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The Most Sensitive Exchange Rates for Tin Based on the Major Commodity Production Countries

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This paper examines the most sensitive exchange rates for tin price based on China and Indonesia that these are the world's first and second largest tin producers. The export data from these countries have shared over 75 per cent of global tin supply that relates significantly with the Indonesian exchange rate based on the Canonical Correlation Analysis (CCA). Furthermore, the future tin prices are forecasted using the weighted least squares (WLS) model. This model is selected since it takes into account the non-normally distribution and heteroscedasticity of the original data. Overall, this result suggests that the Indonesian exchange rate is superior in predicting the future tin price rather than the Chinese exchange rate while China is the largest tin producer in the world. This is caused that the Chinese exchange rate cannot appreciate to other currency baskets.

Keywords: tin, Indonesian exchange rates, Chinese exchange rates, canonical correlation analysis, weighted least squares

Introduction

In this study, the Indonesian exchange rate and Chinese exchange rate are examined to determine the most sensitive variables to forecast the future tin prices. One reason why the Indonesian exchange rate and Chinese exchange rate have been selected is that these countries are the world's second and first largest tin supply to share 75% of global tin market. It is now understood what is the most significant exchange rates have associated to the future tin price fluctuations.

The existing literature on the exchange rates affecting the commodity prices is focused particularly on the most significant commodity exporting countries. Chen, Rogoff, and Rossi (2010) pointed out that the exchange rates of the most significant commodity exporting sources can forecast the global commodity prices. Ciner (2017) revealed a correlation between the South African currency and platinum and palladium prices. It is consistent that South Africa is the largest platinum and the second largest palladium exporters in the world. Brown and Hardy (2019) demonstrated the Chilean exchange rate as one of the most relevant predictor variables to copper prices. Copper is a major influence in Chilean exports that is approximately 23% shares of the global copper supply. While, it has stimulated over 45% of the foreign direct investment (FDI) with copper that has been over a half of total Chilean exports.

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This paper is fundamental to address the commodity exporting countries model using the Indonesian exchange rate and Chinese exchange rate to forecast the future tin prices. The CCA was employed in this study to determine the most significant predictor variable to forecast the future tin prices. The evidence from this study using CCA suggests that the Indonesian exchange rate is the most relevant predictor variable to forecast the future tin price. The most relevant predictor variables in forecasting the future metal prices can play a crucial role in developing an accurate forecasting result (Kristjanpoller & Minutolo, 2015; Alameer, Elaziz, Ewees, Ye, & Jian, 2019).

Using the most significant predictor variable, the WLS model is applied to forecast the future tin price since it can accept the non-normal distribution and heteroscedasticity data rather than the MVE distribution approach. The results obtained from the WLS model suggest that the forecasting performance has a minimum normalized root mean square error (nRMSE) using the Indonesian exchange rate. One possible implication of this is that the Indonesian exchange rate can perform well as the predictor variable to forecast the future tin price.

The rest of the paper is divided into several sections. The literature review is presented in Section 2. The proposed model based on a CCA using the WLS model for forecasting tin prices is described in Section 3 and Section 4. The data set used in this study in Section 5 and the results obtained are discussed in Section 6. Finally, the main conclusions of this study are summarized in Section 7.

Literature Review

The selection of input variables is a major problem in developing the most relevant forecasting model. Alameer et al. (2019) employed 10 input variables to predict the future gold prices. These input variables consist of three exchange rates (South African rand, Indian rupee, and Chinese yuan), two inflation rates (US and China inflation rates), and five commodity prices (WTI crude oil, copper, silver, iron, and gold). Such approaches, however, have failed to address the most relevant predictor variable.

Recently, there has been renewed interest in studying the most relevant variable that is focused on the commodity exporting countries. There is evidence that the exchange rate of a bundle of specific commodity exporting country can be able to forecast the future commodity prices since this country has been recognized as a major producer. This paper appears closely linked (Ciner, 2017; Brown & Hardy, 2019). Ciner (2017) focused particularly on the South Africa country to forecast the white metal prices (e.g., platinum, palladium, and silver). The most interesting of his argument was the South African exchange rate that can be a predictive power to forecast the future platinum and palladium prices. One possible implication of this is that the South Africa is the largest platinum and the second largest palladium supply globally.

