WASM: Minerals, Energy and Chemical Engineering

Estimation of Iron Ore Price in reference to Major Economic Indices using Artificial Neural Network

Yoochan Kim

ORCID ID: 0000-0001-7649-3903

This thesis is presented for the Degree of

Master of Philosophy (Mining and Metallurgical Engineering)

of

Curtin University

February 2024

Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made. This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Signature:

Date: 06-Feb-2024

Abstract

Understanding the interconnectedness of pricing systems in the commodity market is crucial for accurately predicting commodity prices, especially for the successful operation of a mining business. The mining industry requires substantial investments, often in the range of hundreds of millions of dollars. Consequently, each mining project is highly susceptible to fluctuations in commodity prices, which have experienced some volatility in recent years. Having an accurate forecast of commodity prices can prove advantageous for both producers and investors, as it allows them to effectively prepare for significant price changes in both the short and long term. For producers, an accurate forecast of commodity prices facilitates precise predictions of the optimized Ultimate Pit Limit (UPL) and the Net Present Value (NPV) of mines. The decline in UPL and NPV significantly impacts the operational income of iron ore mines. Therefore, it becomes imperative to assess the potential factors influencing the fluctuations in iron ore prices. This analysis can contribute to the prediction of short-term and long-term iron ore prices, enabling effective management of production output. Large mining companies often engage in the production of various commodities through diverse portfolios. This research on understanding commodity market interdependencies will greatly benefit mining companies and investors by maximizing profit margins and minimizing risks in the business. It achieves this by optimizing the ratio of different commodities within the investment portfolio and accurately predicting changes in iron ore prices.

In recent times, various global issues have arisen, leading to disruptions in the worldwide supply chain of goods. These issues include the COVID-19 pandemic, the Russo-Ukrainian war, the US-China trade war, and the strained relationship between China and Australia, among others. As a result, commodity prices have experienced significant fluctuations. This situation has given rise to a phenomenon known as 'resource nationalism', where different nations impose restrictions on exports and imports, impose tariffs or sanctions on one another. The underlying reason for these actions is the pursuit of national security or individual interests by each country. Consequently, the demand for commodities has surged, causing a sharp increase in prices. Notably, iron ore has emerged as a crucial commodity, leading to tensions between Australia and China. Australia heavily relies on iron ore exports, while China's heavy industry is equally dependent on affordable supplies from Australia.

After investigating twelve different commodity prices over a period of 30 years using multivariate modelling, the trend line reveals the presence of cointegrations that resemble a sine

curve. This indicates that there are three commodities that consistently co-integrate with changes in the price of iron ore, spanning all time lags up to 27 months. Consequently, any impact on commodity prices will take a minimum of 20 months and a maximum of 27 months to manifest in the overall commodity market. Furthermore, the Granger causality test and Vector Error Correction Modelling (VECM) have confirmed a bidirectional influence between the price of iron ore and the prices of oil, copper, and Australian coal. This implies that changes in the prices of oil, copper, and Australian coal have an impact on the price of iron ore. The normalizing vector $\beta 1$ indicates that a 1% increase in the prices of oil, Australian coal, and copper leads to an approximate appreciation of 1.34%, 1.29%, and 0.017% in the price of iron ore, respectively. The speed of adjustment parameter $\alpha 1$, which represents approximately 3.6% of oil price, 1.33% of Australian coal price, and 6.53% of copper price change per month, is attributed to the disequilibrium between the actual and equilibrium levels.

After establishing the relationship, the study has examined five distinct methods for estimation. These methods include bivariate non-linear regression (BNLR), multiple linear regression (MLR), and multiple non-linear regression (MNLR). Additionally, the logsig and tansig models of Levenberg-Marquardt artificial neural network (ANN) modelling were utilized to forecast the future iron ore price. The predictions were based on twelve other monthly commodity prices and indices, namely LNG, aluminium, nickel, silver, Australian coal, zinc, gold, oil, tin, copper, lead, and CPI (metals).

It should be emphasized that the purelin model of the Levenberg-Marquardt ANN modelling demonstrated the most favourable outcome, exhibiting an average accuracy of 5.92% for one month ahead, 9.48% for two months, and 11.21% for three months during a 10-month testing period spanning from July 2020 to April 2021. It is worth mentioning that the purelin model achieves high accuracy, with forecasts and actuals differing by less than 5% in 40-50% of cases, for up to two months of forecasting. This suggests that utilizing the purelin model allows for predicting the iron ore price for the upcoming month within a 2-month timeframe. It is worth noting that the tested period was characterized by instability in iron ore prices, with a notable surge observed. The same principle can be applied to future commodity price cycles.

The study has provided valuable insights into the correlation between iron ore prices and other commodities. It has been established that oil, copper, and coal are closely linked to the demand for iron ore, particularly in steel production and the manufacturing of other industrial metals, as indicated by Granger causality and VECM findings. Furthermore, the utilization of the purelin model, specifically the Levenberg-Marquardt ANN model, has demonstrated the potential for short-term iron ore price forecasting. The purelin model can be effectively utilized in developing predictive models for iron ore price projections in mining operations, boasting a high level of accuracy (40–50% accuracy with a 5% variance between forecasts and actual prices) for both one-month and three-month forecasts, even in volatile market conditions. Precise iron ore price predictions using the logsig model can enhance the UPL and net NPV of mining ventures, leading to increased profitability and reduced financial risks for iron ore mining firms.

Acknowledgements

I would like to appreciate my supervisor Dr Apurna Kumar Ghosh for his for opportunity given to me to gain great deal of research experience, and valuable supervision. I also express my 'thank you' to my co-supervisor Professor Erkan Topal for his guiding the direction for me and my research and supportive supervision and encouragement.

My big thanks go to my father who has always encouraged and shared his knowledge and passion for science and engineering as a former academic himself ever since I was a child. He has been the mentor of this journey. I pray for him for his sound recovery from his cancer diagnosis.

I would also like to thank my mother, sister, aunt and especially my wife who has given unconditional support to my time throughout this research. Lastly, my love to my daughter Ji-Sue.

List of publications included as part of the thesis

Some of papers have been published during the period of thesis preparation and details of previous publications are listed below:

1) Kim Y, Ghosh A, Topal E, Chang P (2022) Relationship of iron ore price with other major commodity prices, Mineral Economics, Vol 35, pp 295–307, https://doi.org/10.1007/s13563-022-00301-x.
2) Kim Y, Ghosh A, Topal E, Chang P (2023) Performance of different models in iron ore price prediction during the time of commodity price spike, Resources Policy, Vol 80: p. 103237, https://doi.org/10.1016/j.resourpol.2022.103237

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Chapter 1 – Introduction

Mining is an industry that requires significant financial investments. Each mining project is highly influenced by the prices of commodities, and there has been some instability in commodity prices in recent years. As a result, investments in the mining and minerals sector are considered risky (Topal, 2008) and extremely sensitive to changes in commodity prices. Having an accurate forecast of commodity prices can be advantageous for producers, as it allows investors to prepare for significant price fluctuations in both the short and long term. Additionally, an accurate forecast of commodity prices enables producers to predict the optimized UPL and NPV of open pit mines (Ma et al., 2019). This research is particularly beneficial for large mining companies that deal with various commodities, as it helps maximize profit margins and minimize risks by optimizing the ratio of different commodities within their investment portfolios and predicting changes in iron ore prices. Therefore, having an accurate prediction of commodity prices is crucial for the success of a mining business.

Iron ore has played a crucial role in human civilization since the Bronze Age, serving as a fundamental resource to produce steel. Its significance lies in its essential role in steel manufacturing, which in turn contributes significantly to economic development. Steel finds extensive application across various industries such as automotive, rail, aerospace, shipbuilding, power/fertilizer plants, and more. In Australia, mining stands as a pivotal industry, accounting for approximately 60% of the country's exports (Observatory of Economic Complexity, Australia, 2021). The Australian economy heavily relies on iron ore exports, while Chinese heavy industry equally depends on cost-effective supplies from Australia (Wilson, 2017). Moreover, a substantial portion of global production (56%) and exports (74%) heavily relies on Australia and Brazil, with China being the largest importer, accounting for 66% of global iron ore imports. Consequently, the diversity of sellers and buyers in the iron ore market remains limited (Observatory of Economic Complexity - Iron Ore, 2021).

In recent times, various global issues have arisen, causing disruptions to the worldwide supply chain of goods. These issues include the COVID-19 pandemic, the Russo-Ukrainian war, the US-China trade war, and the strained relationship between China and Australia. As a result, commodity prices have experienced fluctuations. Among these commodities, iron ore has gained significant importance due to the tensions between Australia and China. Australia heavily relies on iron ore exports, while China's heavy industry depends on low-cost Australian supplies (Wilson, 2017). An illustrative example is the causal relationship between gold price fluctuations and COVID-19 case numbers (Gautam et al., 2022). These events have led to a phenomenon known as 'resource nationalism,' where countries impose bans, tariffs, or sanctions on each other's exports or imports in pursuit of national security or their own interests. Consequently, commodity prices have surged due to increased demand. It is worth noting that China has not banned iron ore imports and has not imposed additional tariffs on it, unlike other commodities such as wine, coal, barley, cotton, lobsters, and wood. This is primarily because China heavily relies on Australia for 64.5% of its iron ore imports (Observatory of Economic Complexity – Iron Ore, 2021). Therefore, the global supply chain for steel production's raw materials is monopolized by these two countries, making it susceptible to disruptions.

Iron ore prices have shown significant volatility over the past decade, ranging from US$40 to nearly US$190 per ton (Indexmundi, n.d.). The importance of iron ore has been further underscored by the recent surge in prices, reaching US$215 on June 1, 2021, up from US$82 on April 1, 2020 (Indexmundi, n.d.). Producers of iron ore must accurately predict price fluctuations to effectively manage risks associated with price drops. A decrease in iron ore prices can lead to a reduction in UPL and NPV for open pit mines, consequently impacting operational income. Therefore, it is crucial to analyse the factors influencing iron ore price changes to forecast short-term and long-term prices and optimize production levels.

The impact of the AUD exchange rate on iron ore prices has been found to be minimal or non-existent according to the Granger causality test conducted by Haque et al. (2015a). As a result, the true driving force behind the long-term iron ore price remains unknown, and it is possible that several economic indicators play a role in determining it. While there have been numerous studies on estimating the prices of gold and oil, there has been limited research on predicting iron ore prices. This leaves unanswered questions in the iron ore industry regarding (1) the actual factors driving changes in the price of iron ore, and (2) whether the price is solely influenced by global supply and demand. To date, there is insufficient engineering research to provide answers to these questions.

The research aims to achieve two main objectives. Firstly, it seeks to establish the correlation between the price of iron ore and other commodity prices. Secondly, it aims to develop a tool for estimating the price of iron ore. The research will focus on the following specific areas:

1. Determine the bivariate and multivariate cointegration between monthly iron ore prices and twelve other monthly commodity prices or indices using the Johansen cointegration test.
2. Examine the short-term reactions to the long-term connection between iron ore prices and twelve distinct commodity prices from 1990 to 2020 utilizing the VECM and Granger causality test.
3. Forecast the iron ore price by utilizing the Directly Influencing Variables (DIVs) and Indirectly Influencing Variables (IIVs) of iron ore.

Chapter 2 – Literature review

2.1 Relationship definition of iron ore price

To make accurate predictions about the price of iron ore, it is crucial to analyse the potential correlation between commodity prices and other econometric variables. According to Haque et al. (2015a), there is a positive relationship between iron ore prices and the value of the Australian dollar, but no significant influence in the opposite direction. Additionally, they have discovered a long-term bidirectional causal relationship between the price of gold (in US $) and the exchange rates of the Australian dollar to US dollar (AUD/USD) from 1996 to 2014. Another study by Ma et al. (2019) has further expanded on these findings, revealing that the prices of oil, gas, coal, and iron ore are all linked to an appreciation of the Australian dollar and a depreciation of the Chinese RMB.

2.2 Commodity prices impacting Net Present Value (NPV) and Internal rate of return (IRR)

It is important to understand that both the Net Present Value (NPV) and Internal rate of return (IRR) are an important part of a feasibility study of a mine, where both are highly influenced by commodity price changes.

NPV and IRR have often been a financial metric or indicator which displays the total value of a potential investment. The NPV captures all the future cashflows, both inflows and outflows associated with an investment, and factors in discounts of all future cash flows to the present day, and then adds them together. IRR, on the other hand, estimates the profitability of potential investments using a percentage value rather than a dollar amount. IRR % is an indication of a cut-off point for investment decisions.

The equation for NPV and IRR are shown in below equations:

$$NPV(t) = \frac{C(t)}{(1+i)^t} \ldots (2.1)$$

Where: NPV = Net Present Value, t = time of cashflow, C(t) = net cashflow at time t, and i = discount rate

$$NPV(t) = \sum_{t=0}^{t} \frac{C(t)}{(1+IRR)^t} = 0 \ldots (2.2)$$

Where: NPV = Net Present Value = 0, t = time of cashflow, and C(t) = net cashflow at time t, IRR = i (discount rate)

As shown in equations 2.1 and 2.2, NPV is directly proportional to cashflow, which is also directly proportional to commodity prices. Therefore, NPV is also directly proportional to commodity prices. Also, projects with a positive NPV also show a higher IRR greater than the base value. Hence, the higher the IRR, the better the return of an investment.

2.3 Prediction methods of other commodity prices

Previous attempts have been made to predict the prices of various commodities. Shafiee and Topal (2010) made advancements in forecasting models for gold prices and discovered a potential correlation between crude oil prices and gold prices. In a recent study, Yang et al. (2022) compared different machine learning models, including Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and ANN, to forecast gold prices. They considered various factors such as Standard and Poor's 500, Dow Jones Industrial Average, Bitcoin price, Ethereum price, silver price, oil price, USD index, USD-Euro exchange rate, and gold trading volume. The results revealed that the SVR model outperformed the other two models. However, it is important to note that the study had limitations. Firstly, the sample size was small, covering the period from 1 January 2017 to 31 December 2020. Secondly, the comparison between forecasted and actual gold prices was based solely on metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Therefore, the conclusion could be more definitive and potentially different if the sample size was more extensive and if a direct comparison between forecasted and actual gold prices was made.

2.4 Prediction methods of iron ore price

Iron ore price movement modelling was done by several researchers. Pustov et al. (2013) compared the existing long-term (LT) forecasting methods, such as the marginal incentive pricing (MIP) vs. marginal cost (MC) approach, which indicates that MIP is a better predictor and showed a difference of ~7.9%. Modelled long-term iron ore price using marginal costs against marginal incentive price and forecasted as $85/tonne and $124/tonne, respectively, considering depletion of iron ore deposits, where the actual was $133.8/tonne. Machine learning based on ANN is widely used by researchers to estimate financial time series models. Out of different ANN methods such as the conjugate gradient algorithm (CGA), steep descent, Gauss-

Newton, and Levenberg-Marquardt, Mammadli (2017) have noted that for financial time series prediction, the Levenberg-Marquardt estimation algorithm significantly outperformed the other ANN methods.

Kakha et al. (2015) applied the logsig transfer function from Levenberg-Marquardt to conclude that the best network for estimation of the monthly price of iron ore is a four-layered feed-forward network with a post-propagation training algorithm when applied with six different input variables: oil price, aluminium price, steel price, world GDP, iron ore production, and steel production, where the root-mean-square error (RMSE) is 0.1885. However, no iron ore price was forecast, and hence the model is not verified. Farajian et al. (2021) only forecasted one-month-ahead prediction of iron ore price with excellent accuracy with a difference of ~2% using the Levenberg-Marquardt method. However, there is a limitation from a practical perspective. Some data are not readily available immediately, such as (1) Chinese and international production rates of iron ore and (2) iron ore imports in China. The production figures are often published after each quarter or year. As real-time monthly iron ore price prediction is vital, the data source must be readily available daily. It is also unsure which transfer function has been applied from the Levenberg-Marquardt method.

Table 2.1 shows different variables applied by respective methods and table 2.2 shows the forecast performance (i.e., difference of % between forecast and actuals) of three different authors, Pustov et al. (2013), Kakha et al. (2015) and Farajian et al. (2021):

Table 2.1: Input variations for iron ore price forecast of different methods applied

	Pustov et al. (2013)	**Kakha et al. (2015)**	**Farajian et al. (2021)**
Methods applied	MC / MIP Global / MIP-BIG4	Levenberg-Marquardt Logsig	Levenberg-Marquardt *
Iron ore demand driven by China	✓	✗	✗
Iron ore supply constraints	✓	✗	✗
Ore deposit depletion and operating costs (NPVs, IRR, etc) and inflation	✓	✗	✗
Shipping fare	✗	✗	✓

Worldwide production rate of iron ore	✗	✓	✓
China iron ore production rate	✗	✗	✓
Iron ore imports to China	✗	✗	✓
Gold price	✗	✗	✓
Steel price	✗	✓	✓
Oil price	✗	✓	✓
US interest rate	✗	✗	✓
Dollar price	✗	✗	✓
Euro currency	✗	✗	✓
Dow Jones stock index	✗	✗	✓
Aluminium price	✗	✓	✓
World GDP	✗	✓	✗
Steel production	✗	✓	✗

*Note: No indication of which transfer function applied

Table 2.2: Difference in % between forecast and actuals of iron ore price for different methods applied

Authors	**Pustov et al. (2013)**			**Kakha et al (2015)**	**Farajian et al. (2021)**
Methods applied	MC	MIP Global	MIP-BIG4	Levenberg-Marquardt Logsig	Levenberg-Marquardt*
Difference in % between forecast and actuals	~57.4%	~18.4%	~7.9%	N/A	~2%

*Note: No indication of which transfer function applied

Understanding that the Levenberg-Marquardt method is outperforming compared with other ANN methods (Mammadli, 2017) for financial time series prediction, this sequence of research is: (1) study the performance of iron ore price forecasting methods other than ANN, such as bivariate regression (BNLR), multiple linear regression (MLR), and multiple non-linear regression (MNLR), to understand the complexity of the model; (2), once determined, complex modelling is required, apply the Levenberg-Marquardt method by modelling different transfer functions with readily available data; and (3) suggest which method is the most optimum or accurate.

2.5 Proposed research method – commodity price relationship definition

2.5.1 Unit root test

Economists often use unit root tests to determine whether the time series data of major economic indices are stationary or not. The Dickey-Fuller test (Dickey and Fuller, 1979) was performed in this study using Microsoft Excel Data Analysis Tool software to determine whether the time series variables contain a unit root or not to investigate the relationship between iron ore prices and all other variables using Johansen cointegration test later in this research. This is because the cointegration test is applicable when the variables contain unit-roots. Unit root is a stochastic trend in a time series, sometimes called a "random walk with drift". If a time series has a unit root, it shows a systematic pattern that is unpredictable. The typical Unit root test formula (Johansen, 1991) is written as:

$$\mathrm{Xt} = \mathrm{Dt} + \mathrm{Zt} + \ \varepsilon\mathrm{t} \ldots (2.3)$$

Testing the stationarity of a time series is performed on the autoregressive (AR) model, which is a stochastic process model to capture interdependencies among multiple time series variables and is written as:

$$\mathrm{X(t)} = \Phi\mathrm{X(t-1)} + \cdots + \Phi\mathrm{X(t-p)} + \ \varepsilon\mathrm{t} \ldots (2.4)$$

Where: X(t) – time series variable (iron ore price history and other variables), D(t) – deterministic component (or signal) that can be modelled through the modelling techniques, Z(t) – stochastic component (a random probability distribution or pattern that may be analysed statistically but may not be predicted precisely), δ – stationary error, ϵt – stochastic disturbances (or error terms) and Φ – k × k matrix

Each component will have its own outcome value and the null hypothesis is that there is a unit root (δ = 0). If a unit root exists, and would be non-stationary, and if no unit root exists, it would be stationary. There are three test models randomly tested as part of the ADF test in this research; autoregressive (AR), AR with drift variant (ARD) and Trend Stationary (TS). The null test models are tested against the alternative models.

The null hypothesis of the Augmented Dickey Fuller (ADF) test is 'The variable contains a unit root and is hence non-stationary' and the outcome is interpreted: if p >0.05, the null hypothesis cannot be rejected, it contains a unit root and is non-stationary and if $p<0.05$, null hypothesis is rejected, does not contain unit root and is stationary.

2.5.2 Johansen cointegration Test

Cointegration tests offer a basic outline of the data, enabling estimation and interpretation of the variables, given that the sequence of random variables is not stationary. The cointegration test provides an effective framework for testing models and estimating long-run relationships among cointegrated variables from the time-series data.

The relationship between cointegration and the error correction model was introduced by Granger (Granger, 1981) and is further developed by Granger and Weiss (Granger and Weiss,1983) who outlined the fundamentals of cointegration, that if each vector of time series variable X(t) first reaching stationary after differencing, while a linear combination $\alpha' X(t)$ is stationary, X(t) is co-integrated with vector α. Engle and Granger (Engle and Granger, 1987) presented the modelling of cointegration for non-stationary time-series variables X(t).

The cointegration test enables estimation of LT relationships for co-integrated variables from the time series variable. The Cointegration test is practically applicable when the variables contain unit-roots. The Johansen test is one of the most used for testing cointegration in multivariate time series variables X(t) (Johansen, 1991). It allows several co-integrating relationships, hence more applicable than the Engle-Granger test, which is based on the ADF test for unit roots from a single estimated co-integrating relationship. The Johansen test is used to test the co-integrating relationship of the price of iron ore against the econometric variables and is carried out according to the following steps:

1) VECM representation and extract the effects of the lagged time series variable using Frisch–Waugh–Lovell (FWL) theorem:

$$\hat{u}(t) = \Pi\hat{v}(t) + \epsilon t \ldots (2.5)$$

Where: Π – matrix of coefficients on the vector error correction term, $\hat{u}(t)$ – residuals for ΔX_t from the left-hand side (LHS), $\hat{v}(t)$ – Residuals for X_{t-1} right hand side (RHS), ϵt – stochastic disturbances (or error terms)

2) All the variables in the cointegration related symmetrically. No endogenous nor exogenous variables exist. This system as written as:

$$\frac{1}{(\tilde{\alpha})} u(t) = (\beta\sim)' v(t) \ldots (2.6)$$

Where: ($\tilde{\alpha}$) – k × k matrix of intercept, a constant, (β~)' – k × k matrix of the coefficients of the lags of X_t, $\tilde{U}(t)$ – residuals for ΔX_t from the LHS, and $\tilde{\upsilon}(t)$ – residuals for X_{t-1} RHS

3) The adjustment parameters α and the Φ∗ 's is estimated as:

$$\Delta X(t) = \phi + \alpha\beta' X(t-1) + \sum_{i=1}^{p-1} \Phi i * \Delta X(t-i) + \epsilon t \ldots (2.7)$$

Where: X_t – time series variable, Φ – k × k matrix, δ – stationary error, ϵt – stochastic disturbances (or error terms), Φ – k × k matrix, β – coefficients of the lags of X_t, and α - intercept, a constant

There are two types of Johansen cointegration tests in VECM, which are the trace test and the maximal eigenvalue test. In the Johansen cointegration test, the rank of the long-run impact matrix is equal to the number of co-integrating relationships. In this research, a maximal eigenvalue test is applied which undergoes two processes. (1) estimate the VECM model with and without trends, with and without, constant and with varying number, k, of co-integrating vectors (2) compare the models using likelihood ratio tests. The maximal eigenvalue test considers the null hypothesis that the co-integrating rank is k against the alternative hypothesis that the co-integrating rank is k+1 and follows a non-standard distribution.

2.5.3 Estimate VECM parameters

Estimation of the VECM using the Engel Granger Test (Engle and Granger, 1987) is carried out between the natural logarithm values of a variable against natural logarithm values of the other variables, followed by the Johansen cointegration test if the variables are cointegrated. VECM parameters are estimated using the following equation to find out the influence of the variables on iron ore price and vice versa:

$$\Delta Xt = \alpha\beta' * X(t-1) + \sum_{j=0}^{k-1} \Gamma j - X(t-j) + v + \delta t + et \ldots (2.8)$$

Where: α – coefficient matrix of the error correction term and the adjusted long run disequilibrium of the variables,

β – coefficient matrix of the co-integrating vectors, Γj – coefficient which estimate short-run shock effects on Δxt,
v – a constant term, δt – linear time trend term, and et – normally distributed error term

The coefficient $\prod$ which is $\alpha\beta'$ has rank r which can be written as the product:

$$\prod(nxn) = \alpha(n\,x\,r)\,\beta'(r\,x\,n) \ldots (2.9)$$

For a bivariate vector auto regression (1) model, equation is written as below:

$$\text{Xt} = \prod(1)X(t-1) + et \ldots (2.10)$$

Since Xt is cointegrated with one cointegrating vector rank ($\prod$) = 1 and can be decomposed to:

$$\Pi = \alpha\beta' = \begin{bmatrix}\alpha 1\\ \alpha 2\end{bmatrix}[1 \quad -\beta] = \begin{bmatrix}\alpha 1 & -\alpha 1\beta\\ \alpha 2 & -\alpha 2\beta\end{bmatrix} \ldots (2.11)$$

VECM equations to show change in X(1t) and X(2t) written:

$$\Delta X(1t) = \alpha 1\,[X(1t-1) - \beta \text{X}(2\text{t}-1)] + e(1t) \ldots (2.12)$$

$$\Delta X(2t) = \alpha 2\,[X(1t-1) - \beta \text{X}(2\text{t}-1)] + e(2t) \ldots (2.13)$$

The VECM parameters are estimated, the estimates which are of interest are the β normalising cointegrating vector and α which is the speed of adjustment.

2.5.4 Granger causality test

Granger (1969) suggested a bivariate model for testing causality relationships in econometrics where a variable Xt is said to be Granger-causal variable for another time series variable Yt, if Xt helps to predict Yt.

$$\Delta Xt = \alpha 10 + \sum_{k=1}^{p} \alpha 1 * kX(t-k) + \sum_{k=1}^{p} \alpha 2 * kY(t-k) + e1t \ldots (2.14)$$

$$\Delta Yt = \beta 10 + \sum_{k=1}^{p} \beta 1 * kX(t-k) + \sum_{k=1}^{p} \beta 2 * kY(t-k) + e2t \ldots (2.15)$$

2.6 Proposed research method – iron ore price prediction

2.6.1 Different types of Artificial Neural Network (ANN) and its concept

Although there are other conventional prediction methods, it is understood that the Artificial Neural Network has been recognized as a powerful machine learning tool that is able to comprehend complex non-linear approximations (Jang and Topal, 2013). The ANN method is used in this research.

The ANN is a parallel computational inference model whose functionality is a simple imitation of a biological neuron. Shown in figure 2.1, the structure of the ANN system for the prediction of iron ore consists of three layers: input, hidden, and output, with each layer consisting of several artificial neurons, a simple mathematical element which is referred to as a neuron. The dependent variable dataset is the output, the independent variable dataset(s) is the input, and each variable dataset makes up a node. The optimum number of hidden layers of neurons can be determined for each model by an iterative loop algorithm, and this is achieved through MATLAB coding, as the number varies even within the same dataset(s), and it is difficult to estimate the number of hidden layers.

The neurons are interconnected to neighbouring layers and their intensity of connection is represented by weight. The ANN consists of three processes: training, validation, and testing. During training, the optimised weights of all connections may be achieved via the forward and backward process which involves calculations. The forward process involves computation of a predicted output then comparing it against a target value to calculate the error for the iteration, which then updates all prior connection weights from the error. The ANN optimization is done by minimizing the error of the optimum weight values of the model.

In comparison, human brains have more than 10 billion neurons and 6 trillion synapse combinations, and it is a far more advanced processor than a digitalised computer. Neurons carry out biochemical reactions to transmit information via synapses, and the complex neural network provides the capacity to process diverse information. In addition, the brain system can learn. The ANN is, therefore, a mathematical algorithmic model of the biological nervous system of the human brain. Just like a brain, neurons receive signals from other neurons, intensified and weakened by activation functions, and the connection weights activate the input signals just like synapsis does in the human brain.

