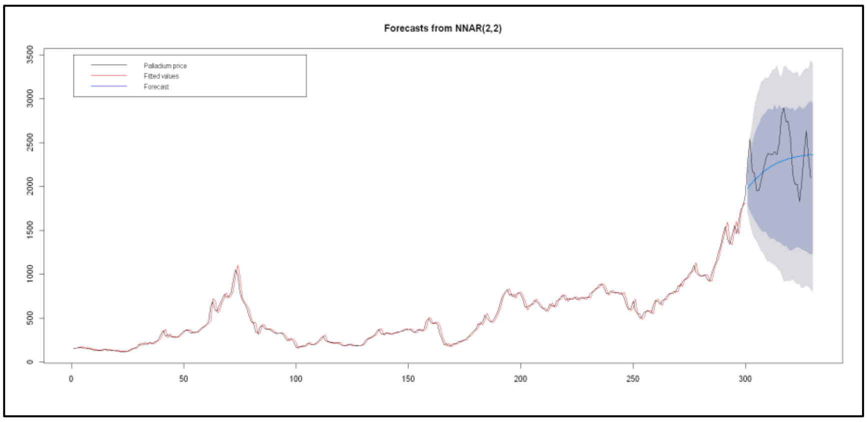

Figure 8: Palladium ANN Forecast

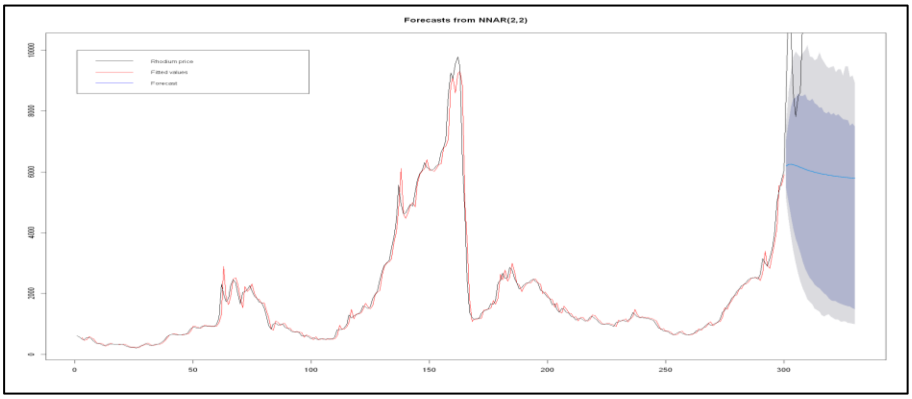

Figure 9: Rhodium ANN Forecast

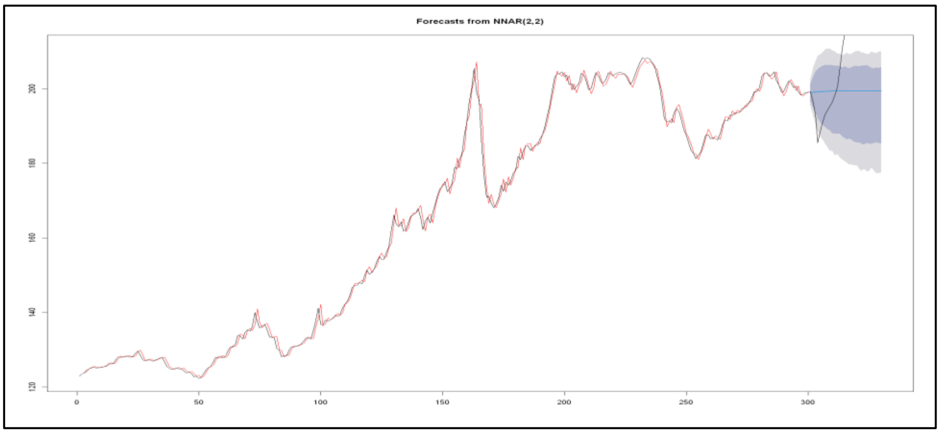

Figure 10: PPI ANN Forecast

This research proposes a conceptual framework to enhance the accuracy of forecasting models for PGMs prices. The framework consists of five stages: data collection and preparation, model identification, estimation, diagnosis, and forecasting. The ARIMA model, widely used in forecasting time series data, captures underlying patterns and trends in PGMs prices. Commonly used for modelling and forecasting financial volatility, the GARCH model captures price fluctuations influenced by factors such as supply and demand dynamics, geopolitical events, and economic conditions. The ANN model, increasingly used in forecasting due to its ability to learn complex patterns from data, can incorporate a wide range of input variables, such as economic indicators, news sentiment, and previous price movements.