Brown and Hardy (2019) showed that the Chilean peso was one of powerful input variables to predict the copper prices. The findings from these studies suggest that the Chile is the world’s largest copper producer to share 23% of global supply. One study by Ciner (2017) examined the forecasting power from the currencies of commodity exporting countries that he concluded the exchange rate fluctuations from a major exporting country to a specific commodity appreciating the commodity prices. However, most studies in the field of a commodity exporting country (Chen et al., 2010; Ciner, 2017) only focused on the currency from a major producer. They failed to specify the most significant input variable as a predictive power using a quantitative approach. In addition, previous studies in selecting the proposed model ignore the statistical analysis of the original data.

This is the first paper to examine the most powerful input variable to forecast the future tin prices using a quantitative approach. As the best of our knowledge, this is also the first study to propose an empirical model based on the statistical analysis of the original data. This proposed model improves the MVE distribution approach as proposed by Kadigi et al. (2020).

Methodology

Correlation Theory

Correlation can play an important role in addressing the issue of the strength of the relationship between one and other variables (Ali & Rahman, 2012). In the history of the price forecasting, the relationship behavior has been thought of as a key factor in determining the prediction model. Several methods currently exist for the measurement of correlation such as:

The Pearson's correlation coefficient. One of the most well-known tools in statistics for assessing correlation between one variable to one or more variables is Pearson's correlation coefficient (PCC). The benefit of this approach is that: firstly, PCC based method provides the significant positive and negative relationship that is confirmed between one variable to another or other variable(s). Secondly, this method is particularly useful in studying the significance degree correlation. Thirdly, this approach can allow calculating the independent variable (*X*) using the dependent variable (*Y*). Fourthly, this approach can examine a goodness fit for a linear regression. Finally, this offers an effective way of eliminating overfitting that may contribute an error in testing the original data (Liu, Mu, Chen, Li, & Guo, 2020). The PCC is expressed as:

$$\rho_{X,Y} = \frac{COV(X,Y)}{\sigma_x \sigma_y} \tag{1}$$

$\rho_{X,Y}$ is defined as PCC to test the linear correlation between variable X and variable Y. $COV(X,Y)$ represents the covariance of *X* and *Y*. Then, σ_x and σ_y are the standard deviations of *X* and *Y*.

PCC value ranges from -1 to +1 that -1 reflects the significant negative relationship between *X* and *Y*. While, +1 implies the significant positive correlation between variable *X* and variable *Y*. This relationship between *X* and *Y* is absent since PCC falls at zero.

Multiple linear regression. Multiple linear regression (MLR) is a classic method in investigating the relationship between an independent variable (*Y*) to several dependent variables $(X_1, X_2, \ldots\ X_n)$. The general form of MLR is defined (Altaf, Ali, & Weber, 2020):

$$Y = \propto + \ \beta_1 X_1 \ + \ \beta_1 X_1 \ \ldots . + \ \beta_n X_{\ n} + \ \varepsilon_i \tag{2}$$

Y expresses dependent variable. $X_{1,2 \ldots n}$ are independent variables. $\propto$ denotes intercept value. $\beta_{1,2,\ldots n}$ are coefficient of independent variables. ε_i represents error term of equation.

In order to assess the correlation between the independent and the dependence variables, it can be seen from regression value (*R*). Since, *R* is close to one that appears the independent variables can perform to predict the dependent variables (Uyanik & Güler, 2013).

A major advantage of MLS is that it can account the dependent variable using an interaction of the independent variables. In addition, MLR can confirm the most significant dependent variables affecting the independent variables (Altaf et al., 2020).