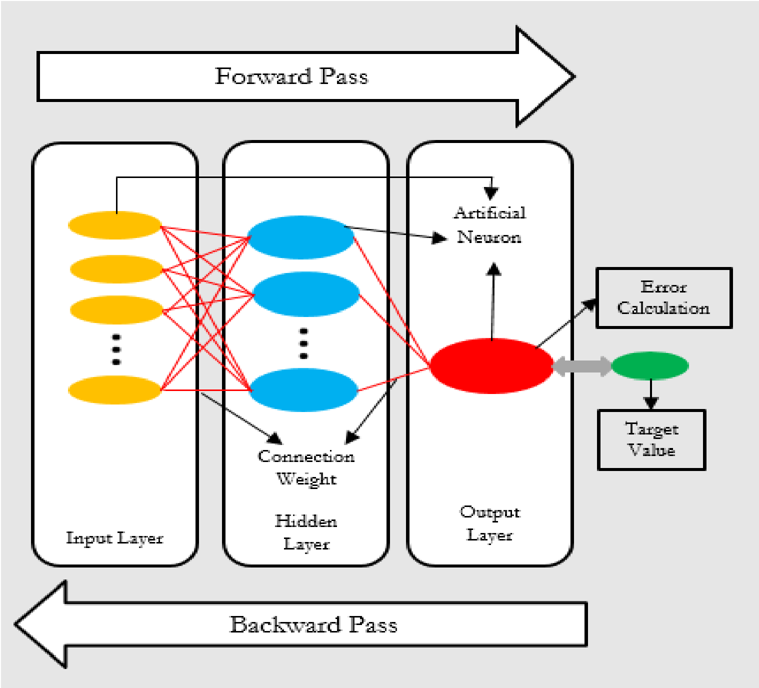


Figure 2.1: Typical flow diagram of feed-forward ANN

McCulloch and Pitts (1943) suggested a first ANN model where each neuron was assumed to be in a binary state. Rosenblatt (1958) presented the concept of a perceptron, which is a neural network unit that processes to detect features in multiple input data points. The limitation of perceptron is that it cannot solve any nonlinear problems, which were overcome by the back-propagation algorithm in the multilayer feed-forward ANN (Bryson and Ho, 1969). The steepest descent algorithm is frequently used to adjust the weights in a basic back-propagation ANN, which searches for the global minima in the error space that directs the negative of the error gradient. The steepest descent algorithm can adjust the weights in back-propagation ANN and is a stable algorithm, but due to its slow convergence, it is less ideal. To overcome the issue of slow convergence of the steepest decent algorithm, the Gauss-Newton algorithm (Osborne, 1992) is suggested, which proved to perform more rapid convergence, but due to its instability issue, it has shown its limitations (Yu and Wilamowski, 2011). Levenberg (1944) and Marquardt (1963) suggested a Levenberg-Marquardt (LM) algorithm that consists of elements from both the steepest descent and Gauss-Newton algorithms. The LM is activated with the steepest decent algorithm, which is then converted into the Gauss-Newton algorithm when the error function curvature becomes quadratic. The conjugate gradient algorithm (CGA) was adopted as an alternative to the LM (Hestenes and Stiefel, 1952). The CGA yields more rapid convergence than that of the steepest descent algorithm (Møller, 1993). Table 2.3 below shows the convergence performance as well as weight update rules for Steep Descent, Gauss-Newton, Levenberg-Marquardt, and Conjugate Gradient.

Table 2.3: Weight Update rules for representative ANN learning algorithms – Yu and Wilamowski (2011)

Algorithm	**Weight update rules**	**Convergence**
Steep Descent	$w^{p+1} = w^p - \alpha g^p$	Stable and Slow
Gauss-Newton	$w^{p+1} = w^p - (J^{p,T} J^p)^{-1} J^p e^p$	Unstable and Fast
Levenberg-Marquardt	$w^{p+1} = w^p - (J^{p,T} J^p + \mu I)^{-1} J^p e^p$	Stable and Fast
Conjugate Gradient	$w^{p+1} = -g w^{p+1} + \beta^{p+1} e^p$	Stable and Fast

Where w^{p+1} = updated weight for p+1, α = learning rate, $g\ (error\ gradient) = \partial E(x,w)/\partial w)$, J^p = Jacobian matrix for the p step, μ = combination coefficient, β^{p+1} = conjugate gradient constant

The Levenberg-Marquardt estimation algorithm (Marquardt, 1963) was used to generate ANN models for iron ore price estimation as it significantly outperforms CGA as well as steep descent for financial time series prediction (Mammadli, 2017). When the multiple regression methods MLR and MNLR are insufficient to reveal the relationship between the iron ore price and the econometric variables, ANN is often applied to a complex non-linear approximation. ANN has been recognized as a powerful machine learning tool in non-linear approximation for complex relationships between numerous variables (Jang and Topal, 2013). ANN is often used as a tool for finding patterns that are far too complex or numerous for humans to extract and interpret and is inspired by the biological nervous system of the human brain. Figure 2.1 shows (1) different layers, which consist of artificial neurons in the input, hidden, and output layers (which replicate the function of human brains), (2) neurons receiving signals from other neurons that are intensified and weakened by activation functions, and (3) connection weight to modulate the input signals like synapsis in the human brain. Learning ability can be activated or deactivated by adjusting the weights with the learning algorithm.

Chapter 3 – Methodology

Presented in Chapter 3 is the research method and data collection procedures used in this research. The chapter is divided into two sections, section 3.1, which details the research method for commodity price relationship definition, and section 3.2, where the research method for iron ore price prediction is outlined. It is confirmed that there are no ethical considerations in the research.

3.1 Research method – commodity price relationship definition

3.1.1 Sources of data - commodity prices and index

The research focuses on analysing monthly iron ore prices from 1990 to 2020, including the periods before and after the transition to shorter-term pricing. The study aims to test the cointegration of input variables with iron ore price, specifically CPI (metals), gold, oil, silver, LNG, aluminium, copper, tin, lead, nickel, zinc, and Australian coal. Data on monthly iron ore prices, as well as other metals and energy prices and indices, were collected from Indexmundi (Indexmundi, n.d.). MATLAB software was utilized for all econometrical and statistical tests. The reason why twelve commodity prices are selected is because they cover the diverse portfolio of different mining companies. LNG, oil and coal price is studied against iron ore prices as these are fuel to run the industry and civilization. Other minerals such as aluminium, copper, nickel, zinc, tin and lead are also studied as they all serve similar purpose to steel which is the end use of iron ore. All the minerals above are the essential use in our civilization especially in different industries, infrastructure, manufacturing as well as construction. economic climate as well as market risk profile. The reason why gold and silver are studied is because gold and silver price are the key indicator for economic climate as well as market risk profile.

3.1.2 Necessity of unit root test – Augmented Dickey Fuller (ADF) Test

Economists often use unit root tests to determine whether the time series data of major economic indices are stationary or not. The Dickey-Fuller test (Dickey and Fuller, 1979) was performed in this study using Microsoft Excel Data Analysis Tool software to determine whether the time series variables contain a unit root or not, to investigate the relationship between iron ore prices and all other variables using investigating Johansen cointegration Test later in this research. This is because the cointegration test is applicable when the variables contain unit-roots. Unit root is a stochastic trend in a time series, sometimes called a “random walk with drift”. If a time series has a unit root, it shows a systematic pattern that is unpredictable. Testing the stationarity of a time series is performed on the AR model, which is a stochastic process model to capture interdependencies among multiple time series variables and is written as:

$$X(t) = \Phi X(t-1) + \cdots + \Phi X(t-p) + \varepsilon t \ldots \ (3.1)$$

Where: X(t) – time series variable (iron ore price history and other variables), D(t) – deterministic component (or signal) that can be modelled through the modelling techniques, Z(t) – stochastic component (a random probability distribution or pattern that may be analysed statistically but may not be predicted precisely), δ – stationary error, ϵt – stochastic disturbances (or error terms) and Φ – k × k matrix

Each component will have its own outcome value and the null hypothesis is that there is a unit root (δ = 0). If a unit root exists, and it would be non-stationary, and if no unit root exists, it would be stationary. There are three test models randomly tested as part of the ADF test in this research: AR, ARD, and TS. The null test models are tested against the alternative models.

The null hypothesis of the ADF test is 'The variable contains a unit root and is hence non-stationary' and the outcome is interpreted as that if $p > 0.05$, the null hypothesis cannot be rejected, contains a unit root and is non-stationary and if $p < 0.05$, a null hypothesis is rejected, does not contain unit root and is stationary.

3.1.3 Johansen cointegration Test

Cointegration tests are necessary to investigate the relationship between iron ore prices and various input variables, whether it is in the short term (ST) or long term (LT). The concept of cointegration and its connection to the error correction model were initially introduced by Granger (Granger, 1981). Granger and Weiss (1983) further developed this concept, outlining the fundamental principles of cointegration. By conducting cointegration tests, we can estimate the long-term relationships between co-integrated variables from the time series data. These tests are particularly useful when the variables exhibit unit roots. Among the various tests available for testing cointegration in multivariate time series variables X(t), the Johansen test is widely used. Introduced by Johansen (1991), this test allows for multiple co-integrating relationships, making it more applicable than the Engle-Granger test, which is based on the ADF test for unit roots from a single estimated co-integrating relationship. In the case of iron ore prices and econometric variables, the Johansen test is employed to examine their co-integrating relationship. The trace test is then conducted to evaluate the null hypothesis H(r) of cointegration rank (r) being less than or equal to n (dimensions of the data) against the alternative hypothesis H(n). An example illustrating the interpretation of the Johansen cointegration result can be found in Table 3.1.

Table 3.1: Example of Interpretation of Johansen cointegration result

Cointegration rank (*r*) tested	**h-value**	**Number of cointegrations**
0 and 1	If h=0 for r=0 and h=0 for r=1	0
	If h=1 for r=0 and h=0 for r=1	Between 0-1
	If h=0 for r=0 and h=1 for r=1	1
	If h=1 for r=0 and h=1 for r=1	1

It is also important to determine a reasonable lag when VECM is tested for cointegration. This process is automated in MATLAB software (MATLAB Mathworks, n.d.a) to limit the valid lags that are applied.

3.1.3.1 Johansen cointegration Test in bivariate model

The time series bivariate model of cointegration test allows interpretation and definition of the relationship between the two variables when the variables are not stationary. In a bivariate model, cointegration for the variables y(t) and x(t), the two variables are co-integrated or are individually stochastic and have a long-run equilibrium relationship. The purpose of bivariate modelling is to define the detailed co-integrating relation between respective variables and iron ore.

3.1.3.2 Johansen cointegration Test in multivariate model

To test for cointegration in multivariate time series, Johansen trace test can be used. The test was derived by Johansen (1991) and tests the null hypothesis at most r cointegration relationships against the alternative that there are more than r cointegration relationships in multivariate time series variables. The purpose of multivariate modelling is to investigate the general trend of the distribution of the test statistic on number of cointegrations against iron ore price, which will be able to observe the change in overall commodity market pricing system.

3.1.4 Estimate VECM parameters for bivariate modelling using Engel Granger test

The estimation is simply done using MATLAB (MATLAB Mathworks, n.d.b). VECM parameters are estimated using the following equation to find out the influence of the variables on iron ore price and vice versa:

$$\Delta Xt = \alpha\beta' * X(t-1) + \sum_{j=0}^{k-1} \Gamma j - X(t-j) + v + \delta t + et \ldots (3.2)$$

Where: α – coefficient matrix of the error correction term and the adjusted long run disequilibrium of the variables,

β – coefficient matrix of the co-integrating vectors, Γj – coefficient which estimate short-run shock effects on Δxt,

v – a constant term, δt – linear time trend term, and et – normally distributed error term

VECM equations to show change in X(1t) and X(2t) written:

$$\Delta X(1t) = \alpha 1\ [X(1t-1) - \beta \mathrm{X}(2\mathrm{t}-1)] + e(1t) \ldots (3.3)$$

$$\Delta X(2t) = \alpha 2\ [X(1t-1) - \beta \mathrm{X}(2\mathrm{t}-1)] + e(2t) \ldots (3.4)$$

From Equations 3.3 and 3.4, the VECM parameters are estimated. The estimates which are of interest are the β normalising cointegrating vector and α which is the speed of adjustment.

3.1.5 Granger causality test

To test the Granger causality, it is required to estimate the following 2×2 unrestricted VAR models for iron ore prices and other commodity prices at different levels.

$$\Delta Xt = \alpha 10 + \sum_{k=1}^{p} \alpha 1 * kX(t-k) + \sum_{k=1}^{p} \alpha 2 * kY(t-k) + e1t \ldots (3.5)$$

$$\Delta Yt = \beta 10 + \sum_{k=1}^{p} \beta 1 * kX(t-k) + \sum_{k=1}^{p} \beta 2 * kY(t-k) + e2t \ldots (3.6)$$

Where Xt represents iron ore prices and Yt represents twelve other commodity prices, e1t and e2t are stochastic disturbances i.e. errors terms.

3.2 Research method – iron ore price prediction

3.2.1 Sources of data - commodity price and index

The monthly iron ore prices over the period from 1990 to 2020 are considered, which include the pre and post-transition periods when the iron ore pricing system was changed to spot market trade in 2006 (Caputo et al., 2013). Twelve different monthly commodity prices and indices, namely LNG, aluminium, nickel, silver, Australian coal, zinc, gold, oil, tin, copper, lead and CPI (metals) are collected from Indexmundi and used to predict iron ore prices (Indexmundi, n.d.). In this research, different commodity prices are presented in abbreviations, especially in the equations represented in the linear and non-linear regression. Table 3.2 below shows the abbreviation for respective commodities studied in the research, especially in equations of linear and non-linear regression.

Table 3.2: Abbreviation for respective commodities studied

Commodity	**Abbreviation**
Gold	GO
Oil	OL
Silver	SV
LNG	LN
Aluminium	AL
Copper	CO
CPI (metals)	CP
Tin	TI
Australian Coal	AC
Nickel	NI
Zinc	ZI
Lead	LE
Iron ore	IO

3.2.2 Bivariate Non-Linear Regression (BNLR)

To understand how each commodity price behaves against the iron ore price, the simplest regression, Bivariate Non-Linear Regression (BNLR), is applied, which is simply tabulating the respective commodity price against the iron ore price and fitting it to available curves. Options include polynomial, logarithmic, power, exponential and linear. The fitted relationship in the graph follows the data and produces a R^2 value. The optimized model is the model with the highest R^2 value.

3.2.3 Multiple Linear Regression (MLR)

As it is determined that BNLR is not a reliable model to forecast the future iron ore price, the next simplest method is to determine iron ore price behaviour against twelve other commodity prices by MLR to test if it performs better than BNLR. The MLR model has been built for each dataset with all twelve independent variables.

3.2.4 Multiple Non-Linear Regression (MNLR)

Compared with BNLR, MLR has made progress with better accuracy. Another method of MNLR is to be applied to determine whether MNLR can outperform BNLR or MLR. MNLR can be used to model a relatively more accurate model for iron ore price prediction. Consider the equation below:

$$Y = \beta o\left(X1^{\beta 1}\right)\left(X2^{\beta 2}\right) \ldots \left(Xn^{\beta n}\right) \ldots (3.7)$$

Where: Y - Predicted value and β_0 to βn – Dependent variables

The equation 3.7 can go through conversion process to transfer into a linear domain through log transformation (Cankaya, 2009) which is expressed as below:

$$\log(Y) = \log(\beta o) + \beta 1 \log(X1) + \beta 2 \log(X2) + \cdots + \beta n \log(Xn) \ldots (3.8)$$

The application also goes through a similar process where a general model (GM) is developed to into an optimum model for the overall interval where equations for each interval will be developed respectively (to be confirmed how long each interval will be).

3.2.5 Artificial Neural Network (ANN)

Understanding that ANN has been recognized as a powerful machine learning tool that is able to comprehend complex non-linear approximations (Jang and Topal, 2013), the ANN method is exercised in this research. McCulloch and Pitts (1943) suggested a first ANN model where each neuron was assumed to be in a binary state. It is important to define dependent and independent commodity prices. The structure of the ANN system for the prediction of iron ore consists of three layers: input, hidden, and output. The dependent variable dataset is the output, the independent variable dataset(s) is the input, and each variable dataset makes up a node. The optimum number of hidden layers of neurons can be determined for each model by an iterative loop algorithm, and this is achieved through MATLAB coding, as the number varies even within the same dataset(s), and it is difficult to estimate the number of hidden layers.

3.2.5.1 Types of Transfer Functions

As the Levenberg-Marquardt estimation algorithm has been applied, there are three types of transfer functions for Levenberg-Marquardt: linear, sigmoid, and hyperbolic tangent. Activation function can improve ANN performance in following ways:

1) Enhance learning ability by introducing linearity, non-linearity and complexity. As a result, accuracy and stability is improved by controlling the output range,

2) Activation functions accelerate the training and inference of ANN by simplification of the computation,

3) Adaptation of the output of ANN to the data, producing more meaningful outcome.

The transfer functions are the key to how neural networks learn complex problems and can discover the solution(s) for supervised machine learning. A linear transfer function is ideal for predicting data showing a linear pattern, whereas hyperbolic tangent and sigmoid functions are used for a non-linear approach. Sigmoid functions transfer an input from zero to one and a hyperbolic tangent from -1 to 1.

The general pattern of each transfer function is illustrated in the graphs below.

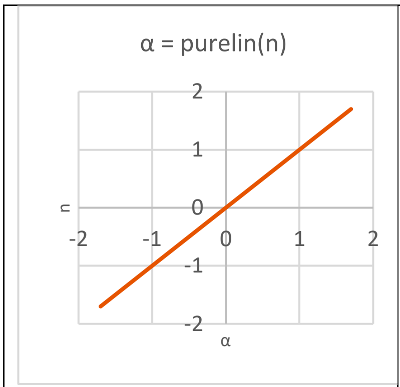
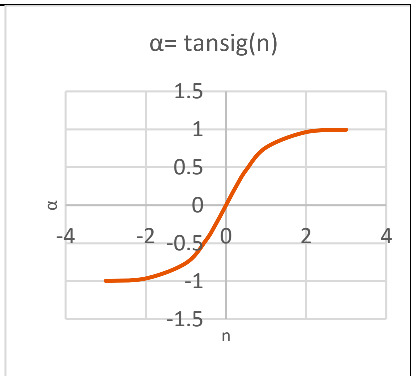
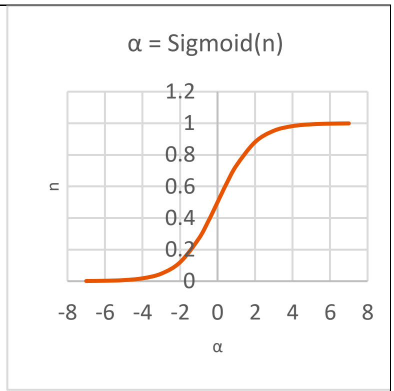
		

Figure 2.2: Linear $[n = \alpha]$ ... (3.9)	Figure 2.3: Hyperbolic Tangent $\left[n = \frac{e^{\alpha} - e^{-\alpha}}{e^{\alpha} + e^{-\alpha}}\right]$ ... (3.10)	Figure 2.4: Sigmoid $\left[n = \frac{1}{1 + e^{-\alpha}}\right]$ ... (3.11)

Three transfer functions of Levenberg-Marquardt estimation will be applied to predict iron ore price in this research to determine which transfer function is optimum for estimation.

3.2.5.2 Iron ore price prediction using Levenberg-Marquardt

Levenberg-Marquardt prediction method for iron ore has been made to replicate the forecast for a ten-month period using 30-year data until June 2020, forecasting one month ahead. The Levenberg-Marquardt prediction method has been applied to forecast for two to six months ahead with all types of Levenberg-Marquardt method; Linear, Sigmoid and Hyperbolic Tangent. The three types of transfer functions are exercised to determine which transfer function can exercise the most accurate iron ore prediction and is also compared against BNLR, MLR and MNLR.

Chapter 4 – Relationship of iron ore price with other major commodity prices

Presented in Chapter 4 is a journal article submitted, peer-reviewed and published in the *Mineral Economics* journal in 2022. Detail of the published journal article is available per below:

Kim, Y., Ghosh, A., Topal, E. and Chang, P. (2022) Relationship of iron ore price with other major commodity prices, Mineral Economics, Vol 35, pp 295–307, https://doi.org/10.1007/s13563-022-00301-x.

The contribution of the paper is indicated in appendix D.

The content of this chapter was adopted from the published paper with few minor changes. Chapter 2 was able to determine the overall relationship between twelve different commodities, both via bivariate and multivariate modelling. Unit root test, followed by Granger causality, Johansen cointegration and VECM estimation method has been used to define its relationships. It is interesting to determine that there is bi-directional causality exist between iron ore prices and copper, oil and coal prices based on results from the Granger causality test. VECM estimation proved that oil, copper and Australian coal prices have influence on and from iron ore prices. Multivariate modelling cointegration test found six out of twelve commodity prices cointegrate each other in one month lag and continues in cyclic pattern till 27 months after which it disappears.

Abstract

It is crucial to comprehend the interconnectedness of the commodity market pricing system to effectively manage a profitable mining enterprise. A significant portion of the iron ore pricing is influenced by the pricing of various other commodities. This research delves into the correlation between monthly iron ore prices and twelve other monthly commodity prices or indices, such as LNG, aluminium, nickel, silver, Australian coal, zinc, gold, oil, tin, copper, lead, and CPI (metals), from both a bivariate and multivariate standpoint.

The ADF test is performed to confirm that all-time series commodity prices and indices are non-stationary. In a multivariate modelling cointegration test, the presence of cointegrations out of twelve is observed for each lag between zero and 45 months. It is noted that six out of twelve commodity prices exhibit cointegrations at a one-month lag, following a cyclic pattern until 27 months, after which it disappears. Three commodities consistently cointegrate with changes in iron ore prices at all lags.

VECM estimation is conducted for bivariate modelling in order to establish the existence of short-term responses to a long-term relationship between iron ore prices. The analysis reveals that oil, copper, and Australian coal prices exert an influence on iron ore prices. Subsequently, the Granger causality test is employed to validate the VECM findings by examining bidirectional causality between iron ore prices and copper, oil, and coal prices. The results indicate that there is a bidirectional influence between iron ore prices and oil, copper, and Australian coal prices.

4.1 Introduction

Mining is a capital-intensive industry that requires hundreds of million-dollar investment in major equipment (Fu et al., 2014), as well as continuous operational and capital expenditure. Investments in the mining and minerals industry are regarded as risky (Topal., 2008). Each mining project is highly sensitive to commodity prices and there has been some turbulence in commodity prices in recent years.

Iron ore is a highly important mineral for human civilization as it is used to produce steel. The vast majority of world production (56%) and export (74%) is heavily reliant on Australia and Brazil, and China is the single largest importer with 66% of world iron ore imports, meaning diversity of seller and buyer is limited (Observatory of Economic Complexity – Iron Ore, 2021). With the declining relationship between Australia and China over the past few years, the importance of iron ore has emerged as a key commodity surrounding tensions between both countries, because the Australian economy is heavily dependent on iron ore exports and Chinese heavy industry is equally reliant on low-cost Australian supplies (Wilson, 2017).

Historically, iron ore was traded on long-term basis contracts. However, since 2006, there has been a change to the annual negotiation system between large producers and large consumers and, subsequently, spot market trades based on prices set by independent benchmarking companies, which consequently have seen rapid fluctuation of iron ore prices (Caputo et al., 2013). Iron ore prices have fluctuated between US$40 to almost US$190/tonne in the past two decades (Indexmundi, n.d.). The forecast of iron ore price trends is vital for its producers and investors to be able to prepare dramatic price changes in both the short and long terms. The fall of iron ore in the price results in decreasing UPL as well as NPV of open pit mines, which in turn heavily affects the operational income of iron ore mines. Hence, it is essential to evaluate the potential causes of the change in iron ore price so that it can eventually be captured in tools to forecast short term (ST) and long term (LT) iron ore prices for managing the targeted production. In order to forecast the iron ore price, the first step is to understand and analyse the possible relationship of iron ore price with other potential variables.

Several studies have been done to understand the relationship between iron ore prices and other economic indices as well as other commodity prices. Pustov et al. (2013) modelled long-term iron ore price using marginal costs (future lows) and marginal incentive price (future highs) and forecasted $85/tonne and $124/tonne respectively, considering depletion of existing iron ore deposits and targeted return on investments for new projects. Haque et al. (2015a) determined that when the iron ore price increases, Australian dollars also increase, but no influence occurs the other way around. Warell (2018) found out that the iron ore price, GDP growth in China and freight rates were cointegrated in the long run. A structural break test was used to conclude that the change in pricing regime did not have a significant impact on the iron ore price when extending the time period; however, the most important factor for iron ore prices up to 2012 was GDP growth in China. (Ma and Wang, 2019) expanded the finding that oil, gas, coal and iron ore prices are all associated with an increase in the appreciation of the Australian dollars and a decline in the Chinese RMB.

Big mining companies often produce different commodities portfolios and yet no study has been explored on the interactions of different commodity prices. It will be beneficial for mining companies and investors to find out the relationship between different commodity prices so that a change in iron ore price can be predicted not only for maximizing profit and also for risk mitigation purposes.

In this research, twelve prices for LNG, aluminium, nickel, silver, Australian coal, zinc, gold, oil, tin, copper, lead and CPI (metals) have been studied against iron ore prices. Twelve commodity prices are readily available and cover the diverse portfolio of different mining companies. LNG, oil and coal prices are studied against iron ore prices as these are fuel to run the industry and civilization. Other minerals such as aluminium, copper, nickel, zinc, tin and lead are also studied as they all serve a similar purpose to steel, which is the end use of iron ore. All the minerals above are essential uses in our civilization, especially in different industries, infrastructure, manufacturing, as well as construction, the economic climate as well as, the market risk profile. The reason why gold and silver are studied is that gold and silver prices are the key indicator of the economic climate as well as the market risk profile.

The objectives of this chapter are to (1) find out the bivariate and multivariate co-integrating relationship of monthly iron ore prices with twelve other monthly commodity prices or indices by employing the Johansen cointegration test, (2) reveal the short-run responses to long-term relationships between iron ore prices and twelve different commodity prices over the period from 1990 to 2020 through VECM and Granger causality test.

4.2 Research results

4.2.1 Augmented Dickey Fuller (ADF) test results

The ADF outcome shows that the iron ore, gold, oil, silver, copper, CPI (metals), Australian coal and tin, LNG, aluminium, lead, nickel and zinc all contain unit root at all lags between zero and six months, in all models and at all test statistics and hence the time series variables are non-stationary.

From the ADF test results as shown in Table 4.1, it can be concluded that the null hypothesis (unit root exists) has been accepted (or cannot be rejected) at 5% significance (or with 95% confidence interval) for all the time series variables (iron ore, gold, oil, silver, copper, CPI (metals), Australian coal and tin, LNG, aluminium, lead, nickel and zinc). This means that all the time series variables have unit roots and are non-stationary. Therefore, an assumption is made throughout this research that iron ore, gold, oil, silver, copper, CPI (metals), tin, LNG, aluminium, lead, nickel, and zinc price data contain unit root, is non-stationary and can apply the Johansen cointegration Test.

Table 4.1: p-value of ADF test for unit roots (at 5% significance)

Lags (months)	**0**	**1**	**2**	**3**	**4**	**5**	**6**
Iron ore	0.43	0.26	0.30	0.28	0.28	0.27	0.25
Gold	0.99	0.98	0.98	0.98	0.98	0.96	0.95
Oil	0.38	0.21	0.20	0.25	0.26	0.28	0.33
Silver	0.51	0.42	0.49	0.49	0.43	0.41	0.45
LNG	0.13	0.12	0.14	0.13	0.13	0.18	0.16
Aluminium	0.46	0.40	0.40	0.34	0.27	0.33	0.42
Copper	0.54	0.42	0.42	0.43	0.44	0.44	0.49
CPI (metals)	0.56	0.45	0.44	0.43	0.39	0.39	0.44
Tin	0.58	0.49	0.43	0.45	0.46	0.50	0.49
Lead	0.50	0.39	0.45	0.42	0.40	0.38	0.37

Nickel	0.34	0.17	0.19	0.25	0.23	0.20	0.20
Zinc	0.42	0.33	0.38	0.39	0.37	0.37	0.32

The reason why a non-stationary time series variable is required as a condition of 'Johansen cointegration' is because Johansen cointegration assumes that the combination of co-integrated variables (or transformed state) produces the stationary system. Consequently, the variables may have a long-term relationship. In other words, the process involves transformation from non-stationary to stationary.

4.2.2 Johansen cointegration test results

4.2.2.1 Johansen cointegration test in bivariate model for twelve different commodity prices and index vs iron ore prices (monthly)

This test finds out whether cointegration exists between CPI (metals) against iron ore price. h=0 means there is no co-integrating relationship exists and h=1 shows there is a cointegrating relationship exists between each commodity price and the index against iron ore prices. The results are interpreted in accordance with section 3.2 and Appendix A shows the number of cointegrations (from zero to one) for different commodities and the index for each lag is from zero to 45 different lags against iron ore.

