Forecasting global market prices of clean energy transition minerals

DATA6000 Assignment 3

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Due Date: 04th October 2024

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Executive Summary

This report focuses on analysing the challenges of investment into the mining of clean energy transition minerals. This report focuses on three critical minerals and attempt to forecast the trading prices of Lithium, Nickel and Cobalt minerals for 2025.After obtaining three relevant data sources, this study utilised multiple forecasting models and evaluate their results to identify the most suitable model -which was the ARIMA model. Afterwards, linear regression analysis was used to identify the significance of clean energy adoption and prices of alternative fuels on clean energy mineral prices. Finally, the report provides insights and recommendations to further improve as well as discuss the importance of data ethics and security.

1.0 Challenges faced by the mining industry of Australia

Mining is a key industry in Australia with a major economic presence, providing with over 200,000 jobs(Australian Bureau of Statistics 2024), and accounting for 14.3% of the industry share output in the country (Reserve Bank of Australia 2024).

However with the recent focus on climate change and environmental sustainability, many major economies around the globe have decided to decrease the amount of emissions released in to the atmosphere through the burning of fossil fuels such as coal and petroleum(The Department of Climate Change, Energy, the Environment and Water 2024).

In order to adopt to these changes, the mining industry need to focus on investing in clean energy transition minerals that will be key to the power generation of the future.

1.1 Clean Energy transition minerals

These minerals are key components in batteries and equipment that is used to generate and store clean energy such as solar, wind or hydrogen power.

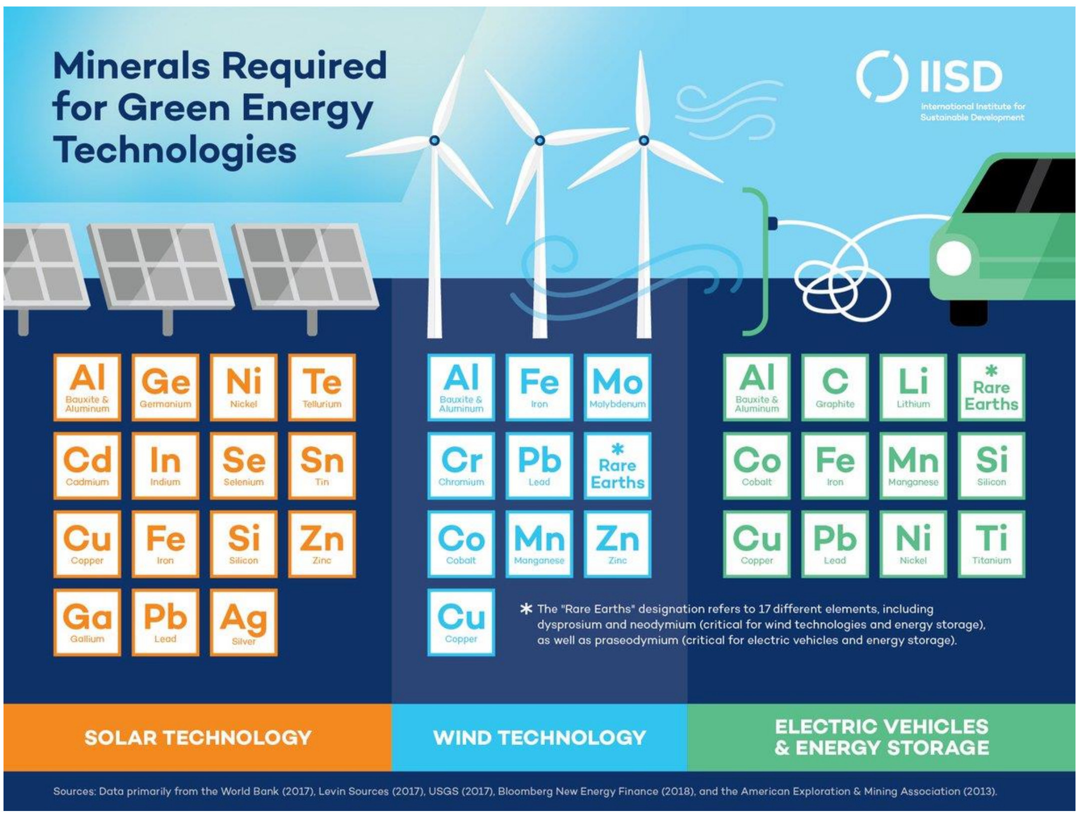

Figure 01: Minerals required for green energy technologies

Image Source: https://www.iisd.org/publications/report/green-conflict-minerals-fuels-conflict-transition-low-carbon-economy