Canonical correlation analysis. Canonical correlation analysis (CCA) has been developed to measure the relationship between two groups of variables that it is purposed to investigate the existence of multivariate. This can be solved using its linear relationship by reducing the computation rate size. CCA is selected because it can determine the relationship for a numerous of independent and dependent variables. The two groups of *X* variables

$(V_1, V_2, \dots\ V_5)^T$ and the dependent two groups $(V_6, V_7, \dots\ V_{10})^T$ can be denoted as a linear combination of A_i and B_i, respectively. Therefore, CCA for A_i and B_i is expressed as follows:

$$\rho^*_{A_iB_i} = \frac{COV(A_i, B_i)}{\sqrt{VAR(A_i)\ VAR(B_i)}}, i = 1, \dots, 5. \quad (3)$$

$\rho^*_{A_iB_i}$ is covariance correlation between A_i and B_i. $COV(A_i, B_i)$ represents the covariance correlation set A_i and B_i. $VAR(A_i)$ and $VAR(B_i)$ are each variance of A_i and B_i. The CCA result is interpreted similar to PCC that the significant value of it can represent strong relationship between two groups of variables. In addition, CCA model can provide the best dependent variables as the predictor parameter to forecast the future prices (Androniceanu, Georgescu, Tvaronavičienė, & Androniceanu, 2020). The best predictor parameter to forecast the independent variables may be linked to the significant value of F-test result (Androniceanu et al., 2020; Fedelis & Anthonia, 2018).

Goodness of Fit Theory

A goodness of fit is fundamental to test normal distribution data from random variables. Recent advances in assessing normal distribution data have facilitated investigating of heteroscedasticity. Hence, there are two main techniques of this study used to identify a normal distribution and heteroscedasticity. Firstly, the Jarque-Bera (JB) test is one of techniques available for measuring the normal distribution. The JB test is defined as follows:

$$\text{JB} = \frac{N}{6}(S^2 + \frac{(K-3)^2}{4}) \quad (4)$$

N is the number of observation. S and K express skewness and kurtosis, respectively. The normal distribution using JB can be determined since JB value at level p-values is greater than or equal to chi-square test result (Thadewald & Büning, 2007). Secondly, the Breusch-Pagan test is one of the more practical ways of identifying the existence of heteroscedasticity. Traditionally, Breusch-Pagan test has been assessed by measuring Lagrange parameter denoted by chi-square test by a number of observations multiplied with regression squared (Gander, 2013; Öaturk & Karabulut, 2018). In order to assess heteroscedasticity, the p-value at level α is used to reject or accept this issue. Since p-value is less than α that data appear heteroscedasticity (Farbmacher & Kögel, 2017).

Forecasting Performance

The following part of this paper describes to determine the quality of the proposed model in forecasting tin prices using Indonesia and Chinese exchange rate variables. Root mean square error (RMSE) is one of the most common procedures for determining the efficiency and effectiveness of comparing between the actual prices with the predicted prices for a same scale in a time series analysis (Shcherbakov et al., 2013). RMSE equation is described as follows (Alameer et al., 2019):

$$\text{RMSE} = \sqrt{\frac{1}{N}}\sum_{t=1}^{N}(y_i - \bar{y})^2 \quad (5)$$

where y_i is the historical prices, $\bar{y}$ expresses the predicted prices, and N denotes the number of observations. In order to assess the accuracy in predicting the future prices, the RMSE is suggested to be normalized using formulation as follows (Shcherbakov et al., 2013):

$$n\text{RMSE} = \frac{1}{Z}RMSE \quad (6)$$

where Z presents the difference between maximum and minimum actual values. This normalized equation ranges from 0 to 1 that the best fitting performance of forecasting is represented closer to 0 (Shcherbakov et al., 2013).