The test rejects a null hypothesis for cointegration if h=1 and fails to reject a null hypothesis for cointegration if h=0. According to the results in Table 4.2, it shows that the null hypothesis has been rejected for cointegration against iron ore price for 5% significance between lag 0-45 in the following orders: LNG – aluminium – nickel – Australian coal – zinc – CPI (metals) – oil – silver – tin – copper – lead – gold. Overall, cointegration is greatest between a lag of one to ten months, then gradually decreases until a lag of twenty months and increases again at a lag of 32 months, then maintains its level until 45 months.

Table 4.2: Number of cointegration options between commodity prices against iron ore prices

Commodity Prices	Number of cointegrations	Between zero and one cointegrations	One cointegration
Aluminium	0	1	45
Copper	32	14	0
CPI (metals)	27	13	6
Gold	42	4	0
Lead	39	7	0

LNG	2	3	41
Nickel	13	11	22
Oil	31	10	5
Silver	20	22	4
Tin	26	20	0
Zinc	32	5	9
Australian Coal	26	9	11

The findings from bivariate analysis using Johansen cointegration are:

- Aluminium and LNG – cointegration exist at almost all lags,
- Copper – cointegration exists until a lag of ten to fourteen months,
- Silver, tin, zinc, and Australian coal – cointegration exist up to ten months of lag, a tendency of no cointegration exists between ten and twenty months, then cointegration exists again at 25–30 months lag until 40 months lag,
- Oil and CPI (metals) – cointegration only exists from lag zero to ten months, then diminish after ten months, and
- Lead, gold – almost no cointegrations exist.

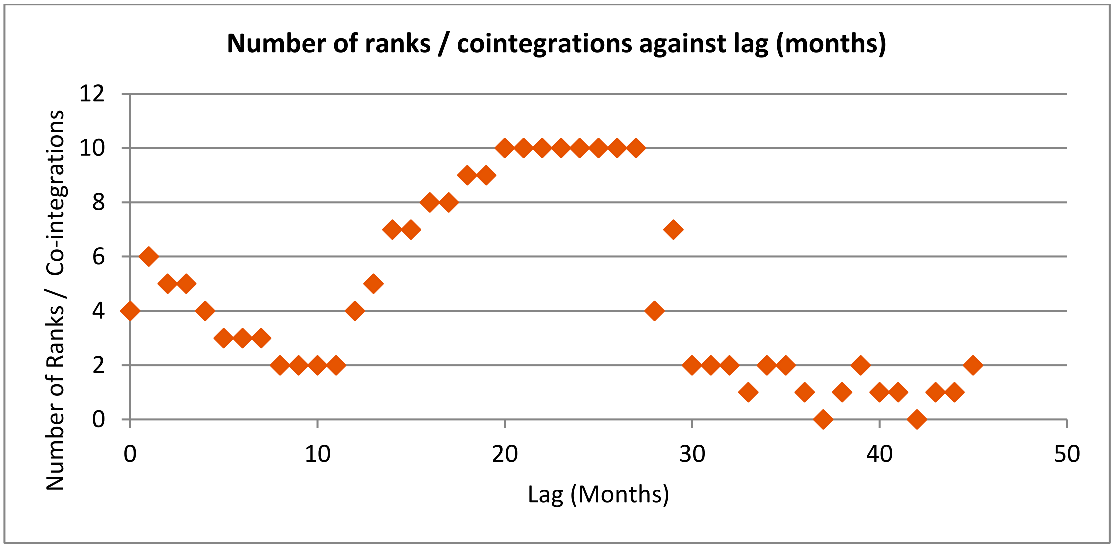
A detailed relationship between iron ore and twelve commodity prices / index can be determined by VECM bivariate modelling in section 3.3.

4.2.2.2 Johansen cointegration test in multivariate model amongst twelve different commodity prices and index as well as iron ore prices (monthly)

Johansen cointegration in a multivariate model was tested for cointegration amongst twelve monthly commodity prices and indices as well as iron ore prices to observe how many cointegrations exist. Different lags were tested to visualize the trend in the number of cointegrations in each lag and to observe the overall relationship between commodity prices and the index against iron ore prices. Since there are 13 different commodity prices (n), there are twelve possible ranks (r). The number of rank (r) words, in other words, is the number of cointegrations.

The rank of the VAR model starts with four at lag zero, meaning that there are four relationships amongst twelve different commodity prices and an index as well as iron ore prices (ie four relationships within thirteen different commodity prices). The rank changes to six at one month, gradually decreases to two ranks until eight months lag, maintains two until eleven months lag, gradually increases to ten until twenty months, maintains ten until 27 months, then gradually decreases between one and two ranks until 45 months. The trend and results are shown in figure 4.1.

Figure 4.1: Number of cointegrations (N) against number of lag months (L) for multivariate model cointegration amongst twelve monthly commodity prices



From figure 4.1, the cyclic effect is exhibited, which enabled wider understanding of the commodity pricing system where:

- There are three commodities which continuously cointegrates with iron ore prices at all lags till 27 months,
- It takes between 20–27 months for at least ten commodities to show similar trends when change (increase or decrease) has been applied to iron ore prices and twelve other commodity prices and indices, and
- The change in the commodity pricing system today diminishes after 30 months.

The trend-line can be drawn from figure 4.1, which shows a strong resemblance to a sine curve and the approximate equation of the curve is shown below:

$$Number\ of\ Co-integrations\ (N) = 8\sin\left[\frac{\pi}{15}(L-10)\right] + 2\ \ [Where\ Range\ 0 \le L \le 45] \ldots (4.1)$$

Where: N is number of cointegrations, and L is number of lag months

4.2.3 Estimate VECM parameters for bivariate modelling using Engel Granger test results

Johansen cointegration using bivariate modelling can be further assessed using VECM using the Engel Granger test to determine the relationship between different commodity prices against iron ore prices. To determine whether VECM is a statistically significant and stable long-term relationship, we need $\alpha 1 < 0$ or $=0$, $\alpha 2 > 0$ or $=0$ and at least one of them cannot be equal 0. The outcome of VECM parameters is largely α – long-term disequilibrium matrix and β – normalising co-integrating vector. The α and β is the 1 x 2 matrix and its interpretation is carried out as: $\alpha = (\alpha 1, \alpha 2)$ and $\beta = (1, -\beta 1)$

Where:

α1 - adjustment coefficient, which indicates how quickly the system comes to equilibrium, must be negative for VECM to be statistically significant,

α2 - adjustment coefficient, which indicates how quickly the system comes to equilibrium, must be positive for VECM to be statistically significant - indicating a positive association,

β1 - normalising the beta value, which is % appreciated per iron ore prices per 1% increase in commodity prices

The VECM of iron ore prices to all other commodity prices and index is defined statistically significantly with stable long-term relationships because all $\alpha 1 < 0$ and $\alpha 2 > 0$ which have been shown in appendix C. It also shows results including α1, α2, β1 and whether positive or negative association exist between iron ore prices and commodity prices.

From the VECM estimation, oil, Australian coal, and copper were the commodities with p-value < 0.05. This indicates that the null hypothesis is rejected. Hence, VECM coefficients are significant for oil, Australian coal, and copper. Long-run disequilibrium adjustment matrix was obtained for oil α (i.e., α1 and α2) = (-0.0360, 0.0374), Australian coal α (i.e., α1 and α2) = (-0.0133; 0.0479), and copper α (i.e., α1 and α2) = (-0.0653; 0.3122) with p-values for α1 and α2 are (0.0305; 0.0093), (0.0350; 0.0232), and (0.0411, 0.0287) respectively. High p-values (> 0.05) for other commodities, gold, silver, LNG, aluminium, CPI (metals), tin, lead, nickel, and zinc indicate that VECM coefficients are insignificant, and that null hypothesis cannot be rejected.

The normalizing cointegrating vector β1 = -1.3415 shows that a 1% increase in the oil price leads to an appreciation of iron ore price by approximately 1.34 %, 1 % increase in the Australian coal price leads to, the appreciation of its iron ore price by approximately 1.29%, and finally 1% increase in the copper price leads to an appreciation of iron ore price by approximately 0.017% are significant and meaningful.

The speed of adjustment parameters for oil price is -0.036 (p-value 0.0305) meaning approximately 3.6% of oil price change per month can be attributed to the disequilibrium between actual and equilibrium levels and 0.0374 (p-value 0.0093) shows that the variability of iron ore price induces a positive change in the oil price. Same principle applies to coal price and copper, where approximately 1.33% of oil price and 6.53% of copper price per month can be attributed to the disequilibrium between actual and equilibrium levels and the variability of iron ore price induces a positive change in both the coal price and copper price.

The speed of adjustment parameters for oil price is -0.036 (p-value 0.0305), meaning approximately 3.6% of the oil price change per month can be attributed to the disequilibrium between actual and equilibrium levels and 0.0374 (p-value 0.0093) shows that the variability of iron ore price induces a positive change in the oil price. The same principle applies to coal and copper prices, where approximately 1.33% of the oil price and 6.53% of the copper price per month can be attributed to the disequilibrium between actual and equilibrium levels and the variability of iron ore price induces a positive change in both coal and copper prices.

4.2.4 Granger causality test results

The Granger causality test is carried out to test the bidirectional causality test performed between iron ore prices and copper, oil and coal prices and the results are tabulated in table 4.3 and 4.4. Results indicate that there was no causality found when no lag was applied; in other words, the null hypothesis for Granger causality is not rejected at a lag of zero months. However, from the lag of one month there is bidirectional causality between iron ore prices and copper and coal prices, meaning the null hypothesis for Granger's causality is rejected because of the lag of one month. Iron ore always showed Granger cause to oil when tested with lag from one month onwards. However, oil did not have Granger cause at a lag of one and two months and Granger cause occurred when tested from twelve months onwards.

Table 4.3: Granger causality test result – iron ore to copper, Australian coal and oil

	Iron ore -> copper			Iron ore -> Australian coal			Iron ore -> oil		
Lag	p-value	stat	c-value	p-value	stat	c-value	p-value	stat	c-value
0	1	0	~ 0	1	0	~ 0	1	0	~ 0
1	0.7161	0.1322	3.8415	~ 0	22.1702	3.8415	~ 0	13.848	3.8415
2	0.5052	1.3656	5.9915	~ 0	34.7015	5.9915	~ 0	16.6379	5.9915
12	0.0077	26.9925	21.0261	~ 0	71.1825	21.0261	~ 0	50.5978	21.0261
18	~ 0	46.1784	28.8693	~ 0	82.8847	28.8693	~ 0	66.8899	28.8693

Table 4.4: Granger causality test result – copper, Australian coal and oil to iron ore

	Copper -> iron ore			Australian coal -> iron ore			Oil -> iron ore		
Lag	p-value	stat	c-value	p-value	stat	c-value	p-value	stat	c-value
0	1	0	~ 0	1	0	~ 0	1	0	~ 0
1	~ 0	10.8205	3.8415	0.1753	1.8374	3.8415	0.9902	~ 0	3.8415
2	~ 0	25.5442	5.9915	~ 0	14.3388	5.9915	0.007	9.9194	5.9915
12	~ 0	50.7066	21.0261	~ 0	45.6003	21.0261	~ 0	33.7044	21.0261
18	~ 0	60.8218	28.8693	~ 0	45.6696	28.8693	~ 0	34.8793	28.8693

4.3 Discussions

The iron ore prices have changed vastly in the past 30 years as shown in Appendix C. In March 1990, the price of iron ore was only US$37.50 per tonne, and in December 2004, it was US$37.90 per tonne. However, between January 2005 and March 2008, the price had risen to US$197.12 per tonne. Then, until April 2009, the price had dramatically dropped to $59.78 per tonne, which was notably during the Global Financial Crisis (GFC) period. The price drop during GFC was followed by a prompt recovery to $187.18 in February 2011. After that, there were notable fluctuations in the price until December 2013; then a sharp decline from January 2014 until December 2015 to $40.50 per tonne. From January 2016 to April 2020, the iron ore price had fluctuated considerably, but had shown a tendency to increase overall.

According to granger causality and VECM analysis, there is a clear connection between oil, copper, and coal with the consumption of iron ore and steel production, as well as the production of other industrial metals. However, the exact reasons for the bidirectional Granger causality between these commodities remain uncertain. For instance, Australian thermal coal is highly used across the Asia Pacific region for power generation purposes even today. It is then used to produce steel and oil is used to consume steel manufactured products such as automobiles, ships, and aircraft. Until reliance on coal powered plants and fossil fuels is reduced at a significant level, this relationship will continue. There have been continuous efforts until that date to minimise the use of thermal coal and oil, and hence this relationship could potentially change in the foreseeable future. Copper is the second highest produced and used base metal after aluminium (LePan, 2020), which is widely used as a power cable. The relationship of power generation, energy production and consumption seem to play a part in the demand for copper. Although aluminium is the highest produced and used base metal, it does not have much relevance to iron ore price and does not have much relevance to power generation, energy production and consumption processes. This would hence lead to the relationship. If the iron ore price or Australian coal price or copper price increases, oil price will start to increase within one month. Vice versa also applies to Australian coal prices or copper prices.

4.4 Conclusions

This research has investigated the relationship between the iron ore price against twelve different monthly commodity prices and the index by application of the Johansen cointegration test in a bivariate model. Multivariate Johansen cointegration was utilized to determine the cointegrating relationship between twelve different monthly commodity prices and the index against iron ore prices. 30-year data (over the period 1990 – 2020) were utilized to investigate the effect with the lag months varying from zero to 45 months. Based on ADF test results, the conclusion is made that all the time series commodity prices and index have unit roots and are non-stationary, and hence the Johansen cointegration test can be applied.

The cointegrating relationship between iron ore prices and 12 different monthly commodity prices and index was confirmed by both the bivariate and multivariate Johansen cointegration tests at a 95% confidence interval, indicating a long-term relationship. The trend-line from a multivariate modelling displays a model of cointegrations resembles a sine curve that is shown in equation 4.1. The sine curve demonstrates that there are three commodities that consistently co-move with changes in the price of iron ore over a period of up to 27 months. This implies that when a change in commodity price(s) is observed, it will take a minimum of 20 months and a maximum of 27 months to observe the corresponding change in the entire commodity market.

VECM estimation has revealed in favor of short-run responses to a long-term relationship between iron ore prices and oil, Australian coal, and copper prices over the period 1990 – 2020. The normalizing vector $\beta 1$ represents that a 1% increase in oil, Australian coal, and copper prices leads to an appreciation of iron ore prices by approximately 1.34 %, 1.29% and 0.017% respectively. The speed of adjustment parameter $\alpha1$, which represents approximately 3.6% of oil price, 1.33% of oil price and 6.53% of copper price change per month, is attributed to the disequilibrium between actual and equilibrium levels. The positive adjustment coefficient $\alpha2$ indicates that the change in iron ore prices induces a positive change in oil, Australian coal price and copper price, which are 0.0374, 0.0479 and 0.3122 respectively.

The Granger causality test results indicate that there is no causality found at zero (no) lag; however, from the lag of one month onwards there is bidirectional causality between iron ore price and copper and coal prices. Oil price does not show Granger causing iron ore price until lag of twelve months, whereas iron ore price has Granger causing oil price from lag of one month onwards. Therefore, the Granger causality result aligns with the multivariate cointegration results which indicate that three commodities cointegrate with iron ore price at all lags, and it is found that these are oil, copper, and Australian coal.

According to the results, it has been revealed that it will be more accurate to consider prolonged periods of data for taking better-informed decisions to find the relationships and their consequent strength of association. This is due to the limitation of shorter periods, wherein data loss inhibits information variability and consequently compromises improved accuracy of results. Therefore, in the present study, approximately 30 years of data was considered. As a result, more accurate relationships have been established. The results and associated information are important for iron ore mining companies across the world when setting up their portfolio amongst different commodities, and for commodity investors. This is because maintaining an optimum ratio between different commodities is paramount to maximise NPV for its operations and to minimise any risk of NPV loss due to a commodity price downturn for mining companies and investors.

This research has given an insight into the relationship between the iron ore price against oil, copper and Australian coal price based on Granger causality and VECM results. Granger causality and VECM results indicate that oil, copper and coal are interlinked with consumption of iron ore, including steel production, as well as production of other industrial metals. In other words, it is closely linked with the energy lifecycle associated with iron ore to steel production. Thermal coal is used to generate power, copper is used for power cables, power is used at iron ore plants and steel mills produce steel using iron ore, oil is then used to operate steel manufactured products such as mechanical equipment, automotive, aerospace etc. Future research should involve economic analysis to determine the economic reason behind the bidirectional Granger causes between iron ore, coal, copper and oil.

Chapter 5 – Performance of different models in iron ore price prediction during the time of commodity price spike

Presented in Chapter 5 is a journal article submitted, peer-reviewed and published in the *Resources Policy* journal in 2023. Detail of the published journal article is available per below:

Kim, Y., Ghosh, A., Topal, E. and Chang, P. (2023) Performance of different models in iron ore price prediction during the time of commodity price spike, Resources Policy, Vol 80: p. 103237, https://doi.org/10.1016/j.resourpol.2022.103237

The contribution of the paper is indicated in appendix D.

The content of this chapter was adopted from the published paper with a few minor changes. Chapter 3 was able to predict future commodity prices based on available data. It is very important for mining businesses to maximise NPV and IRR as well as risk management during a time of rapid commodity price surge or fall. Multiple methods were attempted, such as BNLR, MLR, MNLR, as well as the logsig and tansig model of the Levenberg-Marquardt ANN modelling were tested to simulate the future iron ore price based on twelve other monthly commodity prices and indices. The linear model (purelin) using the Levenberg-Marquardt technique was able to exhibit the best forecast result with average accuracy.

Abstract

Mining investors and operators highly value the ability to predict future commodity prices using available data. The interdependence of commodity prices and their causal relationships are crucial factors to consider. In this study, five distinct estimation techniques were examined: BNLR, MLR, MNLR, as well as the logsig and tansig models of Levenberg-Marquardt ANN modeling. These techniques were employed to forecast the future price of iron ore based on twelve other monthly commodity prices and indices, including LNG, aluminium, nickel, silver, Australian coal, zinc, gold, oil, tin, copper, lead, and CPI (metals).

In the study, six different models were applied to predict iron ore prices over a ten-month span, ranging from one to six months ahead. Among these models, the linear model (purelin) implemented the Levenberg-Marquardt technique and yielded the most accurate forecast results. The average accuracy rates for the purelin model were 5.92% for one month ahead, 9.48% for two months, 11.21% for three months, and so on. It is worth emphasizing that the purelin model achieved high accuracy, with forecasts and actual prices differing by less than 5% in 40-50% of cases, particularly for up to two months ahead. This level of accuracy was observed between

July 2020 and April 2021. Consequently, the purelin model can effectively predict iron ore prices for the upcoming month within a two-month timeframe. Furthermore, it is important to note that the period under examination exhibited instability in iron ore prices, characterized by a significant surge. This finding suggests that the same predictive principle can be applied during future commodity price cycles.

5.1 Introduction

Iron ore has been a very important commodity since the bronze age of human civilization as it is used to produce steel. The Australian economy is heavily dependent on iron ore exports and Chinese heavy industry is equally reliant on low-cost Australian supplies (Wilson, 2017). Mining is a key industry in Australia which constitutes around 60% of Australian exports (Observatory of Economic Complexity – Australia, 2021). In recent years, there have been a number of international issues which have caused a disturbance to the global supply chain of commodities, such as the COVID-19 pandemic, the Russo-Ukrainian war, the US-China trade war as well as the decoupling and decline of the Sino-Australian relationships, etc., which triggered fluctuating commodity price. A typical example was when gold price fluctuations had one-directional causal relations from COVID-19 case numbers (Gautam et al. 2022). A series of events have led to 'resource nationalism' where different countries ban exports or imports, putting extra tariffs or sanctions on and from one another. This is due to the pursuit of national security for each country. Hence, commodity prices have skyrocketed due to soaring demand. Notability, iron ore is the only commodity which is not banned by China nor extra tariffs are imposed unlike other commodities such as wine, coal, barley, cotton, lobsters, and wood. This is because the vast majority of its imports (64.5%) is heavily reliant on Australia (Observatory of Economic Complexity – Iron Ore, 2021), meaning the raw materials for steel production are also monopolized by two countries in the world and are also prone to risk of disturbance in the global supply chain. The importance of iron ore was amplified even further as the iron ore price has soared to US $215 on 1st June 2021 from US $82 on 1st April 2020 (Indexmundi, n.d.).

Investments in the mining and minerals industry are regarded as risky (Topal, 2008) and highly sensitive to the movement of commodity prices. An accurate forecast of commodity prices could benefit producers and investors to be able to prepare dramatic price changes in both the short and long terms. For producers, accurate forecast of commodity prices enables accurate prediction of optimized UPL as well as NPV of open pit mines (Mai et al. (2019). Big mining companies often produce different commodities in diverse portfolios, and this research will benefit mining companies and investors to maximize profit-margin and minimize risk in the business by optimising the ratio of different commodities within the investment portfolio, and prediction of the change in iron ore prices. Hence, an accurate prediction of commodity prices is very important for running a successful mining business.

To forecast the iron ore price, it is important to understand and analyse the possible relationship that commodity prices have with each other or any other econometric variables. Haque et al. (2015a) have determined that when iron ore prices increase, Australian dollars also increase, but no influence occurs the other way around. They also have determined that there is a long-term bidirectional casualty relationship between gold price (in US $) and the Australian dollar to US dollar (AUD/USD) exchange rates from 1996 to 2014. Haque et al. (2015b). Ma et al. (2019) have expanded the finding that oil, gas, coal, and iron ore prices are all associated with an increase in the appreciation of Australian dollars and a decline in the Chinese RMB. Kim et al. (2022) have determined that there is a long-term relationship of iron ore prices and oil, copper, and Australian coal prices on iron ore prices at different lags using VECM and Johansen cointegration test. Kim et al. (2022) also argued that much of the iron ore price is derived from the prices of twelve other commodity prices or indices, including LNG, aluminium, nickel, silver, Australian coal, zinc, gold, oil, tin, copper, lead, and CPI (metals) by applying multivariate Johansen cointegration. Prior to this research, there was research for predicting the iron ore price.

Understanding that the Levenberg-Marquardt method is outperforming the method compared with other ANN methods (Mammadli, 2017) for financial time series prediction, this sequence of research in this chapter is: (1) study performance of iron ore price forecasting methods other than ANN such as BNLR, MLR as well as MNLR to understand the complexity of the model, (2) once determined complex modelling is required, apply Levenberg-Marquardt method by modelling different transfer functions with data which are readily available, and (3) suggest which method is the most optimum or accurate.

5.2 Research Results

5.2.2 Bivariate Non-Linear Regression (BNLR)

To understand how each commodity price behaves against the iron ore price, the simplest regression BNLR is applied, which is simply tabulating the respective commodity price against the iron ore price and fitting it to available curves. Options include polynomial, logarithmic, power, exponential and linear. The fitted relationship in the graph follows the data and produces an R^2 value. The optimized model is the model with the highest R^2 value. Table 5.1 below is tabulated for an optimized model with its equations.

Table 5.1: BNLR model outcomes with equations for iron ore price against twelve different commodity prices

Commodity price	**R^2**	**Type of model**	**Equation of model**
Gold	0.7498	Polynomial	$[IO] = -0.0948\ [GO]^2 + 26.204\ [GO] - 353.53$… (5.1)
Oil	0.8217	logarithmic	$[IO] = 43.506 \ln [OI] - 126.78$… (5.2)
Silver	0.7743	Polynomial	$[IO] = -0.0009\ [SI]^2 + 0.3292\ [SI] - 4.127$… (5.3)
LNG	0.1308	logarithmic	$[IO] = 1.2152 \ln [LN] - 1.2056$… (5.4)
Aluminium	0.5495	logarithmic	$[IO] = 489.7 \ln [AL] - 205.38$… (5.5)
Copper	0.8938	logarithmic	$[IO] = 3656.9 \ln [CO] - 10265$… (5.5)
CPI (metals)	0.9028	logarithmic	$[IO] = 40.767 \ln [CP] - 100.41$… (5.6)
Tin	0.8025	logarithmic	$[IO] = 10247 \ln [TI] - 29041$… (5.7)
Lead	0.8147	logarithmic	$[IO] = 1108.2 \ln [LE] - 3144.3$… (5.8)
Australian Coal	0.7472	logarithmic	$[IO] = 41.151 \ln [AC] - 106.63$… (5.9)
Nickel	0.541	logarithmic	$[IO] = 8654.8 \ln [NI] - 22034$… (5.10)
Zinc	0.6522	Polynomial	$[IO] = 0.0024[ZI]^3 - 0.8929\ [ZI]^2 + 103.07\ [ZI] - 1321.3$… (5.11)

Based on the equations of the model, a prediction has been made using a forecast of one month ahead to forecast the iron ore price. Unfortunately, the variance between the actual and the forecast is too large, as shown in table 5.2 below. Hence, it is revealed that the bivariate regression model is not a reliable model to forecast the future iron ore price.

Table 5.2: Percentage (%) difference of BNLR Forecast of iron ore price with one month ahead against twelve different commodity prices

Commodity price	**% Difference**
Gold	196628%
Oil	72%
Silver	98%
LNG	100%
Aluminium	-2412%
Copper	-15873%
CPI (metals)	41%
Tin	-625354%

Lead	-3670%
Australian Coal	54%
Nickel	-44197%
Zinc	-22384779%

5.2.3 Multiple Linear Regression (MLR)

As it is determined that BNLR is not a reliable model to forecast the future iron ore price, the next simplest method is to determine iron ore price behaviour against twelve other commodity prices by MLR to test if it performs better than BNLR. The MLR model has been built for each dataset with all twelve independent variables.

Regression statistics is tabulated in table 5.3 below:

Table 5.3: R^2 regression statistics for different forecast months applied

Colour represented	**Forecast Options**	**R^2**	**% Difference**
(green)	one month ahead	0.978	8.84%
(orange)	two months ahead	0.948	16.78%
(blue)	three months ahead	0.921	23.46%

The highest R^2 value and lowest standard error are exhibited one-month ahead forecast. It indicates that the one-month ahead forecast model can replicate the non-linear regression model of twelve commodity prices against iron ore prices. As the forecast months increase, the accuracy of regression diminishes (the R^2 value decreases). Regression coefficient and intercept are represented in equations 5.12 – 5.14 below for each different option from one to three months lag. Based on the results, a regression without a one-month ahead forecast was able to predict the iron ore price most accurately with an average 8.84% difference for one month ahead, an average 16.78% difference for two months ahead and 23.46% difference for three months ahead.