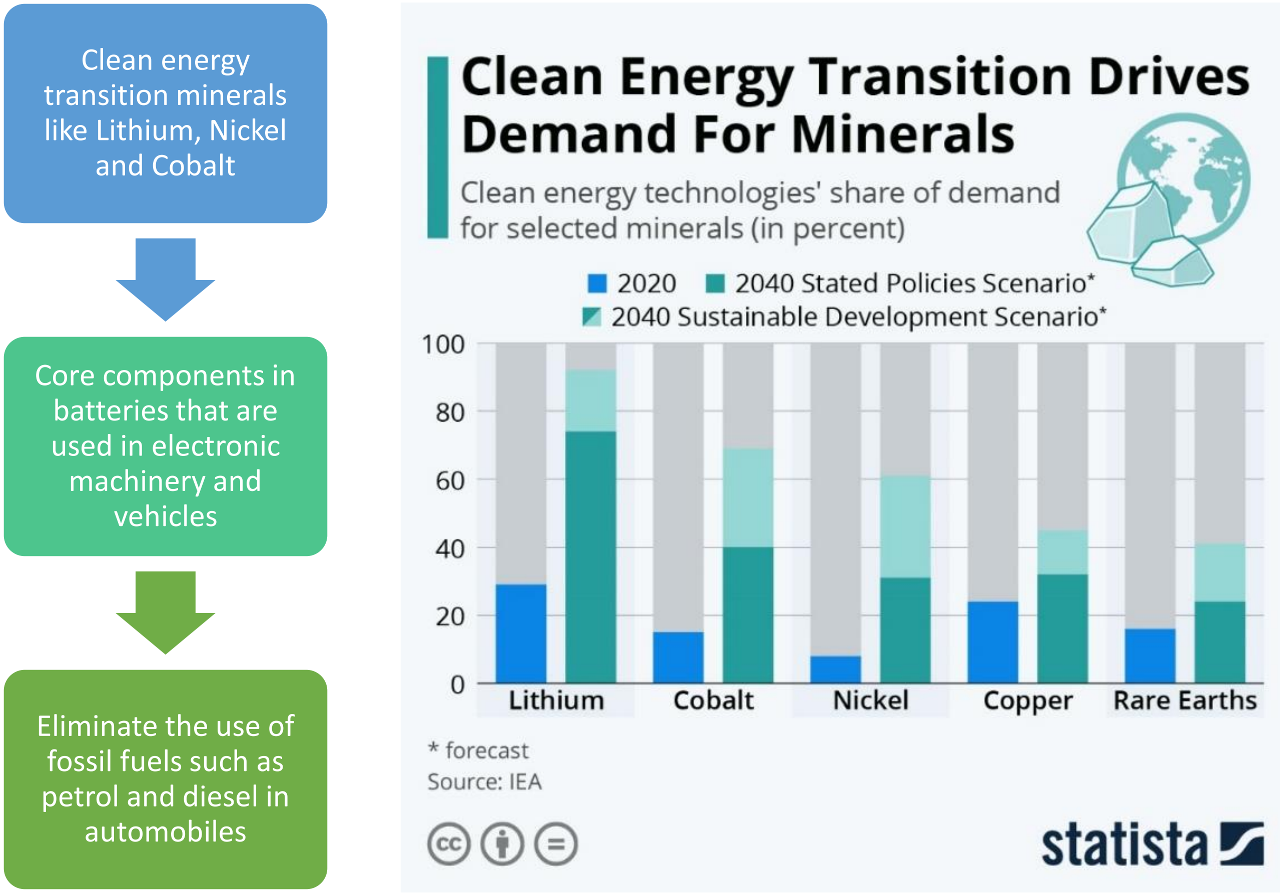

Figure 02: Clean energy demand and clean energy transition minerals

Image Source: https://www.statista.com/chart/24936/clean-energy-transition-mineral-demand/

1.2 Challenges to investment in the Clean Energy transition minerals

While the potential for clean energy transition minerals is strong, Australian mining industry is facing certain challenges, from which the increased volatility of the mineral prices is the subject of this study.