Proposed Model

The following section discusses the proposed model that is selected on the basis of degree of correlation and distribution data for tin prices to oil prices, copper prices, Indonesian and Chinese exchange rates. Eligibility criteria has been used in the past to investigate the maize, sorghum, and rice prices employing the multivariate empirical (MVE) distribution approach (Kadigi et al., 2020). However, the study would have been far more convincing if it addressed the heteroscedasticity issue. Gort and Hoogerbrugge (1995) found the effects of heteroscedasticity on calibration procedure that they conclude to apply the weighted least squares (WLS) approach. For this study, the WLS approach was computed as follows:

$$Y_i = \alpha + \beta x_i + \mathcal{E}_i \quad (7)$$

where Y_i is the predicted tin prices and $\alpha = \bar{y} + \beta\bar{x}$, where $\bar{y}$ and $\bar{x}$ are the weighted mean of variable x and y. β is described in equation below:

$$\beta = \frac{\sum_i W_i \sum_i W_i x_i y_i - \sum_i W_i x_i \sum_i W_i y_i}{\sum_i W_i \sum_i W_i x_i^2 - (\sum_i W_i x_i)^2} \quad (8)$$

W_i is equal to the inverse of the variance and $\mathcal{E}_i$ is mean error of each month.

Experimental Data

The following section is a brief of description of the data, correlation analysis, and goodness of fit analysis. The data describe the collection sources and are used in this study. Then, correlation analysis investigates the relationship between tin prices and predictor variables. The goodness of fit analysis identifies normal distribution and heteroscedasticity issues from the data sources.

Data Description

This research selects the raw dataset for tin price (US$/ton), oil price (US$/barrel), copper price (US$/ton), Indonesian exchange rate (US$/IDR), and Chinese exchange rate (US$/RMB). The data cover the monthly basis of raw datasets ranging from January 2004 to April 2021. The tin price and copper price are downloaded from Indexmundi while the exchange rates are supplied from the Central Banks. The results obtained from the descriptive and statistical test of each variable are summarized in Table 1.

Table 1

Descriptive Statistics for Tin, Crude Oil, Copper, Indonesian and Chinese Exchange Rates

Descriptive statistics	Tin price	Crude oil price	Copper price	Exchange rate US$/IDR	Exchange rate US$/RMB
Mean	17,405	70	6,298	11,214	6.920
Median	18,213	63	6,538	10,084	6.825
Minimum	6,160	21	2,424	8,396	6.052
Maximum	32,363	133	9,868	15,816	8.270
St. dev	5,577	25	1,675	2,196	0.668
Skewness	-0.206	0.451	-0.391	0.353	0.864
Kurtosis	-0.317	-0.822	-0.366	-1.535	-0.433
Sample size	208	208	208	208	208

As can be seen from Table 1 above, the mean of tin and copper reported more than the median crude oil, Indonesian exchange rates, and Chinese exchange rates. These observations have a link with skewness values that tin and copper are a negatively skewed. Conversely, the crude oil, Indonesian exchange rate, and Chinese exchange rate are positively skewed. Further statistical tests for kurtosis reveal that all variables have negative values. These results suggest that these variables are platykurtic.

Correlation Analysis

Correlation analysis aims to explore the relationship between the independent variable to dependent variables. This study uses three different methods to measure their correlations. Firstly, the PCC analysis identifies each variable (i.e., tin price, oil price, copper price, Indonesian exchange rate, and Chinese exchange rate) as presented in Table 2. The current results between tin and other variables are $\rho_{tin,oil} = 0.597$; $\rho_{tin,copper} = 0.754$; $\rho_{tin,idr} = 0.199$, and $\rho_{tin,rnb} = -0.804$. These results suggest that tin and copper have a significant correlation while oil is less significant corelation to tin than tin to copper. However, tin and the Indonesian exchange rate are uncorrelated while tin has a significant negative correlation to Chinese exchange rate.