For one month ahead:

$$IO\ (Lag\_1) = 6.919 * [CP] + (10)^{-2}\{-8.241[AL]\ - 3.56[CO] - 1.516[ZI]\} + (10)^{-3}\{-6.457[LE] - 2.860[NI]\} + (10)^{-4}\{1.05[OL] - 6.98[LN] - 1.914[SI] - 7.943[TI]\} - 7.6565(10)^{-5}[AC] - 4.21(10)^{-6}[GO] - 7.077(10)^{-3} \ldots (5.12)$$

For two months ahead:

$$IO\ (Lag\_2) = 5.866 * [CP] + (10)^{-1}\{2.223[OL] + 4.002[LN] - 2.226[SI] + 1.995[AC]\} + (10)^{-2}\{-6.67[AL]\ - 3.049[CO] - 1.579[ZI] - 1.41[LE] + 1.667[GO]\} + (10)^{-3}\{-2.024[NI]\} + (10)^{-4}\{-5.572[TI]\} - 7.461 \ldots (5.13)$$

For three months ahead:

$$IO\ (Lag\_3) = 4.9 * [CP] + (10)^{-1} * \{2.816[OI] - 2.212[SI] + 7.082[LN] + 3.011[AC]\} + (10)^{-2} * \{2.373[GO] - 5.607[AL] - 2.499[CO]\} - 6.873 - 1.592[LE] - 1.623[ZI]\} + (10)^{-3} * \{-1.543[NI]\} + (10)^{-4} * \{-6.639[TI]\} - 6.873 \ldots (5.14)$$

Using each equation, the iron ore price has been predicted and compared against the actual price. The results are tabulated in tables 5.4, 5.5 and 5.6 below:

Table 5.4: Actual iron ore price vs predicted iron ore price with one month ahead forecast

Month Year	**Actual iron ore price (US $)**	**Predicted iron ore price (US $)**	**% difference**
Jul 2020	108.52	100.26	7.61
Aug 2020	121.07	104.90	13.36
Sep 2020	123.75	115.11	6.98
Oct 2020	119.78	117.78	1.67
Nov 2020	124.36	115.38	7.22
Dec 2020	155.43	119.29	23.25
Jan 2021	169.63	149.06	12.13
Feb 2021	163.8	162.97	0.50
Mar 2021	168.18	157.66	6.25
Apr 2021	179.83	162.86	9.43

Table 5.5: Actual iron ore price vs predicted iron ore price with two months ahead forecast

Month Year	Actual iron ore price (US $)	Predicted iron ore price (US $)	% difference
Jul 2020	108.52	89.43	17.59
Aug 2020	121.07	97.66	19.33
Sep 2020	123.75	102.15	17.46
Oct 2020	119.78	110.94	7.38
Nov 2020	124.36	113.01	9.13
Dec 2020	155.43	111.95	27.97
Jan 2021	169.63	114.98	32.21
Feb 2021	163.8	142.08	13.26
Mar 2021	168.18	155.24	7.70
Apr 2021	179.83	151.53	15.74

Table 5.6: Actual iron ore price vs predicted iron ore price with three months ahead forecast

Month Year	Actual Iron ore price (US $)	Predicted Iron ore price (US $)	% Difference
Jul 2020	108.52	82.04	24.40
Aug 2020	121.07	88.96	26.52
Sep 2020	123.75	96.09	22.35
Oct 2020	119.78	100.54	16.06
Nov 2020	124.36	107.98	13.17
Dec 2020	155.43	109.65	29.41
Jan 2021	169.63	111.88	35.36
Feb 2021	163.8	136.97	31.70
Mar 2021	168.18	149.10	18.56
Apr 2021	179.83	145.97	17.09

5.2.4 Multiple Non-Linear Regression (MNLR)

MNLR is to be applied and following equations are defined as follows:

For one month ahead:

$$IO\ (Lag1) =$$

$$8.8623[GO]^{-0.0424}[OI]^{-0.0581}[SI]^{0.0025}[LN]^{0.0771}[AL]^{-2.5784}[CO]^{-1.6356}[CP]^{5.556}[TI]^{-0.28}[LE]^{0.0414}$$

$$[AC]^{0.2193}[NI]^{-0.2911}[ZI]^{-0.2307} \ldots (5.15)$$

For two months ahead:

$$IO\ (Lag2) =$$

$$8.1379[GO]^{-0.109}[OI]^{-0.0561}[SI]^{0.0997}[LN]^{0.077}[AL]^{-2.4148}[CO]^{-1.4187}[CP]^{4.8567}[TI]^{-0.3246}[LE]^{0.1472}$$

$$[AC]^{0.2201}[NI]^{-0.1762}[ZI]^{-0.1956} \ldots (5.16)$$

For three months ahead:

$$IO\ (Lag3) =$$

$$7.548[GO]^{-0.1337}[OI]^{-0.0638}[SI]^{0.1852}[LN]^{0.0722}[AL]^{-2.2865}[CO]^{-1.272}[CP]^{4.2761}[TI]^{-0.3939}[LE]^{0.237}$$

$$[AC]^{0.2325}[NI]^{-0.0496}[ZI]^{-0.1497} \ldots (5.17)$$

The results are tabulated in tables 5.7, 5.8, 5.9 and 5.10 below. Based on the results, average 10.01% difference for one month ahead, average 17.33% difference for two months ahead and 23.59% difference for three months ahead can be observed.

Table 5.7: R^2 regression statistics for different forecast months applied

Colour represented	**Forecast options**	**R^2**	**% difference**
	one month ahead	0.9818	10.01%
	two months ahead	0.966	17.33%
	three months ahead	0.954	23.59%

Table 5.8: Actual iron ore price vs predicted iron ore price with one month ahead forecast

Month Year	**Actual iron ore price**	**Predicted iron ore price**	**% difference**
Jul 2020	108.52	96.55	11.03%
Aug 2020	121.07	102.73	15.15%
Sep 2020	123.75	112.27	9.28%

Oct 2020	119.78	117.02	2.31%
Nov 2020	124.36	110.95	10.78%
Dec 2020	155.43	115.00	26.01%
Jan 2021	169.63	154.16	9.12%
Feb 2021	163.8	173.00	5.61%
Mar 2021	168.18	168.39	0.12%
Apr 2021	179.83	160.56	10.72%

Table 5.9: Actual iron ore price vs predicted iron ore price with two months ahead forecast

Month Year	**Actual iron ore price**	**Predicted iron ore price**	**% difference**
Jul 2020	108.52	88.46	18.48%
Aug 2020	121.07	92.78	23.36%
Sep 2020	123.75	98.98	20.01%
Oct 2020	119.78	110.05	8.12%
Nov 2020	124.36	113.50	8.73%
Dec 2020	155.43	107.04	31.13%
Jan 2021	169.63	110.98	34.58%
Feb 2021	163.8	144.95	11.51%
Mar 2021	168.18	160.50	4.56%
Apr 2021	179.83	156.74	12.84%

Table 5.10: Actual iron ore price vs predicted iron ore price with three months ahead forecast

Month Year	**Actual iron ore price**	**Predicted iron ore price**	**% difference**
Jul 2020	108.52	84.32	22.30%
Aug 2020	121.07	87.97	27.34%
Sep 2020	123.75	91.17	26.32%
Oct 2020	119.78	97.40	18.69%
Nov 2020	124.36	110.24	11.35%
Dec 2020	155.43	112.79	27.43%
Jan 2021	169.63	105.85	37.60%
Feb 2021	163.8	109.63	33.07%
Mar 2021	168.18	139.97	16.77%
Apr 2021	179.83	152.84	15.01%

5.2.5 Artificial Neural Network (ANN)

5.2.5.1 Iron ore price prediction using Levenberg-Marquardt

Levenberg-Marquardt prediction has been made in effort to replicate the forecast for 10 months period using 30-year data until June 2020, forecasting 1 month ahead. The results are tabulated in table 5.11 and figure 4.2 below. Based on the results, 1 month ahead forecasting was able to exhibit average 12.92% difference for logsig model, 28.36% for tansig model and 5.92% for purelin model. Hence, application of purelin can forecast the 1 month ahead iron ore price most accurately. To define how accurate each model is, this research defines as less than 5% error as accurate forecast in turbulent period of iron ore price where 65% increase within 10 months period has been witnessed. Based on this definition, purelin model can forecast 5 accurate months out of 10 months. These are predictions for July (1.24%), August (1.37%), November (1.00%) 2021 as well as January (1.25%) and March (3.62%) 2022.

Table 5.11: Predicted iron ore price from one month ahead and % difference between prediction and actual iron ore price

		Logsig		**Tansig**		**Purelin**	
Month Year	**Actual iron ore price (US $)**	**Predicted iron ore price (US $)**	**% difference**	**Predicted iron ore price (US $)**	**% difference**	**Predicted iron ore price (US $)**	**% difference**
Jul 2020	108.52	101.07	6.86%	100.6259	7.27%	107.1776	1.24%
Aug 2020	121.07	102.58	15.27%	101.4043	16.24%	119.4064	1.37%
Sep 2020	123.75	98.26	20.60%	26.47	78.61%	132.3984	6.99%
Oct 2020	119.78	109.42	8.65%	127.9725	6.84%	134.9973	12.70%
Nov 2020	124.36	117.52	5.50%	26.47	78.72%	125.5997	1.00%
Dec 2020	155.43	126.09	18.88%	98.8447	36.41%	130.9388	15.76%
Jan 2021	169.63	144.73	14.68%	136.2193	19.70%	167.5127	1.25%
Feb 2021	163.8	180.90	10.44%	172.5935	5.37%	172.0582	5.04%
Mar 2021	168.18	177.92	5.79%	120.5458	28.32%	174.2645	3.62%
Apr 2021	179.83	139.40	22.48%	168.8911	6.08%	161.3497	10.28%
Average			12.92%		28.36%		5.92%

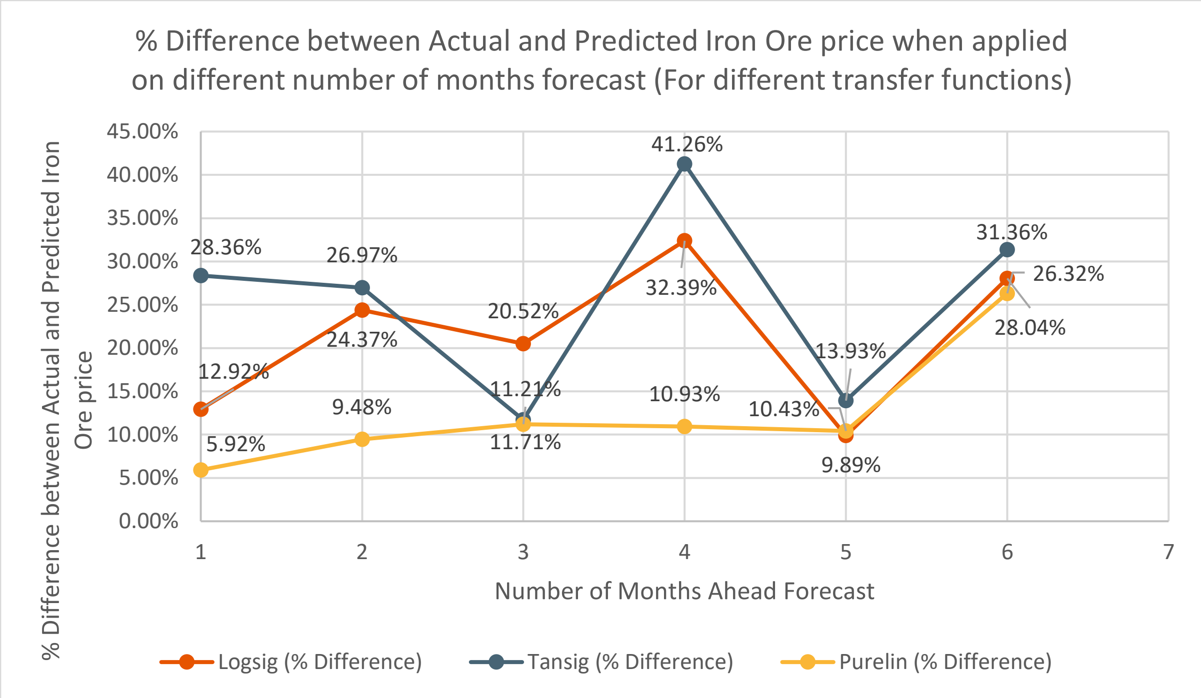


Figure 4.2: % difference between Actual and Predicted Iron Ore price when applied on different number of months forecast (For different transfer functions).

The Levenberg-Marquardt prediction method has been applied to the forecast for two to six months ahead. The overall performance results are tabulated in table 5.12 and figure 4.3 below. Three different data were tabulated for the forecast using logsig, tansig and purelin between one and six months ahead, which is a % difference: accuracy rate (a 5% difference between forecast and actual) and R^2 value. The difference between the average % difference and the accuracy rate is: the average % difference is a quantitative indicator to measure accuracy, but the accuracy rate (within 5% accuracy) is a qualitative indicator showing the ratio of achieving a high accuracy rate. R^2 typically demonstrates the degree of how accurate the model is. The results show that purelin was able to exhibit the best outcome for one to six months ahead. On the other hand, logsig was the best performer for five months ahead.

Table 5.12: R^2, % difference and number of accurate monthly predictions for regression statistics of forecasting different months ahead (Best results highlighted in green)

	% Difference			R^2			Accuracy rate (within 5%) for prediction model (%)		
Forecast Options	**Logsig**	**Tansig**	**Purelin**	**Logsig**	**Tansig**	**Purelin**	**Logsig**	**Tansig**	**Purelin**
	12.92%	28.36%	5.92%	0.992	0.8822	0.9854	0	0	50

1 Month ahead									
2 Months ahead	24.37%	26.97%	9.48%	0.9406	0.8434	0.9722	30	10	40
3 Months ahead	20.52%	11.71%	11.21%	0.9848	0.9857	0.9622	20	30	10
4 Months ahead	32.39%	41.26%	10.93%	0.7959	0.7253	0.9553	0	20	30
5 Months ahead	9.89%	13.93%	10.43%	0.9363	0.9522	0.9497	40	20	20
6 Months ahead	28.04%	31.36%	11.59%	0.8768	0.8785	0.9387	10	0	20

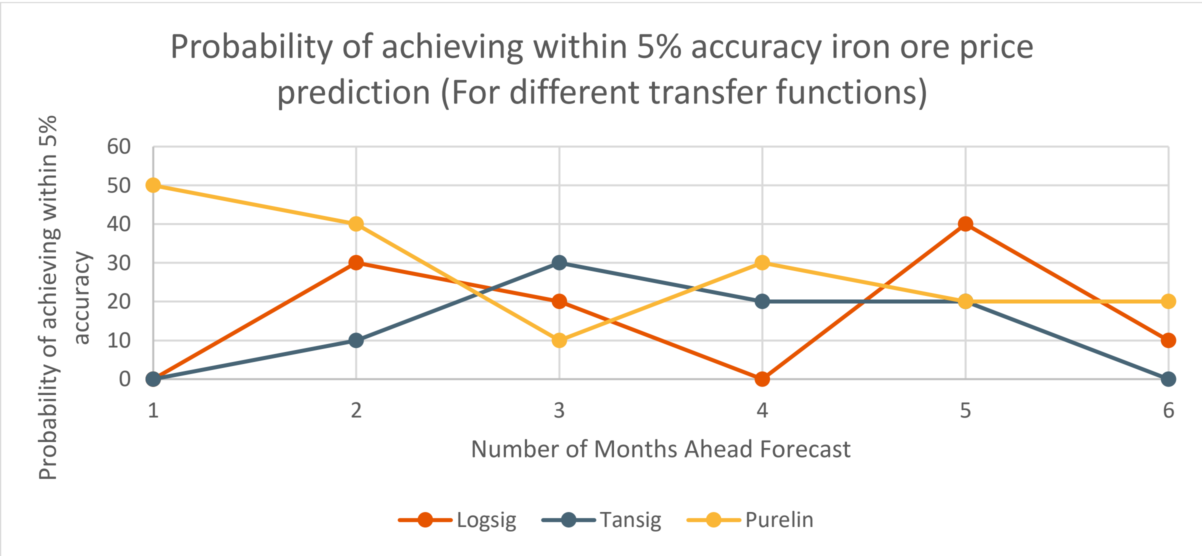


Figure 4.3: Probability of achieving within 5% accuracy iron ore price prediction (For different transfer functions)

5.3 Discussions

There was a total of four models: Bivariate Non-Linear Regression (BNLR), Multiple Linear Regression (MLR), Multiple Non-Linear Regression (MNLR) as well as logsig, tansig and purelin model of Artificial Neural Network which were considered in this research to forecast iron ore price.

Bivariate Non-Linear Regression is not a good model for iron ore price prediction, because of its poor accuracy. Both Multiple Linear Regression (MLR) and Multiple Non-Linear Regression (MNLR) were applied to forecasts up to three months ahead and both models prove that the forecast accuracy performance diminishes when the number of months ahead increases. The % difference for one month ahead were 8.84% and 10.01%, two months ahead were 16.78% and 17.33% and three months ahead were 23.46% and 23.59% for MLR and MNLR respectively. Based on the % difference, MLR is more effective than MNLR.

Models based on Logsig, tansig and purelin transfer functions were able to replicate 12.92%, 28.36% and 5.92% differences between forecast and actuals respectively when 1 month ahead. Figure 4.2 shows the lowest % difference achieved using logsig, tansig and purelin models from 1 month ahead to 6 months ahead forecast. Purelin was able to forecast the most accurate iron ore price from zero to six months ahead; only five months ahead was most accurately predicted by logsig.

The average % difference between forecasted and actual iron ore price for over 10 months for the best performed model was 5.92% (one month ahead with purelin), 9.48% (two months ahead with purelin), 11.21% (three months ahead with purelin), 10.93% (four months ahead with purelin), 9.89% (five months ahead with logsig) and 11.59% (six months ahead with purelin). It is observed that the accuracy rate (within 5% difference between forecasts and actuals) was achieved by purelin (50% at one month ahead), pureline (30% at two months ahead), tansig (30% at 3 months ahead), purelin (30% at 4 months ahead), logsig (40% at five months ahead), purelin (20% at six months ahead). The average % difference in result mostly does align with the probability of accurate forecasts and actual results. It is important to note that the average % difference and accuracy rate are both important indicators, where the average % difference is a quantitative indicator to measure accuracy, and accuracy rate (within 5% accuracy) is a qualitative indicator showing the ratio of achieving a high accuracy rate.

There are no correlations between the R^2 value against the % difference and the probability of accurate forecasts and actuals. A higher R^2 value guarantees a better forecast, however. But the highest R^2 value does not always produce the most accurate results. Hence, the R^2 value can only work as an indicator for discarding the Levenberg-Marquardt models, as none of the best models has an R^2 value lower than 0.9363. Therefore, the R^2 value of 0.9363 can generally be regarded as a critical point when forecasting iron ore prices in the future. In other words, any model with an R^2 value less than ~0.93 can be discarded in future approximation. Based on the outcome of the six-month forecast, the Purelin model has the most accurate and optimum model when forecasting iron ore prices for up to 6 months and there are exceptions, which can be filtered by (1) applying a model with the highest R^2 value and (2) discarding any model with an R^2 value lower than 0.9363.

It is important to understand that the tested period is between Jul 2020 to Apr 2021 when the iron ore prices were unstable with a rapid surge in iron ore prices (67% increase in a ten-month period). However, it has been predicted with a high accuracy rate (between 40-50%) for up to 2 months forecast, although a stable period was not studied in this research. The general assumption is that the Levenberg-Marquardt model will be able to predict the price with higher accuracy than in the turbulent period, which can be studied in future research.

5.4 Conclusions

Out of six different prediction modelling, Bivariate Non-Linear Regression can be discarded as the accuracy rate is unreliable and is way out. This is because the model is solely reliant on one input data to model future iron ore prices. The other five methods, including Multiple Linear Regression (MLR), Multiple Non-Linear Regression (MNLR) as well as the logsig, tansig and purelin model of the Levenberg-Marquardt estimation algorithm were considered in this research to forecast iron ore prices.

It can be concluded from the results that the MLR model is more accurate than MNLR. The Levenberg-Marquardt estimation result ensured that it is far more accurate than MLR and MNLR, and that purelin was generally the best model for one to six months ahead forecast. This result also aligns with the outcome that MLR is a more accurate model than MNLR, meaning that linear modelling is the most accurate method of prediction of iron ore price, regardless of whether regression or ANN is applied.

linear model (purelin) using the Levenberg-Marquardt technique was able to exhibit the best forecast result, which is proven quantitatively by average accuracy of 5.92% difference for 1 month ahead, 9.48% for 2 months, 11.21% for 3 months, etc. Qualitative analysis on the outcome of Levenberg-Marquardt was done by counting the number of months of forecast within a 5% difference achieved out of 10 months, which highlighted that high accuracy rates were achieved (40-50% accuracy under 5% difference between forecasts and actuals) by purelin model for up to 2 months forecast for the period Jul 2020 to Apr 2021. This will enable prediction of iron ore prices up to 2 months ahead using the purelin model. Noting that the period tested was unstable for iron ore prices where a rapid surge in iron ore price was observed, the same principle can be applied in the time of the next commodity price boom, where the purelin model can be applied to Levenberg-Marquardt to ensure R^2 is below ~0.93 (where none of the best models have R^2 value lower than ~0.93).the Levenberg-Marquardt

The purelin model can practically be applied to the setup of iron ore price forecast modelling for mining operations, as it is able to achieve a high accuracy rate (40-50% accuracy, under 5% difference between forecasts and actuals) for both 1 month ahead and 2 months ahead forecast even during turbulent period. The suggested purelin model is more definitive in terms of input quantitative data used and has made progress in accuracy compared to previous models. Accurate iron ore price prediction using the logsig model can optimize Ultimate Pit Limit (UPL) as well as Net Present Value (NPV) of mining projects, which will greatly maximize profit margins and minimize financial risks for iron ore mining companies.

Chapter 6 – Discussions

The research was able to determine the overall relationship between 12 different commodities, both via bivariate and multivariate modelling. Different testing methods were used, such as Granger causality, Johansen cointegration and Vector Error Correction Modelling. It is determined that there is a bidirectional causality exists between iron ore prices and copper, oil and coal prices. Also, oil, copper and Australian coal prices have an influence on and on iron ore prices. The multivariate modelling cointegration test found six out of twelve commodity prices cointegrate with each other in one month lag and continue in a cyclic pattern till 27 months, after which they disappear. The normalizing vector $\beta 1$ represents that a 1% increase in oil, Australian coal, and copper prices leads to an appreciation of iron ore prices by approximately 1.34 %, 1.29% and 0.017% respectively. The speed of adjustment parameter $\alpha 1$, which represents approximately 3.6% of oil price, 1.33% of oil price and 6.53% of copper price change per month attributes to the disequilibrium between actual and equilibrium levels.

It is important to note that understanding commodity market pricing systems is an important step towards prediction of their prices, which, in return, is very important for running a successful mining business. Mining requires multibillion-dollar investments. Hence, the feasibility of every mining project which is determined by NPV and IRR is highly sensitive to commodity prices. Understanding there has been some turbulence in commodity prices in the past decade, the importance of realising the commodity pricing system as well as different efforts of prediction methods is only more important. In addition, several international issues that have caused disturbances to the global supply chain of commodities, such as the COVID-19 pandemic, the Russo-Ukrainian war, the US-China trade war, the decoupling and decline of the Sino-Australian relationship, etc., have greatly caused the fluctuation in commodity prices. In particular, iron ore has experienced great fluctuations, as it is a key raw material for the industry, due to soaring demand in China and limited supply from Australia and Brazil. As the tension may potentially grow between the US and China, due to international reliance on iron ore supply and demand from limited countries, iron ore may play a key role in the future of commodities. Hence, this research may potentially indicate the direction of the iron ore pricing system.

In efforts for predicting iron ore prices, different methods were used in this research, such as bivariate Non-Linear Regression (BNLR), Multiple Linear Regression (MLR), Multiple Non-Linear Regression (MNLR) as well as logsig and tansig model of Levenberg-Marquardt

Artificial Neural Network modelling based on twelve other monthly commodity prices and indices. The Linear model (purelin) using the Levenberg-Marquardt technique was able to exhibit the best forecast result with an average accuracy of 40-50%, under 5% difference between forecasts and actuals for both the one-month ahead and two-months ahead forecasts, even during a turbulent period. In detail, the prediction of iron ore prices was at the difference of 5.92% for one month ahead, 9.48% for two months, and 11.21% for three months.

The suggested purelin model is more definitive in terms of input quantitative data used and has made progress in accuracy compared to other models. Accurate iron ore price prediction using the logsig model can optimize Ultimate Pit Limit (UPL) as well as Net Present Value (NPV) of mining projects, which will greatly maximize profit margins and minimize financial risks for iron ore mining companies. Although there are limitations to the suggested method to predict iron ore price, however this method has provided an advancement to iron ore price prediction. Also, it is important to note that the iron ore price prediction period was between July 2020 and April 2021, when there was a great increase in iron ore prices. Hence, this method can be utilized at the next iron ore price increase, specifically during international crises of different kinds. As NPV is directly proportional to cash flow and commodity prices, and because projects with a positive NPV have higher IRR, this iron ore prediction enables more robust and accurate prediction of NPV and IRR for the feasibility of proposed iron ore projects.

The research was able to determine the relationship between commodity prices and iron ore prices and successfully modelled a prediction tool for short-term iron ore prices. Although economic reasons behind the bidirectional Granger causes between iron ore, coal, copper and oil were not explored, future research should explore economic analysis on such relationships. Also, differences of 5.92% for one month ahead, 9.48% for two months, and 11.21% for three months look fairly accurate. However, they can still be improved. Possibly, economic factors other than commodity prices should be considered as the data for future research or, by applying other artificial neural network techniques, it can be applied to compare it against the Levenberg-Marquardt technique for more accurate models.

Chapter 7 – Conclusions

The research was able to determine the overall relationship between twelve different commodities, both via bivariate and multivariate modelling. Different testing methods were used, such as Granger causality, Johansen cointegration, and Vector Error Correction Modelling. It is determined that bidirectional causality exists between iron ore prices and copper, oil, and coal prices. Also, oil, copper, and Australian coal prices have an influence on and on iron ore prices. Multivariate modelling cointegration test found that six out of twelve commodity prices cointegrate with each other in a one-month lag and continue in a cyclic pattern till 27 months, after which they disappear. The normalizing vector β1 represents that a 1% increase in oil, Australian coal, and copper prices leads to an appreciation of the iron ore price by approximately 1.34 %, 1.29%, and 0.017%, respectively. The speed of adjustment parameter α1, which represents approximately 3.6% of oil price, 1.33% of oil price, and 6.53% of copper price change per month, is attributed to the disequilibrium between actual and equilibrium levels.

Different methods of iron ore price prediction were used in this research, such as bivariate Non-Linear Regression (BNLR), Multiple Linear Regression (MLR), Multiple Non-Linear Regression (MNLR) as well as the logsig and tansig models of Levenberg-Marquardt Artificial Neural Network modelling based on twelve other monthly commodity prices and indices. The Linear model (purelin) using the Levenberg-Marquardt technique was able to exhibit the best forecast result with an average accuracy of 40–50% under a 5% difference between forecasts and actuals for both one month ahead and two months ahead forecasts, even during turbulent periods. In detail, the prediction of iron ore prices was a difference of 5.92% for one month ahead, 9.48% for two months, and 11.21% for three months.

The suggested purelin model is more definitive in terms of the input quantitative data used and has made progress in accuracy compared to other models. Accurate iron ore price prediction using the logsig model can optimize Ultimate Pit Limit (UPL) as well as Net Present Value (NPV) of mining projects, which will greatly maximize profit margins and minimize financial risks for iron ore mining companies. Although there are limitations to the suggested method for predicting iron ore prices, this method has provided an advancement in iron ore price prediction.

The research was able to determine the relationship between commodity prices and iron ore prices and successfully model a prediction tool for short-term iron ore prices. Although the economic reason behind the bidirectional Granger causes between iron ore, coal, copper, and oil were not explored, future research should explore the economic analysis of such a relationship. Also, differences of 5.92% for one month ahead, 9.48% for two months, and 11.21% for three months look fairly accurate, but they can still be improved. Possibly, economic factors other than commodity prices should be considered as the data for future research, or other artificial neural network techniques can be applied to compare against the Levenberg-Marquardt technique for a more accurate model. In addition, possible statistical analysis is required for future research to further investigate why purelin activation function is most effective compared to sigmoid and tansig amongst Levenberg-Marquardt technique as an iron ore price prediction method.

7.1 Key findings

7.1.1 Highlights from Chapter 4

- In a multivariate modelling cointegration test, six out of twelve commodity prices showed cointegrations in a one-month lag and continued in a cyclic pattern till 27 months, after which it disappears.
- VECM estimation proved that oil, copper and Australian coal prices have an influence on and on iron ore prices.
- The Granger causality test reveals the presence of a bidirectional causal connection between iron ore prices and copper, oil, and coal prices.

7.1.2 Highlights from Chapter 5

- Future prediction of commodity prices based on available data is very important for mining businesses to maximise NPV and IRR as well as risk management during a time of rapid commodity price surge or fall.
- Commodity prices cointegrate and show Granger causality to and from one another.
- The BNLR, MLR, MNLR as well as the logsig and tansig model of Levenberg-Marquardt ANN modelling were tested to simulate the future iron ore price based on twelve other monthly commodity prices and indices.
- The linear model (purelin) using the Levenberg-Marquardt technique was able to exhibit the best forecast result with average accuracy (under 5% difference between forecasts and actuals for 40-50% cases) for up to two months forecast for the period between July 2020 and April 2021.
- It is important to note that the period tested was unstable for iron ore prices where a rapid surge in iron ore price was observed, meaning that the same principle can be applied to the time of the next commodity price boom.

7.2 Significance of the research

he importance of iron ore and other commodities has emerged as there were a number of international issues recently which have caused a disturbance to the global supply chain of commodities, such as the COVID-19 pandemic, the Russo-Ukrainian war, the US-China trade war as well as the decoupling and decline of the Sino-Australian relationship, etc. which triggered fluctuating commodity price. In addition, because of limited supply and exponential growth in demand, a series of conflicts between different countries have led to 'resource nationalism' where different countries ban exports or imports, putting extra tariffs or sanctions on and from one another. The primary reason is the pursuit of national security of each nation. The consequences of such events have led to skyrocketing commodity prices. Understanding that iron ore has emerged as a key commodity surrounding tensions between Australia and China, and its main supply and consumption is limited to a few countries, the iron ore price is expected to show turbulent movement in the event of a future crisis. Hence, understanding the interdependency of commodity market pricing systems to be able to predict commodity prices is very important for running a successful mining business. An accurate forecast of commodity prices could benefit producers and investors to be able to prepare dramatic price changes in both the short and long term. This research was able to investigate twelve different commodity prices over the span of 30 years based on multivariate modelling and explored that the trend-line displays the number of cointegrations which resembles a sine curve. Also, the curve trend was able to define that when the impact on commodity price(s) has been observed, it will take at least 20 and up to 27 months to visualize the change to the entire commodity market. Also, it determined that there is bidirectional influence between the iron ore price against oil, copper, and Australian coal price, which means that the oil, copper and Australian coal prices have an influence on iron ore prices.