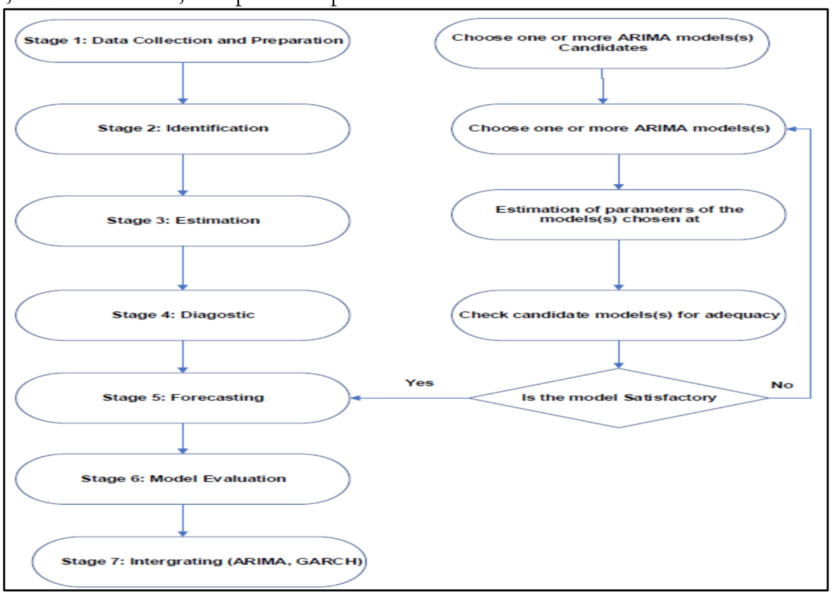

Figure 11: Conceptual framework for predicting prices of PGMs

The first stage of the proposed framework focuses on data collection, a crucial step in the forecasting process. Historical PGM price data from reputable sources such as the London Platinum and Palladium Market (LPPM) and Bloomberg are gathered, along with relevant factors influencing PGM prices. These factors may encompass supply and demand dynamics, geopolitical events, and economic indicators, among others. Data cleaning techniques are then employed to handle missing values and outliers, ensuring data consistency and format. Subsequently, data transformation methods such as normalization or logarithmic transformation may be applied to prepare the data for analysis. The dataset is then divided into training and testing sets to facilitate model development and validation.

The second stage involves model identification, where one or more forecasting models are selected based on the characteristics of the data and the desired forecasting goals. The ARIMA model, known for its ability to capture linear patterns, is suitable for scenarios where the data exhibits a predictable trend. On the other hand, the GARCH model is employed for volatility modeling, particularly in cases where the data displays heteroskedasticity. For capturing non-linear relationships, the Artificial Neural Network (ANN) model proves to be effective. The selection of models is informed by the nature of the data and the specific aspects of PGM price dynamics under consideration.

Following model identification, the third stage entails model estimation, wherein parameters for the chosen models are estimated using the training data. This step involves fitting the models to the historical data to capture underlying patterns and relationships. Subsequently, the estimated models are subjected to diagnostic tests in the fourth stage to evaluate their adequacy. Metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Percentage Error (RMSPE) are utilized to assess the performance of the candidate models. If the model performance is deemed satisfactory, the forecasting process proceeds to the next stage; otherwise, adjustments are made in the model identification stage.

In the fifth stage, the estimated models are utilized to generate future price forecasts. Leveraging the insights gained from the historical data and the estimated parameters, the models extrapolate trends and patterns to predict future price movements. These forecasts provide valuable insights for investors and stakeholders, enabling informed decision-making in the PGM market.

The sixth stage involves model evaluation, wherein the performance of the final models is assessed using the evaluation metrics from the diagnostic stage. This step serves to validate the accuracy and reliability of the forecasting models, enabling comparisons between individual models and their combinations. By evaluating the strengths and weaknesses of each model, stakeholders can gain a deeper understanding of their predictive capabilities and make informed choices regarding model selection.