Table 2

The Correlation Between Each Variable Using the PCC Analysis

	Sn price	Oil price	Copper price	Indonesian exchange rate	Chinese exchange rate
Sn price	1				
Oil price	0.597	1			
Copper price	0.754	0.740	1		
Indonesian exchange rate	0.199	-0.463	-0.152	1	
Chinese exchange rate	-0.804	-0.433	-0.529	-0.378	1

Secondly, the correlation between tin to oil, copper, Indonesian exchange rate, or Chinese exchange rate is computed using the MLR model as presented in Table 3. The regression square analysis compares between tin to other dependent variables with Indonesian exchange rate or Chinese exchange rate. The regression results are 0.736 and 0.794 for Indonesian exchange rate and Chinese exchange rate, respectively. The MLR tests suggest that the dependent variable using Chinese exchange rate is more significant than Indonesian exchange rate. Finally, the result of the correlation analysis using CCA is summarised in Table 3. *F*-tests are used to analyse the significant dependent variable between Indonesian exchange rate and Chinese exchange rate. As a result, *F*-tests concluded that Indonesian exchange rate has a significant value that it is superior as a dependent variable in forecasting the future tin prices.

Table 3

The Correlation Between Two or More Variables Using Multiple Regression, Regression Square, and Canonical Correlation

Correlation test	Exchange rate (USD/IDR)	Exchange rate (USD/RMB)
Multiple *R*	0.860	0.893
R square	0.740	0.797
Adjusted *R* square	0.736	0.794
Canonical correlation	-0.131	-0.947
F-test	892	1.790

Goodness of Fit Tests

Further statistical analysis is required to determine exactly the existence of non-normal distribution and heteroscedasticity from the random data. Jarque-Bera (JB) tests accept the normal distribution for tin, oil, and copper. However, these reject the Indonesian exchange rate and Chinese exchange rate as the normal distribution since the JB values are less than chi-square test.

On the question of heteroscedasticity, both Indonesian exchange rate and Chinese exchange rate are heteroscedasticity since the p values are below the 5% level.

Table 4

The Normal Distribution Test and Heteroscedasticity Using Jarque-Bera (JB) Test and p-Values at 5% Level

Parameter	Sn price	Crude oil price	Copper price	Exchange rate (USD/IDR)	Exchange rate (USD/RMB)
Jarque-Bera	2.343	12.900	6.461	24.744	27.486
p-values	0.310	0.002	0.040	0.000	0.000
Chi-square test	21.255	25.477	14.646	7.935	1.926

Empirical Result Analysis

This study examined the impact of the Indonesian and Chinese exchange rates in forecasting tin prices. The first question is aimed to identify the significant relationship between the Indonesian and Chinese exchange rates to the tin prices. The correlation between the Indonesian and Chinese exchange rates to tin prices was tested using the CCA. The evidence from this study suggests that the CCA can identify the dependence variable to forecast the future tin prices. In order to analyse the most significant dependent variable to tin price the Indonesian and Chinese exchange rates were examined using F-test. As a result, F-test result confirms that the Indonesian exchange rate has a link to tin price which can be a superior as a predictor variable to forecast the future tin prices.

Result and Discussion

This section presents the findings of the research, focusing on the two themes that they are the most relevant predictor variable and the best model to predict the future tin prices. Firstly, the predictor variable was selected based on the most significant link to the tin prices. Secondly, the study uses qualitative analysis in order to gain insights into forecasting commodity prices. The WLS approach was employed since it takes heteroscedasticity issue into account. Figure 1 compares between actual tin prices against the Indonesian exchange rate predictor variable.

To compare the difference between actual tin prices against estimated price using the Indonesian exchange rate predictor variable, these results were plotted as shown in Figure 1. There is a clear trend of decreasing or increasing between actual tin prices versus estimated prices. The results in Figure 1 indicate that the proposed model can successfully be applied to forecast the future tin price using the Indonesian exchange rate as a predictor variable.

The second test was examined using the Chinese exchange rate as shown in Figure 2. Such results, however, have failed to address the similar trend between actual tin prices versus estimated tin prices using the Chinese exchange rate predictor variable. It has commonly been assumed that the Chinese exchange rate is less flexible to appreciate other currency baskets. It applies a fixed rate to other currencies that is less sensitive to appreciate the global trend of macroeconomics (Shimizu & Sato, 2018).