The prediction modelling of iron ore price produced the best outcome with a linear model (purelin) from Levenberg-Marquardt ANN modelling with an average difference of 5.92% for one month ahead, 9.48% for two months, and 11.21% for three months. Hence, the application of the purelin model, Levenberg-Marquardt ANN modelling has proven the possibility of, prediction of short-term iron ore prices. The purelin model can practically be applied to the setup of iron ore price forecast modelling for mining operations, as it is able to achieve a high accuracy rate (40-50% accuracy, under 5% difference between forecasts and actuals) for both one month ahead and two months ahead forecasts even during a turbulent period.

Future research should involve economic analysis to determine the economic reason behind the bidirectional Granger causes between iron ore, coal, copper and oil and explore other ANN techniques can be applied to compare the Levenberg-Marquardt technique for more accurate model. Although, it is proven that the Levenberg-Marquardt estimation algorithm was used to generate the most accurate ANN models for financial time series prediction as it significantly outperforms CGA as well as steep descent, this may need to be verified once more for iron ore price prediction.

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Appendices

Appendix A. Research Data Management Plan

Curtin University

Research Data Management Plan

Estimation of Iron Ore Price in Reference to Major Economic Indices Using Econometric Analysis Tools and Artificial Neural Network

Supervisor	Apurna Ghosh
Data Management Plan Edited by	Yoochan Kim
Modified Date	26/05/2020
Data Management Plan ID	GHOSHA-VC07966
Faculty	Vice Chancellory

1 Research Project Details

1.1 Research project title

Estimation of Iron Ore Price in Reference to Major Economic Indices Using Econometric Analysis Tools and Artificial Neural Network

1.2 Research project summary

The objectives of this research are (a) estimation of the short term (ST) and long term (LT) relationship of iron ore price with several econometric variables and (b) prediction of iron ore price using the Directly Influencing Variables (DIVs) and Indirectly Influencing Variables (IIVs) of iron ore.

To investigate LT relationship, co-integration tests will be performed. For the co-integration test, the Johansen co-integration methodology will be used. The test will be used under the condition that the variables contain unit-roots. This will then be followed by VECM to test the stability of the relationship.

In this research, the variables will be divided into Directly Influencing Variables (DIVs) and Indirectly Influencing Variables (IIVs). DIVs include Global Iron ore Production and Global Steel Production. IIVs are Gold Price, Oil Price, Interest Rate, GDP Growth and Inflation of major economies, etc. Hence, the research will examine time-series data using Unit Root Test (specifically Dickey-Fuller Test) to define the stationary relationships between iron ore price against DIVs and IIVs.

In order to predict iron ore price, this research will employ the Artificial Neural Network (ANN) application which have been recognized as a powerful tool in nonlinear approximation. Until date, there were numerous ANN applications for the approximation of functions, regression analysis, including time series prediction, approximation, and modeling.

1.3 Keywords
Artificial Neural Network, Direct Influencing Variables, Indirect Influencing Variables, Unit Root Test, Co-Integration, Vector Error Correlation Modelling, Vector Autoregressive Modelling

2 Research Project Data Details

2.1 Research project data summary

Any data, which need to be under secure, will be stored in accordance with Research Data and Primary Materials Policy. The data of this research is solely managed and organized personally by Yoochan (Eugene) Kim as for how long it may be required and useful. Paper-based data would be stored into the cabinet with a lock provided by Curtin University if required. Electronic data would be stored in the personal laptop.

2.2 Will the data be identifiable

- Not applicable — no human data used

2.3 Will biospecimens or human participant information be sent overseas?

No

2.4 Will novel information about controlled goods or technologies on the Defence and Strategic Goods List (DSGL) be sent overseas?

No

2.5 Data organisation and structure

The data in this research will be jointly responsible by the researcher (Yoochan Eugene Kim) along with support from the supervisor, for the collection, storage, sharing, security and use of research data and primary materials. Following are key responsibilities of the researcher (Yoochan Eugene Kim):

- Establishing and maintaining a Data Management Plan
- The collection, storage, maintaining records of storage, access, sharing and retention of the research data and primary materials associated with their research program;
- Seeking approval for the destruction of research data and primary materials from Curtin Information Management and Archives;
- Documenting arrangements for the collection, storage, ownership, access, confidentiality, retention and destruction of research data and primary materials when involved in a joint research project, collaborative research or research undertaken in accordance with a contractual agreement;

3 Research Project Data Storage, Retention and Dissemination Details

3.1 Storage arrangements

Any data, which needs to be under secure, will be stored following data storage provisions of Curtin University Research Data and Primary Materials Policy in good condition and personally organized as for how long it may be required and useful. Paper-based data would be stored in the cabinet with a lock provided by Curtin University. Electronic data would be stored on the personal laptop provided by Curtin University.

3.2 Estimated data storage volume

Storage volume is approximately estimated below 300 Gigabytes.

3.3 Safeguarding measures

Paper-based data would be stored in the cabinet with a lock provided by Curtin University if required. Electronic data would be stored on a personal laptop. All safeguarding measures to be made in accordance with Curtin University Research Data and Primary Materials Policy.

3.4 Retention requirements

7 years (All other research with outcomes that are classed as Minor)

3.5 Collaboration

The data in this research will be solely accessed by Yoochan (Eugene) Kim.

3.6 Data dissemination

Data would be available upon paper publication.

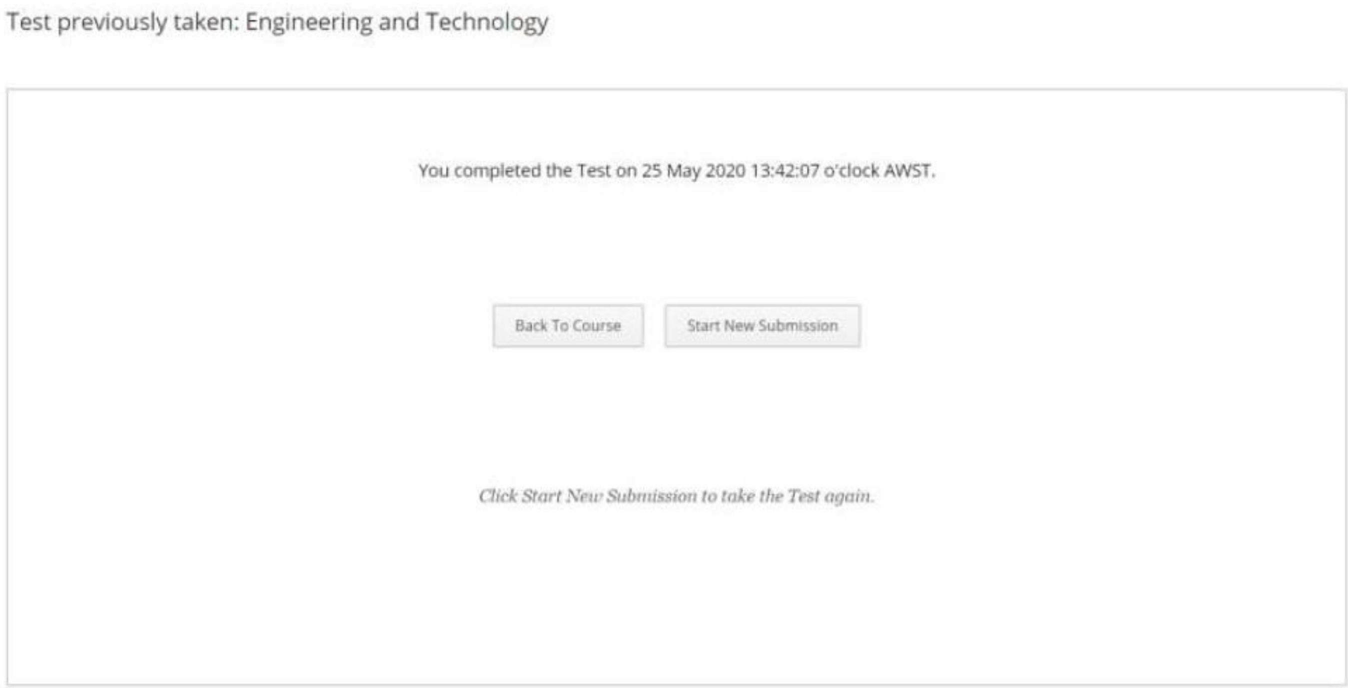
3.7 Embargo period

Embargo period would be tentatively two years after the end of the research project.

University Library is responsible for providing education, training, and support in research data management issues such as copyright, licensing of data, embargoes, re-use, and privacy.

An extension to the embargo period can subsequently be requested in writing. This request should be addressed to the Associate Deputy Vice-Chancellor, Research Training in the Office of Research and Development. The Thesis Examination Officer, on behalf of the Associate Deputy Vice-Chancellor, Research Training, will advise the Digital Thesis Team of the request and whether the extension has been approved.

Appendix B. Research Integrity Test



Appendix C. Research Data

Month Year	Iron Ore price (USD) / metric tonne	Gold Price (USD) / troy ounce	Oil Price (USD) / barrel	Silver Price (USD) / troy ounce	LNG Price (USD) / mmBtu	Aluminium Price (USD) / metric tonne	Copper Price (USD) / metric tonne
Jul 1990	$ 32.50	$ 362.53	$ 17.17	$ 4.87	$ 1.41	$ 1,570.96	$ 2,769.49
Aug 1990	$ 32.50	$ 394.73	$ 26.40	$ 5.01	$ 1.36	$ 1,782.02	$ 2,957.03
Sep 1990	$ 32.50	$ 389.32	$ 32.70	$ 4.80	$ 1.44	$ 2,066.53	$ 3,031.37
Oct 1990	$ 32.50	$ 380.74	$ 34.50	$ 4.39	$ 1.69	$ 1,945.70	$ 2,743.56
Nov 1990	$ 32.50	$ 381.73	$ 31.08	$ 4.17	$ 2.10	$ 1,617.50	$ 2,585.89
Dec 1990	$ 32.50	$ 376.95	$ 26.13	$ 4.08	$ 2.11	$ 1,522.44	$ 2,485.38
Jan 1991	$ 34.76	$ 383.64	$ 22.58	$ 4.05	$ 1.67	$ 1,515.18	$ 2,448.52
Feb 1991	$ 34.76	$ 363.83	$ 18.13	$ 3.74	$ 1.36	$ 1,504.60	$ 2,449.38
Mar 1991	$ 34.76	$ 363.34	$ 18.07	$ 3.94	$ 1.34	$ 1,496.00	$ 2,409.63
Apr 1991	$ 34.76	$ 358.38	$ 18.47	$ 3.98	$ 1.33	$ 1,391.86	$ 2,472.04
May 1991	$ 34.76	$ 356.95	$ 18.82	$ 4.05	$ 1.31	$ 1,296.05	$ 2,305.88
Jun 1991	$ 34.76	$ 366.72	$ 17.93	$ 4.39	$ 1.20	$ 1,275.15	$ 2,219.28

Jul 1991	$ 34.76	$ 367.69	$ 19.05	$ 4.35	$ 1.19	$ 1,296.78	$ 2,236.28
Aug 1991	$ 34.76	$ 356.31	$ 19.37	$ 3.96	$ 1.31	$ 1,256.45	$ 2,233.19
Sep 1991	$ 34.76	$ 348.74	$ 20.05	$ 4.04	$ 1.63	$ 1,211.81	$ 2,324.57
Oct 1991	$ 34.76	$ 358.69	$ 21.47	$ 4.12	$ 1.77	$ 1,150.03	$ 2,363.64
Nov 1991	$ 34.76	$ 360.17	$ 20.77	$ 4.07	$ 1.81	$ 1,134.80	$ 2,379.84
Dec 1991	$ 34.76	$ 361.73	$ 17.75	$ 3.94	$ 1.92	$ 1,097.55	$ 2,223.14
Jan 1992	$ 33.10	$ 354.45	$ 17.38	$ 4.11	$ 1.28	$ 1,177.07	$ 2,139.23
Feb 1992	$ 33.10	$ 353.91	$ 17.62	$ 4.15	$ 1.21	$ 1,266.83	$ 2,205.97
Mar 1992	$ 33.10	$ 344.34	$ 17.45	$ 4.11	$ 1.28	$ 1,280.47	$ 2,227.33
Apr 1992	$ 33.10	$ 338.62	$ 18.63	$ 4.05	$ 1.47	$ 1,317.05	$ 2,215.33
May 1992	$ 33.10	$ 337.24	$ 19.50	$ 4.07	$ 1.59	$ 1,306.79	$ 2,216.52
Jun 1992	$ 33.10	$ 340.81	$ 20.83	$ 4.06	$ 1.56	$ 1,275.55	$ 2,299.20
Jul 1992	$ 33.10	$ 352.72	$ 20.17	$ 3.97	$ 1.75	$ 1,313.05	$ 2,520.32
Aug 1992	$ 33.10	$ 343.06	$ 19.62	$ 3.81	$ 1.97	$ 1,305.05	$ 2,521.64
Sep 1992	$ 33.10	$ 345.43	$ 20.15	$ 3.77	$ 2.33	$ 1,269.61	$ 2,414.06
Oct 1992	$ 33.10	$ 344.38	$ 20.08	$ 3.75	$ 2.42	$ 1,173.78	$ 2,249.15

Nov 1992	$ 33.10	$ 335.02	$ 18.88	$ 3.77	$ 2.24	$ 1,159.05	$ 2,158.32
Dec 1992	$ 33.10	$ 334.82	$ 17.93	$ 3.73	$ 2.16	$ 1,207.10	$ 2,206.82
Jan 1993	$ 29.09	$ 329.01	$ 17.22	$ 3.68	$ 1.88	$ 1,206.76	$ 2,256.85
Feb 1993	$ 29.09	$ 329.31	$ 18.17	$ 3.66	$ 1.69	$ 1,201.85	$ 2,212.60
Mar 1993	$ 29.09	$ 330.08	$ 18.47	$ 3.65	$ 2.18	$ 1,151.33	$ 2,152.59
Apr 1993	$ 29.09	$ 342.15	$ 18.43	$ 3.95	$ 2.35	$ 1,108.53	$ 1,949.88
May 1993	$ 29.09	$ 367.18	$ 18.17	$ 4.46	$ 2.17	$ 1,123.96	$ 1,794.50
Jun 1993	$ 29.09	$ 371.89	$ 17.47	$ 4.38	$ 1.97	$ 1,165.30	$ 1,853.42
Jul 1993	$ 29.09	$ 392.19	$ 16.32	$ 5.02	$ 2.06	$ 1,202.13	$ 1,927.16
Aug 1993	$ 29.09	$ 378.84	$ 16.48	$ 4.84	$ 2.26	$ 1,172.14	$ 1,947.45
Sep 1993	$ 29.09	$ 355.28	$ 15.90	$ 4.22	$ 2.27	$ 1,115.38	$ 1,861.86
Oct 1993	$ 29.09	$ 364.18	$ 16.52	$ 4.34	$ 2.02	$ 1,087.10	$ 1,646.40
Nov 1993	$ 29.09	$ 373.83	$ 15.20	$ 4.53	$ 2.26	$ 1,039.81	$ 1,630.02
Dec 1993	$ 29.09	$ 383.30	$ 13.77	$ 4.97	$ 2.34	$ 1,094.30	$ 1,724.19
Jan 1994	$ 26.47	$ 386.88	$ 14.13	$ 5.15	$ 2.34	$ 1,174.59	$ 1,805.35
Feb 1994	$ 26.47	$ 381.91	$ 13.78	$ 5.25	$ 2.71	$ 1,269.93	$ 1,866.40

Mar 1994	$ 26.47	$ 384.13	$ 13.62	$ 5.44	$ 2.21	$ 1,289.03	$ 1,914.87
Apr 1994	$ 26.47	$ 377.27	$ 15.08	$ 5.35	$ 2.04	$ 1,278.72	$ 1,881.82
May 1994	$ 26.47	$ 381.43	$ 16.28	$ 5.42	$ 1.92	$ 1,322.59	$ 2,150.60
Jun 1994	$ 26.47	$ 385.64	$ 17.17	$ 5.39	$ 1.90	$ 1,400.58	$ 2,364.20
Jul 1994	$ 26.47	$ 385.49	$ 17.88	$ 5.28	$ 1.96	$ 1,492.42	$ 2,458.19
Aug 1994	$ 26.47	$ 380.36	$ 17.00	$ 5.20	$ 1.66	$ 1,455.36	$ 2,406.23
Sep 1994	$ 26.47	$ 391.58	$ 16.20	$ 5.52	$ 1.49	$ 1,569.22	$ 2,505.93
Oct 1994	$ 26.47	$ 389.77	$ 16.47	$ 5.45	$ 1.51	$ 1,698.05	$ 2,547.67
Nov 1994	$ 26.47	$ 384.39	$ 17.08	$ 5.19	$ 1.58	$ 1,892.59	$ 2,802.45
Dec 1994	$ 26.47	$ 379.29	$ 15.94	$ 4.78	$ 1.72	$ 1,878.31	$ 2,985.30
Jan 1995	$ 28.38	$ 378.55	$ 16.90	$ 4.77	$ 1.51	$ 2,060.55	$ 3,008.93
Feb 1995	$ 28.38	$ 376.64	$ 17.42	$ 4.72	$ 1.58	$ 1,916.15	$ 2,877.65
Mar 1995	$ 28.38	$ 382.12	$ 17.35	$ 4.65	$ 1.54	$ 1,805.07	$ 2,924.04
Apr 1995	$ 28.38	$ 391.03	$ 18.65	$ 5.48	$ 1.62	$ 1,849.00	$ 2,903.50
May 1995	$ 28.38	$ 385.22	$ 18.42	$ 5.56	$ 1.64	$ 1,762.69	$ 2,773.31
Jun 1995	$ 28.38	$ 387.56	$ 17.36	$ 5.36	$ 1.62	$ 1,780.05	$ 2,994.64

Jul 1995	$ 28.38	$ 386.23	$ 16.08	$ 5.16	$ 1.44	$ 1,860.10	$ 3,075.67
Aug 1995	$ 28.38	$ 383.67	$ 16.47	$ 5.40	$ 1.56	$ 1,888.32	$ 3,036.84
Sep 1995	$ 28.38	$ 383.06	$ 16.82	$ 5.43	$ 1.64	$ 1,760.83	$ 2,915.52
Oct 1995	$ 28.38	$ 383.14	$ 16.12	$ 5.37	$ 1.77	$ 1,674.32	$ 2,813.55
Nov 1995	$ 28.38	$ 385.31	$ 16.74	$ 5.32	$ 2.04	$ 1,654.07	$ 2,977.36
Dec 1995	$ 28.38	$ 387.44	$ 17.87	$ 5.18	$ 2.71	$ 1,656.74	$ 2,926.26
Jan 1996	$ 30.00	$ 399.45	$ 17.80	$ 5.46	$ 2.93	$ 1,589.34	$ 2,616.41
Feb 1996	$ 30.00	$ 404.76	$ 17.70	$ 5.66	$ 4.40	$ 1,591.55	$ 2,537.71
Mar 1996	$ 30.00	$ 396.21	$ 19.40	$ 5.52	$ 2.95	$ 1,612.48	$ 2,561.02
Apr 1996	$ 30.00	$ 392.85	$ 20.66	$ 5.42	$ 2.23	$ 1,587.23	$ 2,595.78
May 1996	$ 30.00	$ 391.93	$ 19.06	$ 5.37	$ 2.24	$ 1,589.26	$ 2,658.26
Jun 1996	$ 30.00	$ 385.27	$ 18.51	$ 5.16	$ 2.49	$ 1,482.48	$ 2,173.40
Jul 1996	$ 30.00	$ 383.47	$ 19.59	$ 5.07	$ 2.48	$ 1,458.70	$ 1,985.57
Aug 1996	$ 30.00	$ 387.35	$ 20.44	$ 5.14	$ 2.03	$ 1,463.36	$ 2,008.57
Sep 1996	$ 30.00	$ 383.14	$ 22.26	$ 5.04	$ 1.84	$ 1,407.38	$ 1,941.45
Oct 1996	$ 30.00	$ 381.07	$ 23.61	$ 4.93	$ 2.37	$ 1,336.34	$ 1,961.17

Nov 1996	$ 30.00	$ 377.85	$ 22.39	$ 4.83	$ 3.03	$ 1,449.52	$ 2,230.86
Dec 1996	$ 30.00	$ 369.00	$ 23.62	$ 4.83	$ 3.82	$ 1,500.29	$ 2,268.08
Jan 1997	$ 30.15	$ 355.11	$ 23.23	$ 4.77	$ 3.31	$ 1,575.61	$ 2,434.93
Feb 1997	$ 30.15	$ 346.58	$ 20.42	$ 5.07	$ 2.22	$ 1,580.01	$ 2,405.85
Mar 1997	$ 30.15	$ 351.81	$ 19.33	$ 5.20	$ 1.89	$ 1,631.57	$ 2,421.29
Apr 1997	$ 30.15	$ 344.47	$ 17.88	$ 4.77	$ 2.03	$ 1,561.44	$ 2,391.18
May 1997	$ 30.15	$ 343.84	$ 19.37	$ 4.75	$ 2.24	$ 1,625.25	$ 2,514.33
Jun 1997	$ 30.15	$ 340.76	$ 17.92	$ 4.76	$ 2.20	$ 1,567.55	$ 2,612.62
Jul 1997	$ 30.15	$ 324.10	$ 18.33	$ 4.37	$ 2.19	$ 1,591.99	$ 2,450.46
Aug 1997	$ 30.15	$ 324.01	$ 18.70	$ 4.50	$ 2.47	$ 1,710.58	$ 2,251.20
Sep 1997	$ 30.15	$ 322.82	$ 18.66	$ 4.73	$ 2.84	$ 1,610.60	$ 2,107.30
Oct 1997	$ 30.15	$ 324.87	$ 20.04	$ 5.03	$ 3.04	$ 1,607.86	$ 2,052.26
Nov 1997	$ 30.15	$ 306.04	$ 19.09	$ 5.08	$ 3.02	$ 1,598.99	$ 1,917.45
Dec 1997	$ 30.15	$ 288.74	$ 17.09	$ 5.84	$ 2.33	$ 1,530.51	$ 1,762.33
Jan 1998	$ 31.00	$ 289.10	$ 15.00	$ 5.89	$ 2.10	$ 1,485.79	$ 1,688.45
Feb 1998	$ 31.00	$ 297.49	$ 14.10	$ 6.81	$ 2.22	$ 1,465.56	$ 1,664.80

Mar 1998	$ 31.00	$ 295.94	$ 13.12	$ 6.24	$ 2.23	$ 1,437.70	$ 1,747.98
Apr 1998	$ 31.00	$ 308.29	$ 13.50	$ 6.34	$ 2.42	$ 1,418.16	$ 1,800.90
May 1998	$ 31.00	$ 299.10	$ 14.03	$ 5.58	$ 2.14	$ 1,364.72	$ 1,732.53
Jun 1998	$ 31.00	$ 292.32	$ 12.48	$ 5.26	$ 2.17	$ 1,307.24	$ 1,660.52
Jul 1998	$ 31.00	$ 292.87	$ 12.70	$ 5.46	$ 2.17	$ 1,309.21	$ 1,651.04
Aug 1998	$ 31.00	$ 284.11	$ 12.49	$ 5.18	$ 1.85	$ 1,310.90	$ 1,620.93
Sep 1998	$ 31.00	$ 288.98	$ 13.80	$ 5.00	$ 2.01	$ 1,342.27	$ 1,647.64
Oct 1998	$ 31.00	$ 295.93	$ 13.26	$ 5.01	$ 1.89	$ 1,304.06	$ 1,586.39
Nov 1998	$ 31.00	$ 294.12	$ 11.88	$ 4.97	$ 2.10	$ 1,294.96	$ 1,573.95
Dec 1998	$ 31.00	$ 291.68	$ 10.41	$ 4.88	$ 1.74	$ 1,249.06	$ 1,473.57
Jan 1999	$ 27.59	$ 287.08	$ 11.44	$ 5.14	$ 1.86	$ 1,218.46	$ 1,431.18
Feb 1999	$ 27.59	$ 287.33	$ 10.75	$ 5.53	$ 1.77	$ 1,186.85	$ 1,410.78
Mar 1999	$ 27.59	$ 285.96	$ 13.17	$ 5.19	$ 1.79	$ 1,181.59	$ 1,378.35
Apr 1999	$ 27.59	$ 282.62	$ 15.87	$ 5.06	$ 2.15	$ 1,278.20	$ 1,466.00
May 1999	$ 27.59	$ 276.44	$ 16.06	$ 5.26	$ 2.25	$ 1,323.46	$ 1,511.16
Jun 1999	$ 27.59	$ 261.31	$ 16.39	$ 5.03	$ 2.30	$ 1,315.31	$ 1,422.48

Jul 1999	$ 27.59	$ 256.08	$ 18.99	$ 5.18	$ 2.31	$ 1,403.76	$ 1,640.00
Aug 1999	$ 27.59	$ 256.69	$ 20.27	$ 5.26	$ 2.79	$ 1,431.32	$ 1,647.62
Sep 1999	$ 27.59	$ 264.74	$ 22.70	$ 5.21	$ 2.54	$ 1,492.48	$ 1,750.34
Oct 1999	$ 27.59	$ 310.72	$ 21.95	$ 5.41	$ 2.72	$ 1,474.41	$ 1,724.12
Nov 1999	$ 27.59	$ 293.18	$ 24.16	$ 5.15	$ 2.36	$ 1,472.76	$ 1,727.55
Dec 1999	$ 27.59	$ 283.07	$ 25.10	$ 5.16	$ 2.36	$ 1,554.48	$ 1,764.75
Jan 2000	$ 28.79	$ 284.32	$ 25.31	$ 5.19	$ 2.42	$ 1,680.28	$ 1,843.98
Feb 2000	$ 28.79	$ 299.86	$ 27.22	$ 5.25	$ 2.65	$ 1,670.27	$ 1,800.83
Mar 2000	$ 28.79	$ 286.39	$ 27.49	$ 5.06	$ 2.79	$ 1,577.05	$ 1,739.39
Apr 2000	$ 28.79	$ 279.69	$ 23.47	$ 5.06	$ 3.03	$ 1,457.14	$ 1,678.75
May 2000	$ 28.79	$ 275.19	$ 27.19	$ 4.98	$ 3.58	$ 1,466.79	$ 1,785.62
Jun 2000	$ 28.79	$ 285.73	$ 29.62	$ 5.00	$ 4.28	$ 1,506.31	$ 1,753.18
Jul 2000	$ 28.79	$ 281.59	$ 28.18	$ 4.97	$ 3.96	$ 1,563.50	$ 1,799.36
Aug 2000	$ 28.79	$ 274.47	$ 29.26	$ 4.89	$ 4.41	$ 1,527.63	$ 1,855.86
Sep 2000	$ 28.79	$ 273.68	$ 32.08	$ 4.89	$ 5.06	$ 1,601.21	$ 1,960.41
Oct 2000	$ 28.79	$ 270.00	$ 31.40	$ 4.83	$ 5.02	$ 1,500.24	$ 1,898.59

Nov 2000	$ 28.79	$ 266.01	$ 32.33	$ 4.68	$ 5.55	$ 1,473.86	$ 1,795.11
Dec 2000	$ 28.79	$ 271.45	$ 25.20	$ 4.64	$ 8.95	$ 1,565.41	$ 1,850.55
Jan 2001	$ 30.03	$ 265.49	$ 25.96	$ 4.66	$ 8.17	$ 1,615.65	$ 1,787.50
Feb 2001	$ 30.03	$ 261.87	$ 27.24	$ 4.56	$ 5.63	$ 1,604.36	$ 1,765.65
Mar 2001	$ 30.03	$ 263.03	$ 25.02	$ 4.40	$ 5.16	$ 1,509.17	$ 1,738.77
Apr 2001	$ 30.03	$ 260.48	$ 25.72	$ 4.37	$ 5.17	$ 1,496.91	$ 1,664.16
May 2001	$ 30.03	$ 272.36	$ 27.55	$ 4.43	$ 4.21	$ 1,538.77	$ 1,682.21
Jun 2001	$ 30.03	$ 270.23	$ 26.97	$ 4.37	$ 3.71	$ 1,466.13	$ 1,608.45
Jul 2001	$ 30.03	$ 267.53	$ 24.80	$ 4.25	$ 3.10	$ 1,416.39	$ 1,525.21
Aug 2001	$ 30.03	$ 272.39	$ 25.82	$ 4.22	$ 2.95	$ 1,377.08	$ 1,464.43
Sep 2001	$ 30.03	$ 283.42	$ 25.21	$ 4.35	$ 2.15	$ 1,344.56	$ 1,426.33
Oct 2001	$ 30.03	$ 283.06	$ 20.73	$ 4.40	$ 2.45	$ 1,282.50	$ 1,377.28
Nov 2001	$ 30.03	$ 276.16	$ 18.69	$ 4.12	$ 2.36	$ 1,327.46	$ 1,427.73
Dec 2001	$ 30.03	$ 275.85	$ 18.52	$ 4.37	$ 2.41	$ 1,344.63	$ 1,471.74
Jan 2002	$ 29.31	$ 281.51	$ 19.15	$ 4.51	$ 2.25	$ 1,368.59	$ 1,503.96
Feb 2002	$ 29.31	$ 295.50	$ 19.98	$ 4.42	$ 2.31	$ 1,369.34	$ 1,561.90