As per the below example, significant price increases and drops exist between short time periods, is an issue to mining companies as the extraction and refining of these minerals can take a long time and in order for their investments to be feasible, they need to be able to estimate future profitability of investing on these minerals.

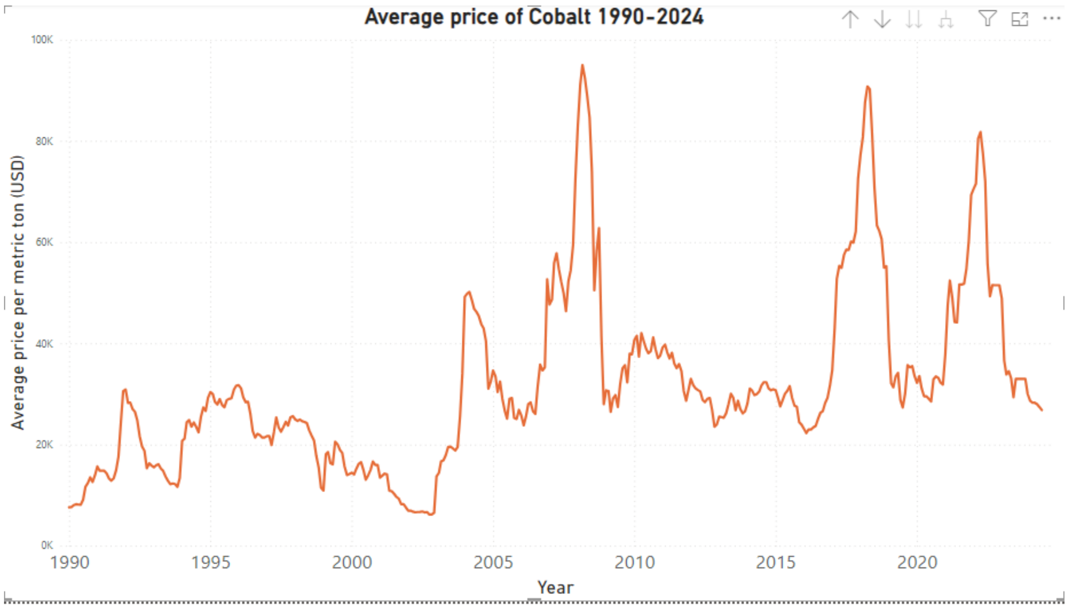

Figure 03: Cobalt price from 1990 – 2024

By having the clarity of price movement and less volatility, mining companies can strategize and invest in these minerals without having to close down or downgrade their operations due to uncertain trading prices, such as the case with the suspension of Western Australia Nickel mining site by the mining giant BHP(BHP 2024).

This study will focus on 3 minerals and therefore, the main objective of the study will be:

Forecasting the trading prices of Lithium, Nickel and Cobalt minerals for 2025

2.0 Data processing and management

2.1 analysing existing academic research

Through previous academic literature, factors affecting the demand and price for these minerals were identified.

Factors affecting the mineral prices	Academic literature sources
Global demand and supply of minerals	(Bustamante & Gaustad 2014, Islam et al. 2022)
Adaptation rate of renewable energy	(Wen et al. 2023, Payam & Taheri 2018)
Cost of alternate energy option	(Foster et al. 2017, Griffith-Jones et al. 2017, Tummalapalli & Robinson 2023)
Government policies and grants provided	(Smyth & Vespignani 2022, Baskaran & Bendig 2013)
Global trade and political issues	(Ghorbani et al. 2024, Pencea 2023)

Table 01: Academic literature and sources

From these factors identified, appropriate and relevant open-access data sources were found for the first three factors.

2.2 Data sources

Github link: https://github.com/ravindudes/Capstone-Project

2.2.1 Data Source 1 – IMF

Dataset of historical global trading prices of minerals from Jan 1990 to Jul 2024 was sourced from the International Monetary Fund website.

> This dataset contains monthly trading prices of each mineral, which is decided by the demand and supply available for each mineral, which can be used in a forecasting model to predict the prices of future periods.