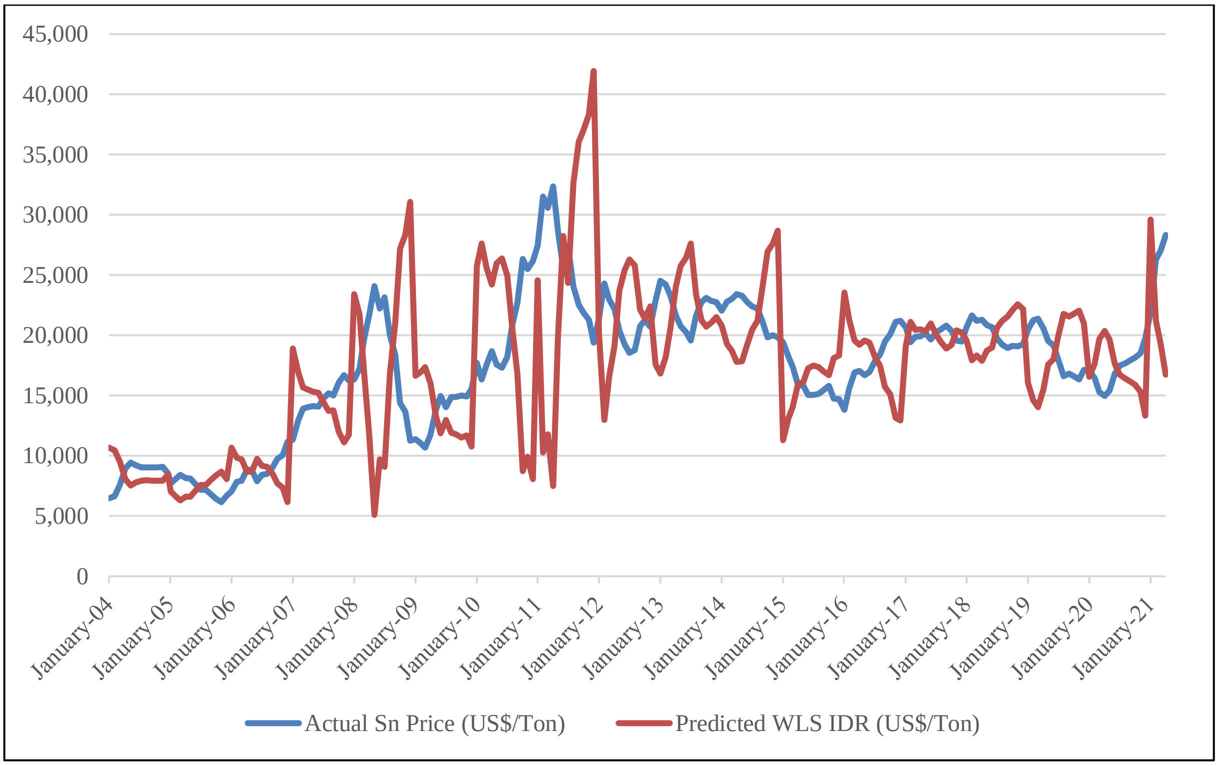

Figure 1. Actual tin price against estimated tin price using the Indonesian exchange rate predictor variable calculated by the weighted least squares (WLS) model.