Mar 2002	$ 29.31	$ 294.06	$ 23.64	$ 4.54	$ 3.03	$ 1,405.00	$ 1,604.88
Apr 2002	$ 29.31	$ 302.68	$ 25.43	$ 4.58	$ 3.42	$ 1,369.99	$ 1,590.33
May 2002	$ 29.31	$ 314.49	$ 25.67	$ 4.70	$ 3.49	$ 1,343.30	$ 1,595.68
Jun 2002	$ 29.31	$ 321.18	$ 24.49	$ 4.90	$ 3.22	$ 1,353.97	$ 1,647.53
Jul 2002	$ 29.31	$ 313.29	$ 25.75	$ 4.92	$ 2.98	$ 1,338.09	$ 1,589.46
Aug 2002	$ 29.31	$ 310.26	$ 26.78	$ 4.54	$ 3.09	$ 1,291.60	$ 1,479.55
Sep 2002	$ 29.31	$ 319.14	$ 28.28	$ 4.55	$ 3.57	$ 1,301.25	$ 1,478.71
Oct 2002	$ 29.31	$ 316.56	$ 27.53	$ 4.40	$ 4.12	$ 1,310.58	$ 1,483.76
Nov 2002	$ 29.31	$ 319.07	$ 24.54	$ 4.51	$ 4.04	$ 1,372.20	$ 1,582.29
Dec 2002	$ 29.31	$ 331.92	$ 27.89	$ 4.63	$ 4.74	$ 1,375.07	$ 1,595.68
Jan 2003	$ 31.95	$ 356.86	$ 30.75	$ 4.81	$ 5.41	$ 1,378.28	$ 1,647.66
Feb 2003	$ 31.95	$ 358.97	$ 32.88	$ 4.66	$ 7.77	$ 1,422.16	$ 1,683.80
Mar 2003	$ 31.95	$ 340.55	$ 30.36	$ 4.53	$ 5.95	$ 1,389.27	$ 1,658.98
Apr 2003	$ 31.95	$ 328.18	$ 25.56	$ 4.49	$ 5.29	$ 1,332.01	$ 1,587.48
May 2003	$ 31.95	$ 355.68	$ 26.06	$ 4.74	$ 5.84	$ 1,398.49	$ 1,648.28
Jun 2003	$ 31.95	$ 356.35	$ 27.92	$ 4.53	$ 5.77	$ 1,409.85	$ 1,686.50

Jul 2003	$ 31.95	$ 351.02	$ 28.59	$ 4.80	$ 5.01	$ 1,436.09	$ 1,710.00
Aug 2003	$ 31.95	$ 359.77	$ 29.68	$ 4.99	$ 4.97	$ 1,456.31	$ 1,760.28
Sep 2003	$ 31.95	$ 378.95	$ 26.88	$ 5.17	$ 4.61	$ 1,415.57	$ 1,789.52
Oct 2003	$ 31.95	$ 378.92	$ 29.01	$ 5.00	$ 4.64	$ 1,474.25	$ 1,920.54
Nov 2003	$ 31.95	$ 389.91	$ 29.12	$ 5.18	$ 4.53	$ 1,508.34	$ 2,055.43
Dec 2003	$ 31.95	$ 406.95	$ 29.97	$ 5.63	$ 6.13	$ 1,554.91	$ 2,201.29
Jan 2004	$ 37.90	$ 413.79	$ 31.37	$ 6.30	$ 6.09	$ 1,606.49	$ 2,423.57
Feb 2004	$ 37.90	$ 404.88	$ 31.33	$ 6.44	$ 5.38	$ 1,685.63	$ 2,759.53
Mar 2004	$ 37.90	$ 406.67	$ 33.67	$ 7.23	$ 5.40	$ 1,655.99	$ 3,008.72
Apr 2004	$ 37.90	$ 403.26	$ 33.71	$ 7.15	$ 5.72	$ 1,729.74	$ 2,948.73
May 2004	$ 37.90	$ 383.78	$ 37.56	$ 5.87	$ 6.34	$ 1,623.22	$ 2,733.50
Jun 2004	$ 37.90	$ 392.37	$ 35.54	$ 5.86	$ 6.27	$ 1,677.72	$ 2,686.71
Jul 2004	$ 37.90	$ 398.09	$ 37.89	$ 6.31	$ 5.93	$ 1,709.27	$ 2,808.43
Aug 2004	$ 37.90	$ 400.51	$ 42.08	$ 6.66	$ 5.40	$ 1,692.19	$ 2,846.10
Sep 2004	$ 37.90	$ 405.28	$ 41.60	$ 6.40	$ 5.14	$ 1,723.60	$ 2,894.86
Oct 2004	$ 37.90	$ 420.46	$ 46.88	$ 7.10	$ 6.41	$ 1,819.57	$ 3,012.24

Nov 2004	$ 37.90	$ 439.38	$ 42.13	$ 7.49	$ 6.09	$ 1,813.90	$ 3,122.80
Dec 2004	$ 37.90	$ 442.08	$ 39.04	$ 7.09	$ 6.58	$ 1,849.18	$ 3,145.45
Jan 2005	$ 65.00	$ 424.03	$ 42.97	$ 6.62	$ 6.15	$ 1,834.43	$ 3,170.00
Feb 2005	$ 65.00	$ 423.35	$ 44.82	$ 7.03	$ 6.14	$ 1,882.85	$ 3,253.70
Mar 2005	$ 65.00	$ 433.85	$ 50.94	$ 7.23	$ 6.97	$ 1,979.85	$ 3,379.49
Apr 2005	$ 65.00	$ 429.23	$ 50.64	$ 7.12	$ 7.15	$ 1,894.29	$ 3,394.48
May 2005	$ 65.00	$ 421.87	$ 47.83	$ 7.02	$ 6.47	$ 1,743.70	$ 3,249.10
Jun 2005	$ 65.00	$ 430.66	$ 53.89	$ 7.31	$ 7.19	$ 1,731.30	$ 3,524.07
Jul 2005	$ 65.00	$ 424.48	$ 56.37	$ 7.01	$ 7.63	$ 1,778.79	$ 3,614.21
Aug 2005	$ 65.00	$ 437.93	$ 61.89	$ 7.03	$ 9.63	$ 1,867.84	$ 3,797.75
Sep 2005	$ 65.00	$ 456.05	$ 61.69	$ 7.15	$ 12.88	$ 1,839.91	$ 3,857.84
Oct 2005	$ 65.00	$ 469.90	$ 58.19	$ 7.67	$ 13.52	$ 1,928.71	$ 4,059.76
Nov 2005	$ 65.00	$ 476.67	$ 55.04	$ 7.87	$ 10.43	$ 2,050.59	$ 4,269.34
Dec 2005	$ 65.00	$ 510.10	$ 56.43	$ 8.63	$ 12.83	$ 2,247.45	$ 4,576.78
Jan 2006	$ 67.20	$ 549.86	$ 62.46	$ 9.14	$ 8.66	$ 2,377.86	$ 4,734.33
Feb 2006	$ 65.20	$ 555.00	$ 59.70	$ 9.53	$ 7.49	$ 2,455.33	$ 4,982.40

Mar 2006	$ 66.70	$ 557.09	$ 60.93	$ 10.38	$ 6.90	$ 2,429.13	$ 5,102.85
Apr 2006	$ 67.30	$ 610.65	$ 67.97	$ 12.61	$ 7.09	$ 2,621.11	$ 6,387.78
May 2006	$ 67.30	$ 675.39	$ 68.68	$ 13.38	$ 6.20	$ 2,861.48	$ 8,045.86
Jun 2006	$ 69.30	$ 596.15	$ 68.29	$ 10.80	$ 6.19	$ 2,477.34	$ 7,197.61
Jul 2006	$ 70.50	$ 633.71	$ 72.45	$ 11.23	$ 6.25	$ 2,512.71	$ 7,712.10
Aug 2006	$ 69.80	$ 632.59	$ 71.81	$ 12.19	$ 7.00	$ 2,459.93	$ 7,695.66
Sep 2006	$ 70.00	$ 598.19	$ 62.12	$ 11.68	$ 4.86	$ 2,472.88	$ 7,602.36
Oct 2006	$ 71.70	$ 585.78	$ 57.91	$ 11.56	$ 5.96	$ 2,654.59	$ 7,500.39
Nov 2006	$ 73.50	$ 627.83	$ 58.14	$ 12.93	$ 7.45	$ 2,702.80	$ 7,029.18
Dec 2006	$ 73.50	$ 629.79	$ 60.99	$ 13.28	$ 6.58	$ 2,813.63	$ 6,675.11
Jan 2007	$ 78.20	$ 631.17	$ 53.52	$ 12.84	$ 6.58	$ 2,809.34	$ 5,669.66
Feb 2007	$ 82.66	$ 664.75	$ 57.56	$ 13.91	$ 7.97	$ 2,832.20	$ 5,676.45
Mar 2007	$ 88.55	$ 654.90	$ 60.60	$ 13.18	$ 7.12	$ 2,761.73	$ 6,452.48
Apr 2007	$ 91.26	$ 679.37	$ 65.06	$ 13.72	$ 7.59	$ 2,814.79	$ 7,766.47
May 2007	$ 102.02	$ 667.31	$ 65.16	$ 13.15	$ 7.61	$ 2,792.75	$ 7,681.42
Jun 2007	$ 103.21	$ 655.66	$ 68.19	$ 13.14	$ 7.30	$ 2,676.93	$ 7,474.38

Jul 2007	$ 106.09	$ 665.38	$ 73.60	$ 12.91	$ 6.22	$ 2,732.44	$ 7,972.57
Aug 2007	$ 121.89	$ 665.41	$ 70.13	$ 12.33	$ 6.20	$ 2,515.77	$ 7,513.50
Sep 2007	$ 148.65	$ 712.65	$ 76.76	$ 12.83	$ 6.10	$ 2,391.25	$ 7,648.98
Oct 2007	$ 168.11	$ 754.60	$ 81.97	$ 13.67	$ 6.80	$ 2,442.37	$ 8,008.44
Nov 2007	$ 195.09	$ 806.25	$ 91.34	$ 14.70	$ 7.14	$ 2,506.89	$ 6,966.71
Dec 2007	$ 190.12	$ 803.20	$ 89.52	$ 14.30	$ 7.15	$ 2,381.69	$ 6,587.67
Jan 2008	$ 193.37	$ 889.60	$ 90.69	$ 15.91	$ 8.00	$ 2,445.52	$ 7,061.02
Feb 2008	$ 186.12	$ 922.30	$ 93.39	$ 17.57	$ 8.55	$ 2,776.93	$ 7,887.69
Mar 2008	$ 197.12	$ 968.43	$ 101.84	$ 19.32	$ 9.40	$ 3,005.29	$ 8,439.29
Apr 2008	$ 195.95	$ 909.71	$ 108.76	$ 17.50	$ 10.13	$ 2,959.27	$ 8,684.93
May 2008	$ 192.95	$ 888.66	$ 122.63	$ 17.06	$ 11.23	$ 2,902.90	$ 8,382.75
Jun 2008	$ 183.93	$ 889.49	$ 131.52	$ 16.97	$ 12.68	$ 2,957.86	$ 8,260.60
Jul 2008	$ 180.50	$ 939.77	$ 132.83	$ 18.03	$ 11.15	$ 3,071.24	$ 8,414.04
Aug 2008	$ 178.74	$ 839.03	$ 114.57	$ 14.64	$ 8.25	$ 2,764.38	$ 7,634.70
Sep 2008	$ 139.64	$ 829.93	$ 99.66	$ 12.37	$ 7.69	$ 2,525.82	$ 6,990.86
Oct 2008	$ 88.67	$ 806.62	$ 72.69	$ 10.44	$ 6.73	$ 2,121.41	$ 4,925.70

Nov 2008	$ 64.95	$ 760.86	$ 53.97	$ 9.87	$ 6.67	$ 1,852.43	$ 3,717.00
Dec 2008	$ 69.98	$ 816.09	$ 41.34	$ 10.29	$ 5.79	$ 1,490.43	$ 3,071.98
Jan 2009	$ 72.51	$ 858.69	$ 43.86	$ 11.27	$ 5.24	$ 1,413.12	$ 3,220.69
Feb 2009	$ 75.59	$ 943.00	$ 41.84	$ 13.41	$ 4.52	$ 1,330.20	$ 3,314.73
Mar 2009	$ 64.07	$ 924.27	$ 46.65	$ 13.12	$ 3.95	$ 1,335.84	$ 3,749.75
Apr 2009	$ 59.78	$ 890.20	$ 50.28	$ 12.48	$ 3.50	$ 1,420.85	$ 4,406.55
May 2009	$ 62.69	$ 928.65	$ 58.15	$ 13.98	$ 3.81	$ 1,460.45	$ 4,568.63
Jun 2009	$ 71.66	$ 945.67	$ 69.15	$ 14.65	$ 3.80	$ 1,573.73	$ 5,013.96
Jul 2009	$ 83.95	$ 934.23	$ 64.67	$ 13.36	$ 3.39	$ 1,667.96	$ 5,215.54
Aug 2009	$ 97.67	$ 949.38	$ 71.63	$ 14.36	$ 3.15	$ 1,933.75	$ 6,165.30
Sep 2009	$ 80.71	$ 996.59	$ 68.35	$ 16.39	$ 2.96	$ 1,834.11	$ 6,196.43
Oct 2009	$ 86.79	$ 1,043.16	$ 74.08	$ 17.24	$ 4.02	$ 1,878.57	$ 6,287.98
Nov 2009	$ 99.26	$ 1,127.04	$ 77.55	$ 17.82	$ 3.69	$ 1,949.29	$ 6,675.60
Dec 2009	$ 105.07	$ 1,134.72	$ 74.88	$ 17.64	$ 5.37	$ 2,180.10	$ 6,981.71
Jan 2010	$ 125.72	$ 1,117.96	$ 77.12	$ 17.75	$ 5.81	$ 2,235.15	$ 7,386.25
Feb 2010	$ 127.49	$ 1,095.41	$ 74.76	$ 15.87	$ 5.34	$ 2,048.93	$ 6,848.18

Mar 2010	$ 139.69	$ 1,113.34	$ 79.30	$ 17.11	$ 4.29	$ 2,205.63	$ 7,462.83
Apr 2010	$ 172.47	$ 1,148.69	$ 84.18	$ 18.06	$ 4.01	$ 2,316.73	$ 7,745.08
May 2010	$ 161.35	$ 1,205.43	$ 75.62	$ 18.43	$ 4.16	$ 2,040.53	$ 6,837.68
Jun 2010	$ 143.63	$ 1,232.92	$ 74.73	$ 18.45	$ 4.79	$ 1,931.39	$ 6,499.30
Jul 2010	$ 126.36	$ 1,192.97	$ 74.58	$ 17.96	$ 4.63	$ 1,988.27	$ 6,735.25
Aug 2010	$ 145.34	$ 1,215.81	$ 75.83	$ 18.39	$ 4.31	$ 2,118.14	$ 7,283.95
Sep 2010	$ 140.63	$ 1,270.98	$ 76.12	$ 20.55	$ 3.90	$ 2,162.34	$ 7,709.30
Oct 2010	$ 148.48	$ 1,342.02	$ 81.72	$ 23.39	$ 3.43	$ 2,346.57	$ 8,292.41
Nov 2010	$ 156.10	$ 1,369.89	$ 84.53	$ 26.54	$ 3.73	$ 2,333.07	$ 8,469.89
Dec 2010	$ 163.10	$ 1,390.55	$ 90.01	$ 29.32	$ 4.24	$ 2,350.67	$ 9,147.26
Jan 2011	$ 179.18	$ 1,360.46	$ 92.69	$ 28.51	$ 4.49	$ 2,439.53	$ 9,555.70
Feb 2011	$ 187.18	$ 1,374.68	$ 97.91	$ 30.78	$ 4.07	$ 2,508.18	$ 9,867.60
Mar 2011	$ 169.36	$ 1,423.26	$ 108.65	$ 35.81	$ 3.97	$ 2,555.50	$ 9,503.36
Apr 2011	$ 179.33	$ 1,480.89	$ 116.24	$ 42.70	$ 4.24	$ 2,678.11	$ 9,492.79
May 2011	$ 177.05	$ 1,512.58	$ 108.07	$ 37.34	$ 4.31	$ 2,596.45	$ 8,959.90
Jun 2011	$ 170.88	$ 1,529.36	$ 105.85	$ 35.80	$ 4.55	$ 2,557.76	$ 9,066.85

Jul 2011	$ 172.98	$ 1,572.75	$ 107.92	$ 37.92	$ 4.41	$ 2,525.43	$ 9,650.46
Aug 2011	$ 177.50	$ 1,759.01	$ 100.49	$ 40.33	$ 4.05	$ 2,379.35	$ 9,000.76
Sep 2011	$ 177.23	$ 1,772.14	$ 100.82	$ 38.15	$ 3.90	$ 2,293.46	$ 8,300.14
Oct 2011	$ 150.43	$ 1,666.43	$ 99.85	$ 31.97	$ 3.57	$ 2,180.65	$ 7,394.19
Nov 2011	$ 135.54	$ 1,739.00	$ 105.41	$ 33.08	$ 3.24	$ 2,079.98	$ 7,581.02
Dec 2011	$ 136.39	$ 1,639.97	$ 104.23	$ 30.30	$ 3.16	$ 2,022.25	$ 7,565.48
Jan 2012	$ 140.26	$ 1,654.05	$ 107.07	$ 30.65	$ 2.68	$ 2,144.20	$ 8,040.47
Feb 2012	$ 140.40	$ 1,744.82	$ 112.69	$ 34.14	$ 2.52	$ 2,207.92	$ 8,441.49
Mar 2012	$ 144.66	$ 1,675.95	$ 117.79	$ 32.95	$ 2.17	$ 2,184.16	$ 8,470.78
Apr 2012	$ 147.64	$ 1,649.20	$ 113.67	$ 31.53	$ 1.95	$ 2,049.67	$ 8,289.48
May 2012	$ 136.61	$ 1,589.04	$ 104.09	$ 28.72	$ 2.44	$ 2,007.63	$ 7,955.64
Jun 2012	$ 134.66	$ 1,598.76	$ 90.73	$ 27.98	$ 2.46	$ 1,890.18	$ 7,423.02
Jul 2012	$ 127.94	$ 1,594.29	$ 96.75	$ 27.43	$ 2.95	$ 1,876.25	$ 7,584.26
Aug 2012	$ 107.50	$ 1,630.31	$ 105.27	$ 28.80	$ 2.84	$ 1,845.38	$ 7,515.53
Sep 2012	$ 99.47	$ 1,744.81	$ 106.28	$ 33.61	$ 2.84	$ 2,064.12	$ 8,087.74
Oct 2012	$ 113.95	$ 1,746.58	$ 103.41	$ 33.19	$ 3.32	$ 1,974.30	$ 8,062.03

Nov 2012	$ 120.35	$ 1,721.64	$ 101.17	$ 32.77	$ 3.54	$ 1,948.83	$ 7,711.23
Dec 2012	$ 128.51	$ 1,684.76	$ 101.19	$ 31.87	$ 3.34	$ 2,086.76	$ 7,966.49
Jan 2013	$ 150.49	$ 1,671.85	$ 105.10	$ 31.06	$ 3.33	$ 2,037.75	$ 8,047.36
Feb 2013	$ 154.64	$ 1,627.57	$ 107.64	$ 30.33	$ 3.33	$ 2,053.60	$ 8,060.93
Mar 2013	$ 139.87	$ 1,593.09	$ 102.52	$ 28.79	$ 3.81	$ 1,909.57	$ 7,645.58
Apr 2013	$ 137.39	$ 1,487.86	$ 98.85	$ 25.36	$ 4.17	$ 1,861.67	$ 7,234.28
May 2013	$ 124.01	$ 1,414.03	$ 99.37	$ 23.04	$ 4.04	$ 1,832.02	$ 7,249.41
Jun 2013	$ 114.82	$ 1,343.35	$ 99.74	$ 21.11	$ 3.83	$ 1,814.54	$ 7,000.24
Jul 2013	$ 127.19	$ 1,285.52	$ 105.26	$ 19.71	$ 3.62	$ 1,769.61	$ 6,906.64
Aug 2013	$ 137.06	$ 1,351.74	$ 108.16	$ 21.89	$ 3.43	$ 1,817.62	$ 7,192.92
Sep 2013	$ 134.19	$ 1,348.60	$ 108.76	$ 22.56	$ 3.62	$ 1,761.30	$ 7,159.27
Oct 2013	$ 132.57	$ 1,316.58	$ 105.43	$ 21.92	$ 3.67	$ 1,814.58	$ 7,203.02
Nov 2013	$ 136.32	$ 1,275.86	$ 102.63	$ 20.76	$ 3.62	$ 1,747.96	$ 7,070.65
Dec 2013	$ 135.79	$ 1,221.51	$ 105.48	$ 19.67	$ 4.24	$ 1,739.81	$ 7,214.90
Jan 2014	$ 128.12	$ 1,244.27	$ 102.10	$ 19.88	$ 4.70	$ 1,727.41	$ 7,291.47
Feb 2014	$ 121.37	$ 1,299.58	$ 104.83	$ 20.85	$ 5.97	$ 1,695.17	$ 7,149.21

Mar 2014	$ 111.83	$ 1,336.08	$ 104.04	$ 20.72	$ 4.88	$ 1,705.37	$ 6,650.04
Apr 2014	$ 114.58	$ 1,298.45	$ 104.87	$ 19.74	$ 4.63	$ 1,810.67	$ 6,673.56
May 2014	$ 100.56	$ 1,288.74	$ 105.71	$ 19.34	$ 4.56	$ 1,751.05	$ 6,891.13
Jun 2014	$ 92.74	$ 1,279.10	$ 108.37	$ 19.89	$ 4.57	$ 1,838.95	$ 6,821.14
Jul 2014	$ 96.05	$ 1,310.59	$ 105.23	$ 20.92	$ 4.01	$ 1,948.30	$ 7,113.38
Aug 2014	$ 92.61	$ 1,295.13	$ 100.05	$ 19.74	$ 3.88	$ 2,030.49	$ 7,001.84
Sep 2014	$ 82.38	$ 1,236.55	$ 95.85	$ 18.37	$ 3.92	$ 1,990.43	$ 6,872.22
Oct 2014	$ 81.06	$ 1,222.49	$ 86.08	$ 17.16	$ 3.77	$ 1,946.19	$ 6,737.48
Nov 2014	$ 73.73	$ 1,175.33	$ 76.99	$ 15.97	$ 4.10	$ 2,055.55	$ 6,712.85
Dec 2014	$ 68.39	$ 1,200.62	$ 60.70	$ 16.30	$ 3.43	$ 1,909.46	$ 6,446.45
Jan 2015	$ 68.23	$ 1,250.75	$ 47.11	$ 17.24	$ 2.97	$ 1,814.72	$ 5,830.54
Feb 2015	$ 62.75	$ 1,227.08	$ 54.79	$ 16.79	$ 2.85	$ 1,817.82	$ 5,729.27
Mar 2015	$ 58.05	$ 1,178.63	$ 52.83	$ 16.24	$ 2.80	$ 1,773.86	$ 5,939.67
Apr 2015	$ 52.28	$ 1,198.93	$ 57.54	$ 16.34	$ 2.58	$ 1,819.19	$ 6,042.09
May 2015	$ 60.30	$ 1,198.63	$ 62.51	$ 16.83	$ 2.84	$ 1,804.04	$ 6,294.78
Jun 2015	$ 62.63	$ 1,181.50	$ 61.31	$ 16.08	$ 2.77	$ 1,687.73	$ 5,833.01

Jul 2015	$ 52.39	$ 1,128.31	$ 54.34	$ 15.05	$ 2.83	$ 1,639.50	$ 5,456.75
Aug 2015	$ 56.19	$ 1,117.93	$ 45.69	$ 14.94	$ 2.76	$ 1,548.13	$ 5,127.30
Sep 2015	$ 56.95	$ 1,124.77	$ 46.28	$ 14.75	$ 2.65	$ 1,589.60	$ 5,217.25
Oct 2015	$ 53.12	$ 1,159.25	$ 46.96	$ 15.81	$ 2.32	$ 1,516.49	$ 5,216.09
Nov 2015	$ 46.86	$ 1,086.44	$ 43.11	$ 14.45	$ 2.08	$ 1,467.89	$ 4,799.90
Dec 2015	$ 40.50	$ 1,075.74	$ 36.57	$ 14.13	$ 1.92	$ 1,497.20	$ 4,638.83
Jan 2016	$ 41.88	$ 1,097.91	$ 29.78	$ 14.11	$ 2.27	$ 1,481.10	$ 4,471.79
Feb 2016	$ 46.83	$ 1,199.50	$ 31.03	$ 15.17	$ 1.96	$ 1,531.26	$ 4,598.62
Mar 2016	$ 56.20	$ 1,245.14	$ 37.34	$ 15.47	$ 1.70	$ 1,531.01	$ 4,953.80
Apr 2016	$ 60.92	$ 1,242.26	$ 40.75	$ 16.36	$ 1.90	$ 1,571.23	$ 4,872.74
May 2016	$ 55.13	$ 1,260.95	$ 45.94	$ 16.95	$ 1.92	$ 1,550.63	$ 4,694.54
Jun 2016	$ 51.98	$ 1,276.40	$ 47.69	$ 17.29	$ 2.57	$ 1,593.51	$ 4,641.97
Jul 2016	$ 57.26	$ 1,336.66	$ 44.13	$ 19.99	$ 2.79	$ 1,629.05	$ 4,864.90
Aug 2016	$ 60.89	$ 1,340.17	$ 44.88	$ 19.59	$ 2.79	$ 1,639.28	$ 4,751.67
Sep 2016	$ 57.79	$ 1,326.61	$ 45.04	$ 19.36	$ 2.97	$ 1,592.36	$ 4,722.20
Oct 2016	$ 59.09	$ 1,266.55	$ 49.29	$ 17.66	$ 2.95	$ 1,665.90	$ 4,731.26

Nov 2016	$ 73.10	$ 1,238.35	$ 45.26	$ 17.41	$ 2.50	$ 1,737.11	$ 5,450.93
Dec 2016	$ 80.02	$ 1,157.36	$ 52.62	$ 16.43	$ 3.58	$ 1,727.74	$ 5,660.35
Jan 2017	$ 80.41	$ 1,192.10	$ 53.59	$ 16.90	$ 3.26	$ 1,791.24	$ 5,754.56
Feb 2017	$ 89.44	$ 1,234.20	$ 54.35	$ 17.93	$ 2.82	$ 1,860.75	$ 5,940.91
Mar 2017	$ 87.65	$ 1,231.42	$ 50.90	$ 17.63	$ 2.87	$ 1,901.47	$ 5,824.63
Apr 2017	$ 70.22	$ 1,266.88	$ 52.16	$ 18.03	$ 3.08	$ 1,921.22	$ 5,683.90
May 2017	$ 62.43	$ 1,246.04	$ 49.89	$ 16.75	$ 3.12	$ 1,913.02	$ 5,599.56
Jun 2017	$ 57.48	$ 1,260.26	$ 46.17	$ 16.93	$ 2.94	$ 1,885.29	$ 5,719.76
Jul 2017	$ 67.74	$ 1,236.84	$ 47.66	$ 16.15	$ 2.96	$ 1,902.96	$ 5,985.12
Aug 2017	$ 76.07	$ 1,283.04	$ 49.94	$ 16.95	$ 2.88	$ 2,030.01	$ 6,485.63
Sep 2017	$ 71.53	$ 1,314.07	$ 52.95	$ 17.43	$ 2.96	$ 2,096.49	$ 6,577.17
Oct 2017	$ 61.66	$ 1,279.51	$ 54.92	$ 16.94	$ 2.87	$ 2,131.49	$ 6,807.60
Nov 2017	$ 64.24	$ 1,281.90	$ 59.93	$ 16.98	$ 2.99	$ 2,097.44	$ 6,826.55
Dec 2017	$ 72.25	$ 1,264.45	$ 61.19	$ 16.17	$ 2.76	$ 2,080.47	$ 6,833.89
Jan 2018	$ 76.34	$ 1,331.30	$ 66.23	$ 17.13	$ 3.88	$ 2,209.73	$ 7,065.85
Feb 2018	$ 77.46	$ 1,330.73	$ 63.46	$ 16.58	$ 2.67	$ 2,181.79	$ 7,006.52