Link: https://www.imf.org/en/Research/commodity-prices

Commodity	PNICK		PCOBA	PZINC	PCOPP	PCOALAU
Commodity.Description	Nickel, melting grade, LME spot price, CIF European ports, US$ per metric ton	Lithium Metal =99%, Battery Grade	Cobalt, minimum 99.80% purity, LME spot price, USD/ton	Zinc, high grade 98% pure, US$ per metric ton	Copper, grade A cathode, LME spot price, CIF European ports, US$ per metric ton	Coal, Australian thermal coal, 12,000-btu/pound, less than 1% sulfur, 14% ash, FOB Newcastle/Port Kembla, US$ per metric ton
Data Type	USD	USD	USD	USD	USD	USD
Frequency	Monthly	Monthly	Monthly	Monthly	Monthly	Monthly
2013M4	15629.31	65464.67	26209.45	1855.60	7221.16	93.23
2013M5	14948.23	65950.20	27984.38	1831.01	7248.71	93.13
2013M6	14280.28	66020.67	30047.54	1839.01	7000.24	89.64
2013M7	13750.32	66023.44	29290.04	1837.62	6906.64	82.22
2013M8	14308.26	66157.09	26803.43	1896.39	7186.25	82.22
2013M9	13801.39	66172.35	28680.43	1846.88	7159.27	83.30
2013M10	14117.65	66349.80	27037.96	1884.84	7203.02	85.44
2013M11	13684.01	66467.29	26172.48	1866.42	7070.65	88.36

Figure 04: Data available in data source 1 - IMF

2.2.2 Data Source 2 – CER

Representing the adoption of renewable technology, a dataset on residential solar panel installations was sourced from the Australian Government Clean Energy Regulator from April 2021 to May 2024.

Link: https://cer.gov.au/markets/reports-and-data/small-scale-installation-postcode-data

By collating the total installation volume for each year, with this dataset the study can measure the rate of solar energy adoption in Australian households. Using this timeseries data, the study will be able to measure the significance of renewable energy adoption on the prices of minerals.

Small Unit Installation Postcode	2021 -	Dec 2021 -	Jan 2022 -	Feb 2022 -	Mar 2022 -	Apr 2022 -	May 2022	Jun 2022 -	Jul 2022 -	Aug 2022 -	Sep 2022 -
0000	0	0	0	0	0	0	0	0	0	0	0
0200	0	0	0	0	0	0	0	0	0	0	0
0800	0	3	0	0	0	0	0	0	1	1	0
0801	0	0	0	0	0	0	0	0	0	0	0
0803	0	0	0	0	0	0	0	0	0	0	0
0804	0	0	0	0	0	0	0	0	0	0	0
0810	23	24	7	18	21	23	22	22	15	25	24
0811	0	0	0	0	0	0	0	0	0	0	0
0812	19	15	9	13	14	8	7	11	12	9	15
0813	0	0	0	0	0	0	0	0	0	0	0
0814	0	0	0	0	0	0	0	0	0	0	0
0820	11	10	2	5	15	10	9	7	8	14	12
0821	0	0	0	0	0	0	0	0	0	0	0
0822	16	15	2	10	11	7	11	12	21	8	16

Figure 05: Data available in data source 2 - CER

2.2.3 Data Source 3 – AIP

To analyse the cost of alternate energy option, a dataset on petrol and diesel from 1/1/2004 to 19/7/2024 was obtained from the from Australian Institute of Petroleum.