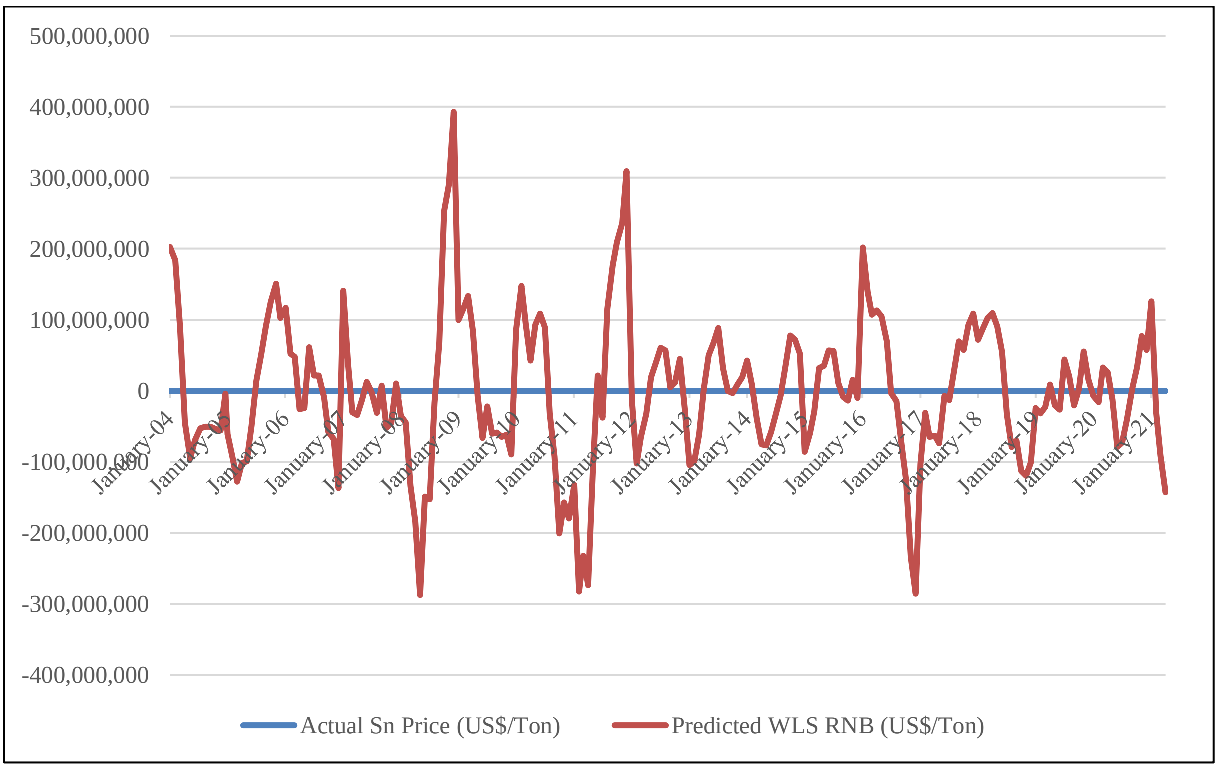

Figure 2. Actual tin price against estimated tin price using the Chinese exchange rate predictor variable calculated by the weighted least squares (WLS) model.

Statistical Analysis

In order to evaluate the performance of the proposed model against actual tin prices, RMSE and nRMSE are taken into account. These tests aim to identify the existence of the significant difference between the model results with the actual data.

Table 5

RMSE and nRMSE Results of the Proposed Model Using the WLS in Comparison Between the Indonesian Exchange Rate With the Chinese Exchange Rate

	RMSE	nRMSE
The WLS using IDR	310.52	0.01
The WLS using RMB	55,411,053	0.08

These nRMSE results are 0.01 using the WLS with the Indonesian exchange rate predictor variable that satisfies with no significant difference to actual tin prices.

Conclusion

This paper examines the most significant input variable to predict the future tin prices using the exchange rates from the major tin exporting countries. Indonesia and China are selected because these countries share 75% of global tin supply. The selection of the most significant input variable to forecast the future tin prices between Indonesian and Chinese currencies has been examined using the CCA. Using the CCA, the Indonesian exchange rate shows a significant link to the historical tin price that it can be concluded as the best predictor variable to forecast the future tin price.

Secondly, the WLS model is calculated using the Indonesian exchange rate, as the most significant predictor variable from the CCA to investigate the future tin prices. The WLS model can improve the MVE distribution approach since it can take non-normal distribution and heteroscedasticity problems into account. As a result, the Indonesia exchange rate demonstrates as a superior variable to forecast the future tin prices that can be seen from the actual tin prices against the estimated tin prices plots. It is reported the actual tin prices have a similar trend against the estimated tin prices from January 2004 to April 2021.

Finally, the forecasting performance as a result from the WLS model is tested using RMSE and nRMSE. The nRMSE result falls at 0.01 that it indicates no significant difference from the actual tin prices to the estimated tin price using the Indonesian currency.

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