Mar 2018	$ 70.35	$ 1,324.66	$ 64.17	$ 16.47	$ 2.69	$ 2,069.24	$ 6,799.18
Apr 2018	$ 65.75	$ 1,334.76	$ 68.79	$ 16.65	$ 2.76	$ 2,254.69	$ 6,851.51
May 2018	$ 66.10	$ 1,303.45	$ 73.43	$ 16.49	$ 2.78	$ 2,299.67	$ 6,825.27
Jun 2018	$ 65.04	$ 1,281.57	$ 71.98	$ 16.54	$ 2.94	$ 2,237.62	$ 6,965.86
Jul 2018	$ 64.56	$ 1,237.71	$ 72.67	$ 15.72	$ 2.80	$ 2,082.24	$ 6,250.75
Aug 2018	$ 67.15	$ 1,201.71	$ 71.08	$ 14.99	$ 2.96	$ 2,051.51	$ 6,051.05
Sep 2018	$ 68.44	$ 1,198.39	$ 75.36	$ 14.27	$ 3.00	$ 2,026.46	$ 6,050.76
Oct 2018	$ 73.41	$ 1,215.39	$ 76.73	$ 14.60	$ 3.29	$ 2,029.86	$ 6,219.59
Nov 2018	$ 73.26	$ 1,220.65	$ 62.32	$ 14.35	$ 4.14	$ 1,938.51	$ 6,195.92
Dec 2018	$ 69.15	$ 1,250.40	$ 53.96	$ 14.77	$ 3.95	$ 1,920.38	$ 6,075.32
Jan 2019	$ 76.16	$ 1,291.75	$ 56.58	$ 15.62	$ 3.08	$ 1,853.72	$ 5,939.10
Feb 2019	$ 88.22	$ 1,320.07	$ 61.13	$ 15.82	$ 2.72	$ 1,862.99	$ 6,300.49
Mar 2019	$ 86.47	$ 1,300.90	$ 63.79	$ 15.30	$ 2.94	$ 1,871.21	$ 6,439.46
Apr 2019	$ 93.70	$ 1,285.91	$ 68.58	$ 15.06	$ 2.65	$ 1,845.42	$ 6,438.36
May 2019	$ 100.15	$ 1,283.70	$ 66.83	$ 14.66	$ 2.63	$ 1,781.26	$ 6,017.90
Jun 2019	$ 108.94	$ 1,359.04	$ 59.76	$ 15.04	$ 2.40	$ 1,755.95	$ 5,882.23

Jul 2019	$ 120.24	$ 1,412.89	$ 61.48	$ 15.79	$ 2.36	$ 1,796.99	$ 5,941.20
Aug 2019	$ 93.07	$ 1,500.41	$ 57.67	$ 17.22	$ 2.22	$ 1,740.68	$ 5,709.44
Sep 2019	$ 93.08	$ 1,510.58	$ 60.04	$ 18.16	$ 2.58	$ 1,753.51	$ 5,759.25
Oct 2019	$ 88.53	$ 1,494.81	$ 57.27	$ 17.65	$ 2.33	$ 1,725.96	$ 5,757.30
Nov 2019	$ 84.98	$ 1,470.79	$ 60.40	$ 17.17	$ 2.65	$ 1,774.79	$ 5,859.95
Dec 2019	$ 92.65	$ 1,479.13	$ 63.35	$ 17.14	$ 2.24	$ 1,771.38	$ 6,077.06
Jan 2020	$ 95.76	$ 1,560.67	$ 61.63	$ 17.97	$ 2.03	$ 1,773.09	$ 6,031.21
Feb 2020	$ 87.68	$ 1,597.10	$ 53.35	$ 17.88	$ 1.92	$ 1,688.10	$ 5,687.75
Mar 2020	$ 88.99	$ 1,591.93	$ 32.20	$ 14.88	$ 1.79	$ 1,610.89	$ 5,182.63
Apr 2020	$ 84.73	$ 1,683.17	$ 21.04	$ 15.07	$ 1.74	$ 1,459.93	$ 5,057.97
May 2020	$ 93.65	$ 1,715.91	$ 30.38	$ 16.26	$ 1.75	$ 1,466.37	$ 5,239.83
Jun 2020	$ 103.30	$ 1,732.22	$ 39.46	$ 17.71	$ 1.62	$ 1,568.57	$ 5,754.60
Jul 2020	$ 108.52	$ 1,846.51	$ 42.07	$ 20.65	$ 1.74	$ 1,643.81	$ 6,372.46
Aug 2020	$ 121.07	$ 1,968.63	$ 43.44	$ 27.00	$ 2.30	$ 1,737.26	$ 6,498.94
Sep 2020	$ 123.75	$ 1,921.92	$ 40.60	$ 25.74	$ 1.92	$ 1,743.77	$ 6,704.90
Oct 2020	$ 119.78	$ 1,900.27	$ 39.90	$ 24.23	$ 2.25	$ 1,806.10	$ 6,713.81

Nov 2020	$ 124.36	$ 1,866.30	$ 42.30	$ 24.08	$ 2.59	$ 1,935.28	$ 7,068.91
Dec 2020	$ 155.43	$ 1,858.42	$ 48.73	$ 24.97	$ 2.54	$ 2,014.67	$ 7,772.24
Jan 2021	$ 169.63	$ 1,866.98	$ 53.60	$ 25.88	$ 2.67	$ 2,003.98	$ 7,972.15
Feb 2021	$ 163.80	$ 1,808.17	$ 60.46	$ 27.29	$ 5.04	$ 2,078.59	$ 8,470.94
Mar 2021	$ 168.18	$ 1,718.23	$ 63.83	$ 25.65	$ 2.56	$ 2,190.48	$ 8,988.25
Apr 2021	$ 179.83	$ 1,760.04	$ 62.95	$ 25.69	$ 2.62	$ 2,319.39	$ 9,324.82

Month Year	**CPI (metals), 2005 = 100)**	**Tin Price (USD) / metric tonne**	**Lead Price (USD) / metric tonne**	**Australian Coal Price (USD) / metric tonne**	**Nickel Price (USD) / metric tonne**	**Zinc Price (USD) / metric tonne**
Jul 1990	$ 45.49	$ 5,924.40	$ 875.40	$ 40.50	$ 9,318.20	$ 1,637.00
Aug 1990	$ 49.60	$ 5,905.20	$ 876.10	$ 40.50	$ 10,957.40	$ 1,615.10
Sep 1990	$ 53.23	$ 5,707.00	$ 838.50	$ 40.50	$ 10,844.00	$ 1,537.50
Oct 1990	$ 49.27	$ 6,061.40	$ 760.90	$ 40.50	$ 9,145.40	$ 1,352.60
Nov 1990	$ 44.03	$ 5,981.30	$ 701.20	$ 40.50	$ 8,587.40	$ 1,277.70
Dec 1990	$ 42.07	$ 5,615.20	$ 624.80	$ 40.50	$ 8,157.60	$ 1,265.40

Jan 1991	$ 42.11	$ 5,623.20	$ 600.40	$ 40.50	$ 8,568.80	$ 1,206.20
Feb 1991	$ 41.98	$ 5,583.70	$ 593.80	$ 40.50	$ 8,672.30	$ 1,188.10
Mar 1991	$ 41.70	$ 5,517.40	$ 603.00	$ 39.50	$ 8,700.80	$ 1,198.60
Apr 1991	$ 40.96	$ 5,560.00	$ 600.90	$ 39.50	$ 9,021.00	$ 1,252.90
May 1991	$ 38.40	$ 5,701.70	$ 555.20	$ 39.50	$ 8,452.40	$ 1,090.90
Jun 1991	$ 37.58	$ 5,710.60	$ 549.40	$ 39.50	$ 8,280.00	$ 1,061.60
Jul 1991	$ 38.02	$ 5,669.60	$ 548.10	$ 39.50	$ 8,541.30	$ 1,063.10
Aug 1991	$ 37.32	$ 5,638.80	$ 540.20	$ 39.50	$ 8,144.70	$ 1,046.30
Sep 1991	$ 37.02	$ 5,570.30	$ 539.80	$ 39.50	$ 7,680.70	$ 1,023.20
Oct 1991	$ 36.30	$ 5,549.60	$ 522.30	$ 39.50	$ 7,443.00	$ 991.70
Nov 1991	$ 36.29	$ 5,505.50	$ 506.20	$ 39.50	$ 7,244.60	$ 1,093.30
Dec 1991	$ 35.19	$ 5,510.10	$ 532.10	$ 39.50	$ 7,117.80	$ 1,188.00
Jan 1992	$ 35.59	$ 5,476.90	$ 514.90	$ 39.50	$ 7,517.30	$ 1,153.70
Feb 1992	$ 37.12	$ 5,615.70	$ 505.00	$ 39.50	$ 7,861.90	$ 1,130.70
Mar 1992	$ 37.41	$ 5,632.00	$ 521.20	$ 39.50	$ 7,417.70	$ 1,214.60
Apr 1992	$ 38.00	$ 5,838.90	$ 532.80	$ 39.50	$ 7,420.60	$ 1,304.30

May 1992	$ 37.99	$ 6,121.10	$ 520.30	$ 39.50	$ 7,326.80	$ 1,372.90
Jun 1992	$ 38.08	$ 6,618.80	$ 548.10	$ 39.50	$ 7,192.80	$ 1,385.20
Jul 1992	$ 39.76	$ 6,989.40	$ 626.10	$ 39.50	$ 7,497.90	$ 1,320.20
Aug 1992	$ 39.66	$ 6,780.40	$ 654.50	$ 39.50	$ 7,268.00	$ 1,360.40
Sep 1992	$ 38.52	$ 6,643.20	$ 621.10	$ 39.50	$ 6,917.50	$ 1,366.90
Oct 1992	$ 35.75	$ 6,016.70	$ 537.40	$ 37.25	$ 6,305.30	$ 1,163.60
Nov 1992	$ 34.52	$ 5,723.00	$ 460.40	$ 35.00	$ 5,564.88	$ 1,046.90
Dec 1992	$ 35.44	$ 5,756.20	$ 454.60	$ 35.00	$ 5,724.07	$ 1,057.90
Jan 1993	$ 35.25	$ 5,900.90	$ 436.50	$ 35.00	$ 5,930.93	$ 1,061.10
Feb 1993	$ 35.00	$ 5,790.90	$ 414.00	$ 31.00	$ 6,038.68	$ 1,072.10
Mar 1993	$ 33.88	$ 5,659.40	$ 405.90	$ 31.00	$ 5,971.30	$ 996.10
Apr 1993	$ 32.34	$ 5,590.90	$ 420.70	$ 31.00	$ 5,972.33	$ 1,004.60
May 1993	$ 31.60	$ 5,503.50	$ 407.20	$ 31.00	$ 5,762.55	$ 980.40
Jun 1993	$ 32.17	$ 5,112.70	$ 393.90	$ 31.00	$ 5,532.43	$ 926.00
Jul 1993	$ 32.80	$ 4,972.60	$ 388.20	$ 31.00	$ 5,036.20	$ 927.60
Aug 1993	$ 32.32	$ 4,809.30	$ 388.40	$ 31.00	$ 4,721.81	$ 884.00

Sep 1993	$ 30.98	$ 4,493.60	$ 375.70	$ 31.00	$ 4,352.89	$ 874.20
Oct 1993	$ 29.68	$ 4,681.10	$ 384.30	$ 31.00	$ 4,448.90	$ 914.90
Nov 1993	$ 29.12	$ 4,640.90	$ 400.30	$ 31.00	$ 4,633.89	$ 928.40
Dec 1993	$ 30.60	$ 4,777.90	$ 461.20	$ 31.00	$ 5,119.12	$ 974.40
Jan 1994	$ 31.91	$ 4,942.80	$ 490.10	$ 31.00	$ 5,577.95	$ 996.70
Feb 1994	$ 33.48	$ 5,443.40	$ 485.40	$ 31.00	$ 5,824.95	$ 968.90
Mar 1994	$ 33.78	$ 5,405.40	$ 451.50	$ 29.50	$ 5,587.54	$ 935.90
Apr 1994	$ 33.38	$ 5,385.70	$ 439.90	$ 29.50	$ 5,407.97	$ 923.60
May 1994	$ 35.64	$ 5,504.40	$ 473.50	$ 31.40	$ 6,086.65	$ 955.60
Jun 1994	$ 37.83	$ 5,509.20	$ 525.10	$ 33.60	$ 6,281.84	$ 966.20
Jul 1994	$ 39.43	$ 5,311.20	$ 580.10	$ 33.10	$ 6,226.76	$ 964.00
Aug 1994	$ 38.52	$ 5,161.50	$ 570.80	$ 33.10	$ 5,859.50	$ 944.90
Sep 1994	$ 40.75	$ 5,321.10	$ 613.50	$ 33.10	$ 6,364.75	$ 992.40
Oct 1994	$ 42.85	$ 5,473.60	$ 641.80	$ 33.10	$ 6,748.29	$ 1,058.50
Nov 1994	$ 47.11	$ 6,161.10	$ 667.20	$ 33.10	$ 7,556.14	$ 1,151.70
Dec 1994	$ 48.11	$ 5,946.80	$ 634.30	$ 36.10	$ 8,555.50	$ 1,114.30

Jan 1995	$ 51.23	$ 6,199.30	$ 666.60	$ 37.10	$ 9,592.55	$ 1,156.50
Feb 1995	$ 48.01	$ 5,478.30	$ 579.90	$ 37.60	$ 8,505.45	$ 1,032.20
Mar 1995	$ 46.51	$ 5,532.40	$ 585.60	$ 38.35	$ 7,531.91	$ 1,022.20
Apr 1995	$ 47.03	$ 5,872.10	$ 608.50	$ 37.10	$ 7,397.83	$ 1,061.40
May 1995	$ 45.19	$ 5,926.50	$ 596.50	$ 38.77	$ 7,232.19	$ 1,036.20
Jun 1995	$ 46.81	$ 6,670.70	$ 611.80	$ 40.77	$ 7,871.57	$ 1,009.60
Jul 1995	$ 48.51	$ 6,668.90	$ 621.90	$ 41.05	$ 8,596.57	$ 1,026.80
Aug 1995	$ 48.80	$ 6,992.30	$ 623.60	$ 40.88	$ 8,944.66	$ 1,014.40
Sep 1995	$ 46.27	$ 6,328.10	$ 592.70	$ 40.93	$ 8,405.21	$ 986.20
Oct 1995	$ 44.58	$ 6,220.70	$ 639.10	$ 40.97	$ 8,061.73	$ 979.10
Nov 1995	$ 45.50	$ 6,386.90	$ 713.60	$ 39.59	$ 8,505.91	$ 1,030.70
Dec 1995	$ 45.10	$ 6,289.50	$ 731.60	$ 39.35	$ 8,090.89	$ 1,018.10
Jan 1996	$ 42.80	$ 6,271.60	$ 709.50	$ 39.37	$ 7,862.05	$ 1,019.10
Feb 1996	$ 42.63	$ 6,195.50	$ 769.70	$ 39.28	$ 8,215.55	$ 1,035.80
Mar 1996	$ 43.03	$ 6,196.40	$ 817.90	$ 39.01	$ 8,021.74	$ 1,063.90
Apr 1996	$ 42.90	$ 6,480.90	$ 815.00	$ 39.33	$ 8,042.85	$ 1,045.40

May 1996	$ 43.23	$ 6,412.40	$ 840.20	$ 38.20	$ 8,026.55	$ 1,035.80
Jun 1996	$ 39.22	$ 6,191.90	$ 796.50	$ 38.20	$ 7,709.48	$ 1,008.50
Jul 1996	$ 37.76	$ 6,250.20	$ 783.70	$ 38.40	$ 7,203.65	$ 1,000.10
Aug 1996	$ 37.91	$ 6,110.20	$ 815.70	$ 38.35	$ 7,054.36	$ 1,006.90
Sep 1996	$ 36.94	$ 6,101.90	$ 796.40	$ 38.10	$ 7,318.05	$ 1,000.30
Oct 1996	$ 36.01	$ 5,941.90	$ 741.90	$ 37.60	$ 7,031.39	$ 1,003.10
Nov 1996	$ 38.81	$ 5,991.70	$ 716.60	$ 35.70	$ 6,943.38	$ 1,046.50
Dec 1996	$ 39.43	$ 5,836.30	$ 688.80	$ 35.35	$ 6,580.75	$ 1,036.30
Jan 1997	$ 41.51	$ 5,877.70	$ 692.30	$ 35.23	$ 7,071.55	$ 1,086.50
Feb 1997	$ 41.81	$ 5,883.20	$ 660.20	$ 34.60	$ 7,734.53	$ 1,179.40
Mar 1997	$ 42.75	$ 5,909.20	$ 694.60	$ 34.50	$ 7,895.87	$ 1,254.80
Apr 1997	$ 41.43	$ 5,713.30	$ 642.50	$ 35.40	$ 7,315.52	$ 1,240.40
May 1997	$ 43.02	$ 5,711.20	$ 618.60	$ 35.73	$ 7,482.85	$ 1,310.50
Jun 1997	$ 42.72	$ 5,566.10	$ 614.90	$ 34.50	$ 7,062.48	$ 1,354.20
Jul 1997	$ 42.42	$ 5,442.70	$ 634.30	$ 35.00	$ 6,835.50	$ 1,518.00
Aug 1997	$ 43.06	$ 5,428.40	$ 608.10	$ 36.93	$ 6,761.30	$ 1,653.50

Sep 1997	$ 41.01	$ 5,496.30	$ 634.30	$ 37.15	$ 6,503.84	$ 1,640.90
Oct 1997	$ 39.95	$ 5,561.30	$ 600.30	$ 37.15	$ 6,380.33	$ 1,280.10
Nov 1997	$ 38.84	$ 5,658.00	$ 563.40	$ 33.60	$ 6,139.50	$ 1,173.00
Dec 1997	$ 36.96	$ 5,513.80	$ 526.60	$ 31.40	$ 5,945.36	$ 1,102.20
Jan 1998	$ 35.94	$ 5,206.30	$ 531.60	$ 31.40	$ 5,491.75	$ 1,097.20
Feb 1998	$ 35.42	$ 5,242.50	$ 516.40	$ 33.44	$ 5,386.88	$ 1,044.00
Mar 1998	$ 35.58	$ 5,476.80	$ 559.80	$ 31.88	$ 5,395.80	$ 1,047.60
Apr 1998	$ 35.73	$ 5,714.80	$ 572.70	$ 31.18	$ 5,393.88	$ 1,097.00
May 1998	$ 34.51	$ 5,874.70	$ 543.50	$ 30.28	$ 5,020.00	$ 1,061.10
Jun 1998	$ 33.14	$ 5,970.00	$ 528.30	$ 30.00	$ 4,475.70	$ 1,009.80
Jul 1998	$ 33.10	$ 5,653.70	$ 546.20	$ 30.00	$ 4,325.43	$ 1,040.30
Aug 1998	$ 32.85	$ 5,691.50	$ 536.70	$ 26.20	$ 4,080.63	$ 1,029.80
Sep 1998	$ 33.29	$ 5,485.70	$ 520.20	$ 27.09	$ 4,102.16	$ 1,000.00
Oct 1998	$ 32.28	$ 5,432.10	$ 492.80	$ 27.10	$ 3,871.93	$ 940.50
Nov 1998	$ 32.26	$ 5,478.30	$ 494.20	$ 26.10	$ 4,131.91	$ 967.10
Dec 1998	$ 31.06	$ 5,257.60	$ 501.30	$ 26.10	$ 3,878.21	$ 959.20

Jan 1999	$ 30.10	$ 5,109.80	$ 492.30	$ 26.10	$ 4,268.75	$ 932.80
Feb 1999	$ 29.93	$ 5,268.50	$ 513.70	$ 26.10	$ 4,626.38	$ 1,017.30
Mar 1999	$ 29.87	$ 5,360.20	$ 507.80	$ 26.10	$ 5,011.30	$ 1,030.00
Apr 1999	$ 31.53	$ 5,393.00	$ 519.30	$ 26.10	$ 5,102.63	$ 1,019.00
May 1999	$ 32.51	$ 5,649.20	$ 541.50	$ 26.10	$ 5,399.34	$ 1,040.30
Jun 1999	$ 31.73	$ 5,265.90	$ 496.10	$ 26.10	$ 5,195.00	$ 1,000.50
Jul 1999	$ 34.25	$ 5,230.00	$ 495.80	$ 26.10	$ 5,700.11	$ 1,072.10
Aug 1999	$ 35.02	$ 5,230.20	$ 503.10	$ 26.10	$ 6,448.69	$ 1,130.60
Sep 1999	$ 36.64	$ 5,342.50	$ 507.30	$ 26.10	$ 7,028.41	$ 1,193.80
Oct 1999	$ 36.31	$ 5,430.70	$ 497.10	$ 25.60	$ 7,321.19	$ 1,148.70
Nov 1999	$ 36.56	$ 5,842.10	$ 478.30	$ 25.10	$ 7,949.55	$ 1,147.20
Dec 1999	$ 37.86	$ 5,721.30	$ 479.10	$ 25.10	$ 8,083.38	$ 1,183.80
Jan 2000	$ 40.05	$ 5,927.80	$ 472.10	$ 25.10	$ 8,309.50	$ 1,178.80
Feb 2000	$ 40.00	$ 5,642.10	$ 452.40	$ 25.10	$ 9,653.33	$ 1,094.90
Mar 2000	$ 38.79	$ 5,457.80	$ 441.30	$ 25.10	$ 10,280.11	$ 1,116.40
Apr 2000	$ 36.80	$ 5,384.40	$ 421.10	$ 25.10	$ 9,727.50	$ 1,127.60

May 2000	$ 37.67	$ 5,451.20	$ 412.10	$ 25.60	$ 10,130.24	$ 1,156.90
Jun 2000	$ 37.29	$ 5,456.80	$ 419.60	$ 25.60	$ 8,410.91	$ 1,117.90
Jul 2000	$ 38.18	$ 5,343.80	$ 452.10	$ 25.60	$ 8,164.41	$ 1,136.20
Aug 2000	$ 38.05	$ 5,304.80	$ 473.10	$ 25.60	$ 8,006.71	$ 1,169.80
Sep 2000	$ 39.85	$ 5,474.30	$ 487.10	$ 27.15	$ 8,637.98	$ 1,224.40
Oct 2000	$ 37.68	$ 5,282.30	$ 486.10	$ 27.15	$ 7,678.07	$ 1,095.90
Nov 2000	$ 36.62	$ 5,269.50	$ 468.00	$ 27.15	$ 7,339.77	$ 1,059.00
Dec 2000	$ 38.01	$ 5,233.70	$ 462.30	$ 30.75	$ 7,314.34	$ 1,059.80
Jan 2001	$ 38.30	$ 5,170.50	$ 478.10	$ 32.10	$ 6,994.77	$ 1,033.10
Feb 2001	$ 37.87	$ 5,121.80	$ 501.80	$ 32.10	$ 6,524.13	$ 1,020.90
Mar 2001	$ 36.38	$ 5,046.40	$ 498.40	$ 32.60	$ 6,133.52	$ 1,004.70
Apr 2001	$ 35.82	$ 4,949.20	$ 477.50	$ 33.50	$ 6,329.87	$ 969.40
May 2001	$ 36.63	$ 4,945.00	$ 466.70	$ 33.80	$ 7,060.83	$ 938.00
Jun 2001	$ 35.10	$ 4,828.30	$ 444.10	$ 33.90	$ 6,641.19	$ 894.90
Jul 2001	$ 33.69	$ 4,350.90	$ 461.60	$ 34.00	$ 5,937.05	$ 852.40
Aug 2001	$ 32.67	$ 3,895.70	$ 483.00	$ 33.80	$ 5,520.80	$ 828.10

Sep 2001	$ 31.80	$ 3,694.50	$ 464.80	$ 32.80	$ 5,027.00	$ 798.60
Oct 2001	$ 30.65	$ 3,750.70	$ 468.10	$ 32.40	$ 4,825.33	$ 761.50
Nov 2001	$ 31.62	$ 4,041.80	$ 486.50	$ 29.40	$ 5,078.41	$ 772.90
Dec 2001	$ 32.08	$ 4,018.50	$ 483.30	$ 27.35	$ 5,263.82	$ 754.70
Jan 2002	$ 32.82	$ 3,861.90	$ 513.10	$ 27.35	$ 6,043.18	$ 793.20
Feb 2002	$ 33.04	$ 3,730.80	$ 480.00	$ 28.10	$ 6,029.25	$ 771.30
Mar 2002	$ 33.98	$ 3,842.80	$ 480.20	$ 27.80	$ 6,537.50	$ 819.30
Apr 2002	$ 33.63	$ 4,023.60	$ 472.40	$ 27.09	$ 6,958.21	$ 808.20
May 2002	$ 33.17	$ 4,149.80	$ 451.90	$ 26.88	$ 6,761.36	$ 769.50
Jun 2002	$ 33.70	$ 4,286.10	$ 440.00	$ 24.90	$ 7,119.86	$ 767.10
Jul 2002	$ 33.28	$ 4,331.30	$ 446.10	$ 23.15	$ 7,142.72	$ 794.90
Aug 2002	$ 31.83	$ 3,834.00	$ 423.20	$ 22.25	$ 6,717.14	$ 747.60
Sep 2002	$ 31.95	$ 3,957.40	$ 421.30	$ 22.70	$ 6,640.24	$ 756.20
Oct 2002	$ 32.17	$ 4,241.50	$ 418.20	$ 24.50	$ 6,804.46	$ 754.70
Nov 2002	$ 33.66	$ 4,230.00	$ 442.20	$ 24.50	$ 7,313.93	$ 765.30
Dec 2002	$ 33.78	$ 4,236.80	$ 443.60	$ 24.50	$ 7,193.16	$ 797.70

Jan 2003	$ 34.72	$ 4,435.68	$ 444.66	$ 24.90	$ 8,026.02	$ 781.41
Feb 2003	$ 35.71	$ 4,570.75	$ 475.83	$ 25.15	$ 8,623.00	$ 785.15
Mar 2003	$ 35.09	$ 4,604.52	$ 456.67	$ 24.40	$ 8,378.81	$ 790.95
Apr 2003	$ 33.76	$ 4,565.75	$ 437.38	$ 23.45	$ 7,910.13	$ 754.65
May 2003	$ 35.12	$ 4,736.75	$ 463.50	$ 23.30	$ 8,330.63	$ 775.65
Jun 2003	$ 35.69	$ 4,694.76	$ 468.02	$ 24.10	$ 8,874.76	$ 790.69
Jul 2003	$ 36.21	$ 4,739.35	$ 514.78	$ 24.35	$ 8,797.39	$ 827.54
Aug 2003	$ 36.90	$ 4,822.50	$ 496.53	$ 25.33	$ 9,351.38	$ 817.88
Sep 2003	$ 36.80	$ 4,911.59	$ 521.27	$ 26.70	$ 9,965.34	$ 818.18
Oct 2003	$ 38.83	$ 5,236.74	$ 587.33	$ 27.50	$ 11,047.17	$ 897.96
Nov 2003	$ 40.40	$ 5,362.75	$ 622.33	$ 29.91	$ 12,086.50	$ 914.53
Dec 2003	$ 42.73	$ 6,057.62	$ 692.07	$ 34.00	$ 14,162.50	$ 977.76
Jan 2004	$ 45.87	$ 6,485.00	$ 758.38	$ 37.75	$ 15,326.55	$ 1,017.00
Feb 2004	$ 48.75	$ 6,672.75	$ 888.48	$ 41.75	$ 15,145.13	$ 1,087.68
Mar 2004	$ 49.26	$ 7,619.78	$ 886.48	$ 48.94	$ 13,715.00	$ 1,105.78
Apr 2004	$ 49.42	$ 8,955.75	$ 753.68	$ 53.25	$ 12,848.13	$ 1,032.73