Link: https://www.aip.com.au/historical-ulp-and-diesel-tgp-data

Average Unleaded petrol terminal gate prices (inclusive of GST)	Sydney	Melbourne	Brisbane	Adelaide	Perth	Darwin	Hobart	National Average
Thursday, January 1, 2004	86.3	85.1	86.4	87.2	88.5	89.7	87.9	86.4
Friday, January 2, 2004	86.3	85.1	86.4	87.2	88.5	89.7	87.9	86.4
Monday, January 5, 2004	86.4	85.3	86.4	87.2	89.0	89.7	87.9	86.5
Tuesday, January 6, 2004	86.8	85.6	87.0	87.7	89.1	90.3	88.5	86.9
Wednesday, January 7, 2004	86.7	85.5	87.0	87.7	89.1	90.3	88.5	86.8
Thursday, January 8, 2004	86.7	85.7	87.0	87.7	90.0	90.3	88.5	87.0
Friday, January 9, 2004	87.7	86.3	88.3	88.8	90.4	91.7	89.8	87.9
Monday, January 12, 2004	87.8	86.5	88.3	88.8	90.8	91.7	89.8	88.0
Tuesday, January 13, 2004	88.9	87.5	89.3	89.8	91.4	92.7	90.8	89.0
Wednesday, January 14, 2004	89.0	87.8	89.3	89.8	91.4	92.7	90.8	89.1
Thursday, January 15, 2004	89.0	88.0	89.3	89.8	92.1	92.7	90.8	89.3
Friday, January 16, 2004	90.1	88.8	90.7	91.2	92.8	94.1	92.2	90.4
Monday, January 19, 2004	90.2	88.9	90.7	91.2	92.7	94.1	92.2	90.4
Tuesday, January 20, 2004	90.1	88.8	90.5	91.0	92.6	93.9	92.0	90.2
Wednesday, January 21, 2004	89.9	88.5	90.5	91.0	92.6	93.9	92.0	90.1

Figure 06: Data available in data source 3 – AIP

This timeseries data shows the petrol and diesel prices of Australia, by which the cost of alternate energy source for solar energy can be identified and can be utilised in a regression analysis for measure its significance against the prices of minerals.

2.3 Data pre-processing

All datasets were in excel or csv format. Prior to merging the datasets, the date format had to be updated into a compatible common format, which was done using Microsoft Excel.

Feature selection was also used to identify and separate the columns of data that relevant to the study. Null values in IMF for Lithium prices were replaced with zeros as the mining of the mineral was not stared till mid-2012.Afterwards the data AIP, had to be averaged to get monthly data as the dataset had daily prices and data in CER, had to be collated to get a comparable format among all 3 datasets with date being the common feature.

Finally, all 3 datasets were merged together using excel, which was used in data analytics and mining software such as Orange and Exploratory for analysis.

3.0 Data Analytics Methodology

For predictive analysis, a forecasting model and regression model was utilised.

3.1 Forecasting Model

With the usability for the main objective of the study and the appropriateness of the datasets, which were all time series datasets, a forecasting data model was developed to predict the clean energy mineral prices for 2025.

Through data analytics software such as Orange, Exploratory and Tableau, 4 forecasting models were utilized for the study:

3.1.1 ARIMA model

Autoregressive Integrated Moving Average (ARIMA) model is an effective timeseries forecasting model especially dealing with univariate data, where seasonal and trend effects are decomposed to maintain stationarity of the data. This model 3 components in a timeseries dataset such as the:

- Autoregression (AR) that analyses the relationship between an observation and lagged observations.
- Integration (I) which ensures the stationarity of the data to maintain properties such as mean and variance of the timeseries constant
- Moving Average (MA) which analyse the relationship between an observation and the residual error(Benvenuto et al. 2020, Satrio et al. 2021).

3.1.2 VAR model

Vector Auto-Regression (VAR) model is best suitable for forecasting models with multivariate timeseries data, where the interrelated dependencies of the multiple variances are analysed to understand their impact on the target variable and its future behaviour/performance(Hartini et al. 2015)

3.1.3 Prophet model

Prophet model is utilised for datasets with strong seasonal effects as the model can accommodate trends and seasonality well including the ability to accommodate historical seasonality, holiday effects as well as dealing with missing data(Satrio et al. 2021).

3.1.4 Holt-Winter's model

With Holt-Winter's or the triple exponential smoothing, the model can facilitate the weight driven by historical data to reduce through the assignment of decreasing weights/values against them, thus smoothing random fluctuations(Holt 2004).

The performance of each model was then evaluated to identify the most fitting forecasting model for the selected dataset and objective.

3.2 Regression Model

A linear regression model is able to identify and statistically estimate the relationship between a dependable or target variable and multiple independent variables(Uyanık & Güler 2013).

Therefore, in order to evaluate the significance of two independent variables – clean energy adoption rate and alternate energy cost against the target variable of price of clean energy minerals, a multiple linear regression model was utilised as the suitable model.