Finally, in the seventh stage, the strengths of ARIMA, GARCH, and ANN models are integrated using techniques such as model ensembling and hybrid models. Model ensembling involves combining individual model forecasts through techniques such as weighted averaging, thereby leveraging the strengths of each model to improve overall forecasting accuracy. Hybrid models, such as ARIMA-GARCH or ANN-GARCH, integrate the complementary aspects of different models to enhance predictive performance further.

In conclusion, the proposed conceptual framework provides a systematic approach to develop robust forecasting models for PGM prices, addressing the complexities of price dynamics in the PGM market. By leveraging the strengths of multiple models and integrating them effectively, stakeholders can enhance the accuracy of price forecasts and make informed investment decisions. As the PGM market continues to evolve, the adoption of advanced forecasting techniques becomes increasingly vital, underscoring the significance of frameworks such as the one presented herein in navigating the intricacies of price prediction.

6. Conclusions.

The suggested conceptual framework offers a systematic method to effectively tackle the difficulties associated with properly predicting the costs of PGM. Stakeholders may improve their comprehension of PGM pricing dynamics and make better-informed choices by methodically advancing through the phases of data collection and preparation, model identification, estimate, diagnostic, and forecasting. Subsequent investigations might prioritise the enhancement of the framework and the examination of supplementary variables that impact the prices of precious group metals (PGM), therefore augmenting the precision of forecasting. Through adherence to this conceptual framework, stakeholders are able to construct resilient forecasting models that can effectively anticipate the prices of Platinum Group Metals. This, in turn, enables them to make well-informed decisions and effectively manage risks within the PGM markets.

The successful execution of the conceptual framework for price prediction of PGM requires the completion of many sequential stages. Initially, it is important to gather historical price data pertaining to precious group metals (PGM), in conjunction with pertinent elements that exert effect on their pricing. These aspects include supply and demand dynamics, macroeconomic indicators, and geopolitical events. Additionally, the ARIMA model is used to effectively capture the temporal patterns and seasonal variations present in the dataset (Correa et al., 2016). To address the issues of volatility clustering and heteroskedasticity, the GARCH model is used. Ultimately, the artificial neural network (ANN) model is used to effectively capture intricate non-linear associations and enhance the accuracy of price forecasts. The amalgamation of these models yields an improved level of precision in forecasting prices of precious group metals (PGM) (Ngai & Wu, 2022; Abreu et al., 2019).

The precise forecasting of prices for precious group metals (PGM) has great importance for several stakeholders. To improve the accuracy of these forecasts, it is crucial to provide a conceptual framework that combines ARIMA, GARCH, and ANN forecasting methodologies. The conceptual framework effectively utilises the advantages of various methodologies to capture time-series patterns, volatility clustering, and intricate non-linear interactions, resulting in more precise forecasts. This approach has the potential to assist producers, consumers, and investors in making well-informed choices and effectively managing the risks associated with pricing of precious group metals (PGM).

In conclusion, this research makes a noteworthy scholarly addition to the domain of price prediction for precious group metals (PGM), presenting a complete theoretical framework influenced by the techniques of ARIMA, GARCH, and ANN. Through the pursuit of our research aims, we have established the foundation for forthcoming study, cooperation, and tangible implementation in this crucial field. In order to improve the precision and dependability of PGM price forecasts, it is essential to persistently develop and validate our system. This will eventually yield advantages for stakeholders in sectors that heavily depend on these crucial commodities.

7. Implications for future research.

The conceptual framework offers a systematic method to improve the accuracy of PGMs price forecasts. It helps producers, consumers, and investors make well-informed decisions and manage risks associated with PGMs pricing.

In conclusion, this study has laid the foundation for a comprehensive framework for addressing the accuracy of forecasting models in predicting Platinum Group Metals prices. By integrating insights from ARIMA, GARCH, and ANN approaches, we have made significant progress towards developing robust forecasting methodologies for PGM markets. Moving forward, continued research, collaboration, and transparency will be essential to further refine and enhance the effectiveness of forecasting models in this critical domain.

Based on the findings, several recommendations emerge for future research and practical applications in the field of PGM price forecasting:

- Continued Research: Further research is needed to refine and validate the proposed conceptual framework, including the exploration of alternative forecasting techniques and the integration of additional data sources.
- Model Evaluation: Ongoing evaluation and comparison of forecasting models are essential to identify strengths, weaknesses, and areas for improvement. Robust validation techniques should be employed to assess model performance under different market conditions.

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