May 2004	$ 46.47	$ 9,459.47	$ 808.90	$ 56.44	$ 11,118.29	$ 1,028.29
Jun 2004	$ 47.80	$ 9,204.77	$ 870.32	$ 59.55	$ 13,533.52	$ 1,021.46
Jul 2004	$ 49.34	$ 9,044.32	$ 939.59	$ 61.38	$ 15,023.30	$ 988.32
Aug 2004	$ 48.79	$ 9,021.91	$ 921.81	$ 59.25	$ 13,679.52	$ 975.81
Sep 2004	$ 49.28	$ 9,019.55	$ 935.46	$ 55.38	$ 13,270.91	$ 975.18
Oct 2004	$ 51.65	$ 9,045.24	$ 932.76	$ 56.63	$ 14,404.29	$ 1,064.95
Nov 2004	$ 52.10	$ 9,070.46	$ 967.80	$ 52.83	$ 14,045.46	$ 1,095.64
Dec 2004	$ 52.66	$ 8,553.81	$ 974.91	$ 52.25	$ 13,768.81	$ 1,180.21
Jan 2005	$ 56.40	$ 7,735.75	$ 953.15	$ 53.05	$ 14,505.00	$ 1,246.38
Feb 2005	$ 57.94	$ 8,088.75	$ 977.55	$ 49.90	$ 15,349.50	$ 1,326.18
Mar 2005	$ 60.22	$ 8,407.39	$ 1,004.00	$ 50.93	$ 16,190.65	$ 1,372.15
Apr 2005	$ 59.05	$ 8,143.81	$ 985.76	$ 51.25	$ 16,141.91	$ 1,300.14
May 2005	$ 56.65	$ 8,125.00	$ 988.08	$ 51.31	$ 16,931.50	$ 1,243.63
Jun 2005	$ 57.62	$ 7,618.86	$ 986.07	$ 51.00	$ 16,159.55	$ 1,275.73
Jul 2005	$ 57.77	$ 7,169.29	$ 854.48	$ 50.90	$ 14,580.71	$ 1,194.43
Aug 2005	$ 60.14	$ 7,188.86	$ 887.02	$ 49.13	$ 14,892.73	$ 1,298.39

Sep 2005	$ 60.04	$ 6,783.86	$ 933.07	$ 45.25	$ 14,228.18	$ 1,397.52
Oct 2005	$ 61.68	$ 6,422.86	$ 1,004.76	$ 42.46	$ 12,402.86	$ 1,488.38
Nov 2005	$ 64.36	$ 6,160.00	$ 1,018.41	$ 38.06	$ 12,115.68	$ 1,610.93
Dec 2005	$ 69.37	$ 6,713.50	$ 1,124.08	$ 38.23	$ 13,429.25	$ 1,821.83
Jan 2006	$ 73.13	$ 7,051.43	$ 1,256.33	$ 43.19	$ 14,555.24	$ 2,090.31
Feb 2006	$ 75.58	$ 7,826.25	$ 1,277.05	$ 47.70	$ 14,978.75	$ 2,219.38
Mar 2006	$ 76.35	$ 7,939.57	$ 1,192.09	$ 49.75	$ 14,897.39	$ 2,416.91
Apr 2006	$ 87.80	$ 8,853.06	$ 1,170.42	$ 52.88	$ 17,942.22	$ 3,084.78
May 2006	$ 101.27	$ 8,837.38	$ 1,166.86	$ 52.60	$ 21,077.14	$ 3,565.69
Jun 2006	$ 91.46	$ 7,896.36	$ 963.86	$ 52.38	$ 20,754.55	$ 3,225.68
Jul 2006	$ 97.17	$ 8,418.57	$ 1,052.38	$ 52.75	$ 26,586.19	$ 3,339.86
Aug 2006	$ 98.01	$ 8,502.05	$ 1,174.14	$ 50.94	$ 30,743.64	$ 3,347.30
Sep 2006	$ 97.79	$ 9,039.29	$ 1,342.38	$ 47.10	$ 30,130.71	$ 3,403.02
Oct 2006	$ 101.70	$ 9,768.18	$ 1,531.14	$ 44.05	$ 32,702.96	$ 3,822.96
Nov 2006	$ 101.07	$ 10,079.09	$ 1,624.52	$ 46.00	$ 32,113.86	$ 4,382.23
Dec 2006	$ 101.77	$ 11,158.68	$ 1,725.50	$ 49.75	$ 34,570.26	$ 4,405.40

Jan 2007	$ 96.83	$ 11,361.82	$ 1,666.09	$ 51.29	$ 36,811.14	$ 3,786.68
Feb 2007	$ 98.69	$ 12,933.25	$ 1,779.60	$ 52.90	$ 41,184.25	$ 3,309.50
Mar 2007	$ 104.59	$ 13,892.96	$ 1,914.05	$ 55.38	$ 46,324.77	$ 3,271.30
Apr 2007	$ 114.38	$ 14,052.90	$ 2,000.95	$ 56.12	$ 50,266.84	$ 3,557.47
May 2007	$ 116.38	$ 14,140.00	$ 2,101.25	$ 56.00	$ 52,179.05	$ 3,831.26
Jun 2007	$ 110.02	$ 14,099.76	$ 2,425.20	$ 61.60	$ 41,718.57	$ 3,602.85
Jul 2007	$ 111.06	$ 14,737.84	$ 3,082.76	$ 67.31	$ 33,425.68	$ 3,545.58
Aug 2007	$ 105.49	$ 15,174.32	$ 3,119.46	$ 69.35	$ 27,652.27	$ 3,252.52
Sep 2007	$ 108.18	$ 15,023.00	$ 3,226.55	$ 68.44	$ 29,537.50	$ 2,881.40
Oct 2007	$ 114.42	$ 16,071.30	$ 3,719.72	$ 74.81	$ 31,055.44	$ 2,975.33
Nov 2007	$ 112.14	$ 16,691.82	$ 3,328.18	$ 84.60	$ 30,610.23	$ 2,541.32
Dec 2007	$ 105.31	$ 16,263.06	$ 2,596.03	$ 91.00	$ 25,991.94	$ 2,353.08
Jan 2008	$ 109.55	$ 16,337.27	$ 2,608.14	$ 91.75	$ 27,689.55	$ 2,340.11
Feb 2008	$ 117.66	$ 17,210.00	$ 3,079.88	$ 132.00	$ 27,955.48	$ 2,438.14
Mar 2008	$ 126.26	$ 19,803.95	$ 3,008.58	$ 118.25	$ 31,225.26	$ 2,511.47
Apr 2008	$ 125.45	$ 21,658.64	$ 2,822.75	$ 123.00	$ 28,763.18	$ 2,263.80

May 2008	$ 121.31	$ 24,062.25	$ 2,234.63	$ 133.20	$ 25,735.00	$ 2,182.10
Jun 2008	$ 117.98	$ 22,229.29	$ 1,863.05	$ 159.75	$ 22,549.05	$ 1,894.48
Jul 2008	$ 118.91	$ 23,139.35	$ 1,944.91	$ 180.00	$ 20,160.22	$ 1,852.37
Aug 2008	$ 109.90	$ 20,026.25	$ 1,923.58	$ 158.40	$ 18,927.75	$ 1,723.28
Sep 2008	$ 98.02	$ 18,368.86	$ 1,868.36	$ 150.00	$ 17,794.55	$ 1,735.48
Oct 2008	$ 72.29	$ 14,401.74	$ 1,480.11	$ 108.00	$ 12,139.78	$ 1,302.11
Nov 2008	$ 58.71	$ 13,643.50	$ 1,291.10	$ 92.25	$ 10,701.50	$ 1,152.60
Dec 2008	$ 50.63	$ 11,240.00	$ 962.88	$ 78.65	$ 9,686.43	$ 1,100.57
Jan 2009	$ 51.69	$ 11,372.86	$ 1,132.74	$ 79.40	$ 11,306.91	$ 1,187.41
Feb 2009	$ 51.01	$ 11,039.25	$ 1,100.53	$ 75.38	$ 10,408.75	$ 1,112.08
Mar 2009	$ 51.82	$ 10,675.91	$ 1,238.91	$ 61.00	$ 9,696.36	$ 1,216.75
Apr 2009	$ 56.74	$ 11,743.50	$ 1,383.10	$ 63.56	$ 11,166.00	$ 1,378.85
May 2009	$ 59.43	$ 13,793.42	$ 1,440.16	$ 64.50	$ 12,634.74	$ 1,483.79
Jun 2009	$ 65.57	$ 14,985.68	$ 1,674.46	$ 71.38	$ 14,960.46	$ 1,557.27
Jul 2009	$ 69.67	$ 14,038.91	$ 1,678.61	$ 73.80	$ 15,984.57	$ 1,578.61
Aug 2009	$ 81.63	$ 14,869.75	$ 1,900.10	$ 72.50	$ 19,641.75	$ 1,821.68

Sep 2009	$ 77.94	$ 14,869.09	$ 2,204.55	$ 67.64	$ 17,473.18	$ 1,884.02
Oct 2009	$ 80.53	$ 15,008.86	$ 2,240.77	$ 71.07	$ 18,525.23	$ 2,071.59
Nov 2009	$ 84.70	$ 14,942.38	$ 2,308.76	$ 78.80	$ 16,991.19	$ 2,193.38
Dec 2009	$ 90.29	$ 15,546.91	$ 2,328.52	$ 83.10	$ 17,066.43	$ 2,375.95
Jan 2010	$ 96.58	$ 17,714.75	$ 2,368.38	$ 97.00	$ 18,439.25	$ 2,434.45
Feb 2010	$ 91.11	$ 16,361.75	$ 2,123.68	$ 94.19	$ 18,976.00	$ 2,156.90
Mar 2010	$ 99.42	$ 17,549.35	$ 2,172.09	$ 94.38	$ 22,461.30	$ 2,275.07
Apr 2010	$ 108.15	$ 18,683.50	$ 2,264.85	$ 100.15	$ 26,030.75	$ 2,366.68
May 2010	$ 96.02	$ 17,566.05	$ 1,882.68	$ 100.13	$ 22,008.16	$ 1,968.37
Jun 2010	$ 89.09	$ 17,319.77	$ 1,703.96	$ 98.19	$ 19,388.64	$ 1,742.84
Jul 2010	$ 89.20	$ 18,191.36	$ 1,836.98	$ 95.98	$ 19,517.50	$ 1,843.89
Aug 2010	$ 97.59	$ 20,754.76	$ 2,075.24	$ 89.78	$ 21,413.33	$ 2,044.57
Sep 2010	$ 100.64	$ 22,701.14	$ 2,184.23	$ 94.90	$ 22,643.41	$ 2,151.41
Oct 2010	$ 108.27	$ 26,342.62	$ 2,379.67	$ 97.45	$ 23,807.38	$ 2,372.14
Nov 2010	$ 109.43	$ 25,519.09	$ 2,376.73	$ 107.16	$ 22,909.32	$ 2,291.68
Dec 2010	$ 114.52	$ 26,163.33	$ 2,412.93	$ 118.29	$ 24,111.19	$ 2,280.93

Jan 2011	$ 120.81	$ 27,465.25	$ 2,601.65	$ 132.48	$ 25,646.25	$ 2,371.55
Feb 2011	$ 125.82	$ 31,526.00	$ 2,586.68	$ 128.36	$ 28,252.25	$ 2,465.13
Mar 2011	$ 121.37	$ 30,590.93	$ 2,624.02	$ 126.13	$ 26,710.35	$ 2,341.48
Apr 2011	$ 124.29	$ 32,363.31	$ 2,701.17	$ 122.50	$ 26,408.33	$ 2,362.22
May 2011	$ 118.49	$ 28,676.45	$ 2,428.32	$ 119.12	$ 24,236.73	$ 2,167.35
Jun 2011	$ 116.98	$ 25,519.68	$ 2,524.99	$ 120.09	$ 22,420.93	$ 2,234.47
Jul 2011	$ 120.99	$ 27,398.10	$ 2,681.02	$ 120.75	$ 23,847.95	$ 2,397.75
Aug 2011	$ 114.77	$ 24,042.43	$ 2,397.28	$ 120.13	$ 21,845.09	$ 2,200.17
Sep 2011	$ 109.08	$ 22,526.60	$ 2,287.67	$ 123.09	$ 20,377.59	$ 2,075.22
Oct 2011	$ 98.39	$ 21,868.64	$ 1,960.38	$ 119.39	$ 19,039.05	$ 1,871.42
Nov 2011	$ 95.84	$ 21,291.70	$ 1,994.22	$ 113.78	$ 17,873.00	$ 1,935.32
Dec 2011	$ 95.08	$ 19,375.01	$ 2,022.35	$ 111.56	$ 18,266.76	$ 1,904.73
Jan 2012	$ 100.50	$ 21,438.63	$ 2,096.16	$ 116.46	$ 19,854.77	$ 1,981.86
Feb 2012	$ 104.01	$ 24,293.31	$ 2,121.26	$ 117.02	$ 20,393.67	$ 2,057.79
Mar 2012	$ 103.54	$ 22,985.43	$ 2,056.69	$ 107.46	$ 18,660.81	$ 2,035.92
Apr 2012	$ 100.95	$ 22,200.62	$ 2,071.07	$ 103.59	$ 17,939.79	$ 2,002.14

May 2012	$ 96.63	$ 20,405.24	$ 2,012.82	$ 95.83	$ 17,068.19	$ 1,936.00
Jun 2012	$ 91.63	$ 19,271.07	$ 1,854.15	$ 87.19	$ 16,549.14	$ 1,858.70
Jul 2012	$ 91.19	$ 18,546.09	$ 1,881.48	$ 88.24	$ 16,128.41	$ 1,847.75
Aug 2012	$ 87.65	$ 18,772.62	$ 1,900.62	$ 91.00	$ 15,735.21	$ 1,818.16
Sep 2012	$ 93.59	$ 20,771.26	$ 2,177.67	$ 88.96	$ 17,287.96	$ 2,009.85
Oct 2012	$ 94.00	$ 21,233.70	$ 2,141.97	$ 81.85	$ 17,168.74	$ 1,903.96
Nov 2012	$ 92.42	$ 20,713.07	$ 2,181.97	$ 85.89	$ 16,335.36	$ 1,912.40
Dec 2012	$ 97.42	$ 22,880.89	$ 2,279.80	$ 92.88	$ 17,448.50	$ 2,040.43
Jan 2013	$ 100.29	$ 24,545.90	$ 2,333.68	$ 92.77	$ 17,472.50	$ 2,032.20
Feb 2013	$ 101.34	$ 24,211.74	$ 2,365.79	$ 94.94	$ 17,690.10	$ 2,128.69
Mar 2013	$ 94.55	$ 23,296.52	$ 2,169.42	$ 90.98	$ 16,724.93	$ 1,926.07
Apr 2013	$ 90.73	$ 21,662.25	$ 2,027.39	$ 87.76	$ 15,672.95	$ 1,856.00
May 2013	$ 88.32	$ 20,775.83	$ 2,032.98	$ 87.71	$ 14,947.96	$ 1,831.55
Jun 2013	$ 85.41	$ 20,267.40	$ 2,099.69	$ 82.75	$ 14,280.28	$ 1,839.01
Jul 2013	$ 85.67	$ 19,563.83	$ 2,047.73	$ 77.26	$ 13,750.32	$ 1,837.62
Aug 2013	$ 89.64	$ 21,644.43	$ 2,174.18	$ 76.96	$ 14,314.93	$ 1,898.82

Sep 2013	$ 88.15	$ 22,735.07	$ 2,084.92	$ 77.61	$ 13,801.39	$ 1,846.88
Oct 2013	$ 89.07	$ 23,101.59	$ 2,115.43	$ 79.41	$ 14,117.65	$ 1,884.84
Nov 2013	$ 87.82	$ 22,826.88	$ 2,089.56	$ 82.25	$ 13,684.01	$ 1,866.42
Dec 2013	$ 88.71	$ 22,762.13	$ 2,136.73	$ 84.34	$ 13,924.55	$ 1,974.98
Jan 2014	$ 88.08	$ 22,063.86	$ 2,143.17	$ 81.61	$ 14,101.25	$ 2,036.93
Feb 2014	$ 86.16	$ 22,820.67	$ 2,108.03	$ 76.29	$ 14,203.55	$ 2,034.53
Mar 2014	$ 82.98	$ 23,024.31	$ 2,053.08	$ 73.34	$ 15,678.10	$ 2,007.90
Apr 2014	$ 85.48	$ 23,405.20	$ 2,087.09	$ 72.82	$ 17,373.60	$ 2,027.21
May 2014	$ 84.85	$ 23,271.25	$ 2,097.32	$ 73.69	$ 19,401.08	$ 2,058.97
Jun 2014	$ 84.36	$ 22,762.00	$ 2,106.94	$ 71.48	$ 18,628.81	$ 2,128.10
Jul 2014	$ 88.18	$ 22,424.01	$ 2,193.24	$ 68.75	$ 19,117.65	$ 2,310.62
Aug 2014	$ 88.03	$ 22,231.05	$ 2,236.84	$ 68.94	$ 18,600.20	$ 2,326.99
Sep 2014	$ 85.07	$ 21,090.52	$ 2,117.24	$ 65.94	$ 18,034.80	$ 2,294.59
Oct 2014	$ 82.62	$ 19,830.41	$ 2,034.26	$ 63.71	$ 15,812.37	$ 2,276.83
Nov 2014	$ 82.86	$ 20,033.47	$ 2,030.18	$ 62.55	$ 15,807.05	$ 2,253.22
Dec 2014	$ 78.83	$ 19,829.71	$ 1,938.11	$ 62.44	$ 15,962.05	$ 2,175.76

Jan 2015	$ 73.85	$ 19,454.12	$ 1,843.13	$ 61.44	$ 14,849.19	$ 2,113.05
Feb 2015	$ 72.37	$ 18,233.91	$ 1,795.66	$ 69.05	$ 14,573.84	$ 2,097.76
Mar 2015	$ 71.78	$ 17,421.91	$ 1,792.47	$ 64.76	$ 13,755.50	$ 2,028.73
Apr 2015	$ 72.14	$ 15,900.88	$ 2,005.36	$ 56.24	$ 12,830.92	$ 2,212.72
May 2015	$ 74.64	$ 15,803.59	$ 1,991.78	$ 61.19	$ 13,511.34	$ 2,281.80
Jun 2015	$ 70.31	$ 15,064.94	$ 1,829.50	$ 58.96	$ 12,825.23	$ 2,082.09
Jul 2015	$ 65.75	$ 15,071.53	$ 1,763.04	$ 59.90	$ 11,413.10	$ 2,000.68
Aug 2015	$ 62.65	$ 15,163.77	$ 1,703.60	$ 59.14	$ 10,386.00	$ 1,807.64
Sep 2015	$ 63.40	$ 15,453.34	$ 1,684.25	$ 57.65	$ 9,937.55	$ 1,720.23
Oct 2015	$ 62.22	$ 15,794.61	$ 1,720.11	$ 54.26	$ 10,316.83	$ 1,724.34
Nov 2015	$ 57.83	$ 14,745.29	$ 1,618.35	$ 52.47	$ 9,244.33	$ 1,583.31
Dec 2015	$ 56.31	$ 14,691.69	$ 1,706.58	$ 52.21	$ 8,707.79	$ 1,527.79
Jan 2016	$ 55.21	$ 13,808.08	$ 1,646.20	$ 49.02	$ 8,507.29	$ 1,520.36
Feb 2016	$ 57.68	$ 15,610.14	$ 1,765.75	$ 50.27	$ 8,298.50	$ 1,709.85
Mar 2016	$ 61.19	$ 16,897.60	$ 1,802.19	$ 52.21	$ 8,717.25	$ 1,801.69
Apr 2016	$ 62.00	$ 17,032.71	$ 1,732.27	$ 50.69	$ 8,878.86	$ 1,855.37

May 2016	$ 59.98	$ 16,706.95	$ 1,707.80	$ 51.31	$ 8,660.35	$ 1,869.03
Jun 2016	$ 60.26	$ 16,966.69	$ 1,712.77	$ 52.85	$ 8,928.35	$ 2,026.19
Jul 2016	$ 63.49	$ 17,826.23	$ 1,834.79	$ 61.24	$ 10,262.86	$ 2,183.25
Aug 2016	$ 63.78	$ 18,427.02	$ 1,835.52	$ 67.39	$ 10,335.99	$ 2,279.14
Sep 2016	$ 62.83	$ 19,499.52	$ 1,947.64	$ 72.72	$ 10,191.78	$ 2,292.31
Oct 2016	$ 64.13	$ 20,099.76	$ 2,024.49	$ 94.20	$ 10,259.74	$ 2,311.50
Nov 2016	$ 71.53	$ 21,126.09	$ 2,180.58	$ 103.43	$ 11,128.91	$ 2,566.20
Dec 2016	$ 73.54	$ 21,204.35	$ 2,209.84	$ 88.15	$ 10,972.27	$ 2,664.81
Jan 2017	$ 74.54	$ 20,691.79	$ 2,242.62	$ 83.73	$ 9,971.46	$ 2,714.80
Feb 2017	$ 77.94	$ 19,446.47	$ 2,311.50	$ 79.98	$ 10,643.30	$ 2,845.55
Mar 2017	$ 77.34	$ 19,875.20	$ 2,280.92	$ 80.90	$ 10,204.66	$ 2,776.88
Apr 2017	$ 74.04	$ 19,910.32	$ 2,220.61	$ 83.65	$ 9,609.28	$ 2,614.92
May 2017	$ 72.24	$ 20,200.33	$ 2,125.11	$ 74.42	$ 9,155.12	$ 2,590.21
Jun 2017	$ 71.71	$ 19,658.84	$ 2,132.93	$ 81.09	$ 8,931.76	$ 2,573.40
Jul 2017	$ 75.39	$ 20,223.48	$ 2,269.86	$ 87.49	$ 9,491.39	$ 2,787.19
Aug 2017	$ 81.56	$ 20,521.00	$ 2,348.47	$ 98.58	$ 10,889.98	$ 2,980.73

Sep 2017	$ 82.68	$ 20,796.62	$ 2,374.39	$ 97.82	$ 11,215.79	$ 3,116.86
Oct 2017	$ 83.39	$ 20,376.09	$ 2,498.22	$ 97.11	$ 11,335.77	$ 3,264.60
Nov 2017	$ 83.46	$ 19,557.52	$ 2,461.43	$ 96.64	$ 11,972.00	$ 3,229.31
Dec 2017	$ 84.11	$ 19,476.37	$ 2,509.92	$ 100.81	$ 11,495.11	$ 3,195.95
Jan 2018	$ 88.57	$ 20,696.91	$ 2,584.09	$ 106.45	$ 12,864.88	$ 3,441.52
Feb 2018	$ 88.61	$ 21,651.55	$ 2,581.06	$ 105.95	$ 13,595.88	$ 3,532.90
Mar 2018	$ 84.47	$ 21,211.94	$ 2,390.00	$ 96.66	$ 13,392.50	$ 3,269.18
Apr 2018	$ 86.45	$ 21,291.10	$ 2,352.41	$ 93.69	$ 13,938.10	$ 3,188.05
May 2018	$ 86.79	$ 20,858.83	$ 2,360.93	$ 105.29	$ 14,366.49	$ 3,059.87
Jun 2018	$ 86.98	$ 20,660.52	$ 2,436.29	$ 114.33	$ 15,105.65	$ 3,088.57
Jul 2018	$ 79.77	$ 19,729.80	$ 2,207.02	$ 119.57	$ 13,793.86	$ 2,656.13
Aug 2018	$ 78.12	$ 19,228.77	$ 2,053.53	$ 117.34	$ 13,411.35	$ 2,512.00
Sep 2018	$ 77.44	$ 18,967.13	$ 2,022.91	$ 114.16	$ 12,510.35	$ 2,434.68
Oct 2018	$ 79.35	$ 19,121.48	$ 1,987.55	$ 108.73	$ 12,314.91	$ 2,673.67
Nov 2018	$ 77.50	$ 19,064.86	$ 1,937.11	$ 100.73	$ 11,239.72	$ 2,595.69
Dec 2018	$ 76.07	$ 19,259.58	$ 1,972.32	$ 101.37	$ 10,835.08	$ 2,616.29

Jan 2019	$ 75.77	$ 20,457.75	$ 1,997.14	$ 98.56	$ 11,523.09	$ 2,569.70
Feb 2019	$ 80.12	$ 21,263.95	$ 2,062.79	$ 95.42	$ 12,685.23	$ 2,707.19
Mar 2019	$ 81.10	$ 21,393.40	$ 2,046.46	$ 93.12	$ 13,026.27	$ 2,850.60
Apr 2019	$ 81.60	$ 20,604.30	$ 1,938.99	$ 86.77	$ 12,772.79	$ 2,932.65
May 2019	$ 78.65	$ 19,523.90	$ 1,815.19	$ 82.32	$ 12,016.31	$ 2,742.81
Jun 2019	$ 78.53	$ 19,193.20	$ 1,899.70	$ 72.49	$ 11,943.94	$ 2,601.22
Jul 2019	$ 81.03	$ 17,977.85	$ 1,975.64	$ 72.08	$ 13,546.30	$ 2,446.51
Aug 2019	$ 76.05	$ 16,608.99	$ 2,044.55	$ 65.55	$ 15,748.64	$ 2,273.01
Sep 2019	$ 77.32	$ 16,830.62	$ 2,071.85	$ 65.95	$ 17,656.88	$ 2,331.56
Oct 2019	$ 76.46	$ 16,603.39	$ 2,184.09	$ 69.20	$ 17,046.22	$ 2,451.65
Nov 2019	$ 76.22	$ 16,335.48	$ 2,021.15	$ 66.99	$ 15,171.81	$ 2,425.48
Dec 2019	$ 77.47	$ 17,141.05	$ 1,900.54	$ 66.18	$ 13,829.42	$ 2,272.54
Jan 2020	$ 77.70	$ 17,029.18	$ 1,923.93	$ 69.66	$ 13,506.86	$ 2,354.31
Feb 2020	$ 73.02	$ 16,480.30	$ 1,872.54	$ 67.64	$ 12,715.55	$ 2,113.24
Mar 2020	$ 68.71	$ 15,290.91	$ 1,734.44	$ 66.74	$ 11,846.23	$ 1,903.63
Apr 2020	$ 65.55	$ 14,952.80	$ 1,657.55	$ 58.55	$ 11,804.01	$ 1,903.37

May 2020	$ 68.01	$ 15,401.92	$ 1,626.34	$ 52.49	$ 12,179.61	$ 1,975.32
Jun 2020	$ 73.68	$ 16,837.84	$ 1,744.84	$ 52.21	$ 12,727.15	$ 2,025.71
Jul 2020	$ 79.09	$ 17,469.92	$ 1,817.93	$ 51.56	$ 13,402.30	$ 2,177.20
Aug 2020	$ 83.48	$ 17,650.03	$ 1,935.73	$ 50.14	$ 14,537.75	$ 2,410.05
Sep 2020	$ 85.12	$ 17,951.26	$ 1,872.91	$ 54.60	$ 14,857.49	$ 2,442.46
Oct 2020	$ 85.49	$ 18,176.59	$ 1,776.27	$ 58.40	$ 15,239.36	$ 2,440.65
Nov 2020	$ 90.28	$ 18,522.48	$ 1,915.62	$ 64.40	$ 15,807.73	$ 2,671.60
Dec 2020	$ 99.65	$ 19,731.96	$ 2,020.47	$ 83.03	$ 16,823.04	$ 2,779.85
Jan 2021	$ 102.85	$ 21,920.24	$ 2,014.73	$ 86.83	$ 17,863.18	$ 2,705.34
Feb 2021	$ 106.39	$ 26,315.75	$ 2,080.11	$ 86.74	$ 18,584.38	$ 2,744.50
Mar 2021	$ 110.22	$ 27,061.00	$ 1,948.00	$ 94.92	$ 16,406.66	$ 2,791.94
Apr 2021	$ 115.32	$ 28,328.42	$ 2,011.92	$ 92.22	$ 16,521.25	$ 2,829.01

Appendix D. Copyright Permission Statement from publishers

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Statement of Contribution of Others

I, Yoochan Eugene Kim, contributed:

- 70% of the study design and report to the publication entitled *"Relationship of iron ore price with other major commodity prices"* at Mineral Economics. Dr. Apurna Ghosh and Professor Erkan Topal supervised the research and reviewed the manuscript. Dr Ping Chang reviewed the manuscript.
- 80% of the study design and report writing to the publication entitled *"Performance of Different Models in Iron Ore Price Prediction During the Time of Commodity Price Spike"* at Resources Policy. Dr. Apurna Ghosh and Professor Erkan Topal supervised the research and reviewed the manuscript. Dr Ping Chang reviewed the manuscript.

Name	**Signature**	**Date**
Yoochan Eugene Kim		16-Jun-2024

I, as a Co-Author, endorsed that this level of contribution by the candidate indicated is appropriate.

Name	**Signature**	**Date**
Apurna Kumar Ghosh		16-06-2024
Erkan Topal		18/06/2024
Ping Chang		17/06/2024