The significance level was measured at a confidence interval of 95% ($p<0.05$) to quantify their influence.

- *Data forecasting models in each software is available under Appendix section.*
- *Analysis of trends, seasonality and stationarity of forecasting data is provided under Appendix section.*

4.0 Visualisation and Evaluation of Results

4.1 Descriptive insights

To analyse the descriptive insights, Power BI was used to explore the three datasets and visualise their trends over the available time period.

Data Source	Observation	Reference
Data Source 1 – IMF	By visualising the monthly prices of the minerals, recent increase in price volatility was identified in all 3 minerals.	Figure 07 Figure 08 Figure 09
Data Source 2 – CER	After visualising the data, it was evident that the interest in adopting solar energy have been fluctuating during the time period.	Figure 10
Data Source 3 – AIP	After visualising the data, it was evident that the alternate energy cost has reached long-term highs during the recent years.	Figure 11

Table 02: Descriptive statistics observations

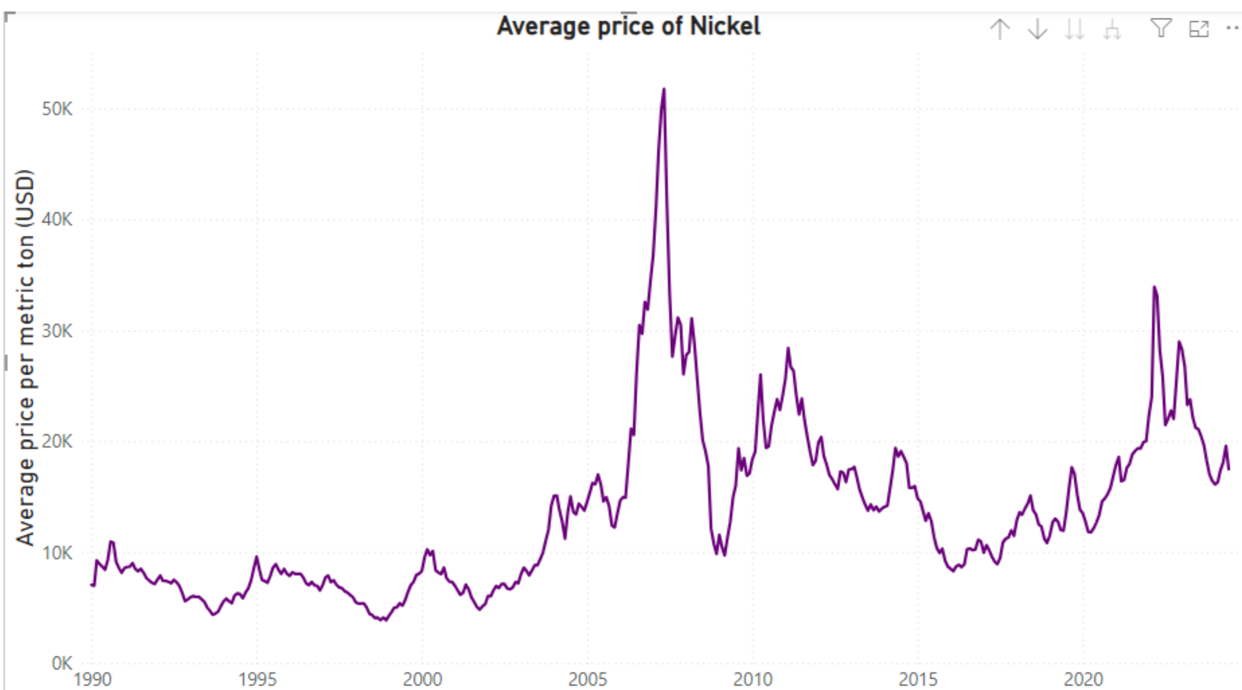

Figure 07: Average price of Nickel 1990 - 2024

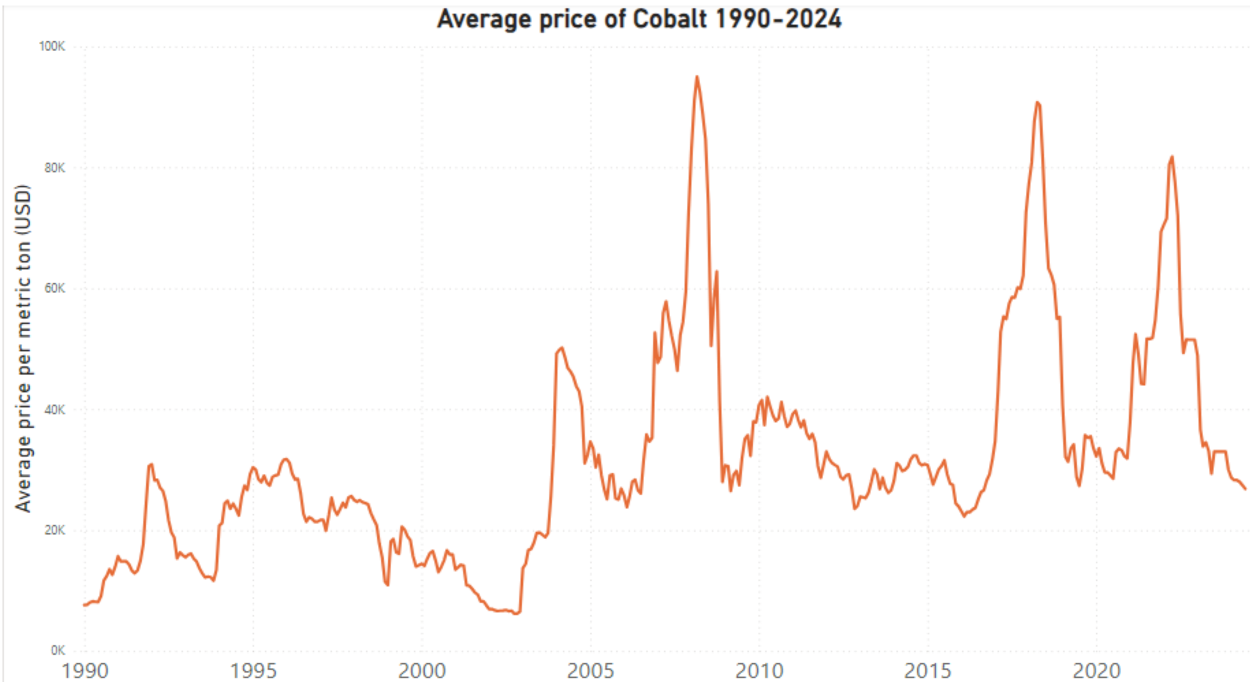

Figure 08: Average price of Cobalt 1990 - 2024

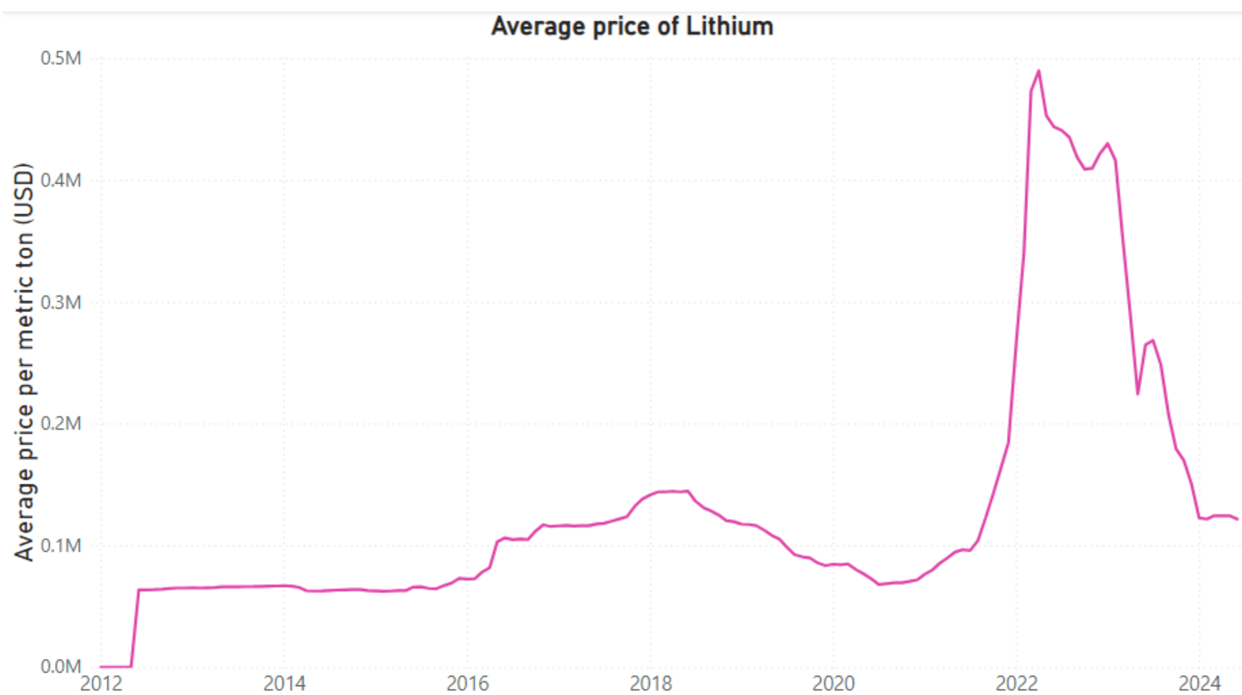

Figure 09: Average price of Lithium 1990 - 2024

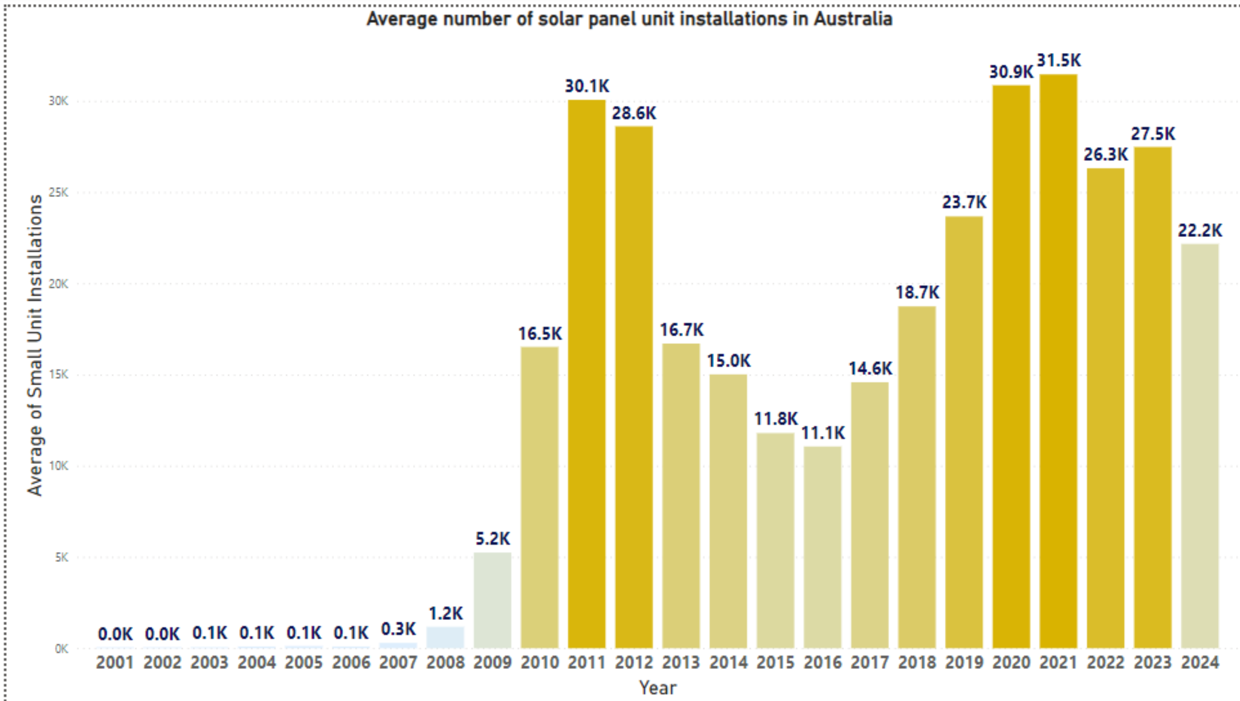

Figure 10: Solar panel installations in Australia from 2001 - 2024

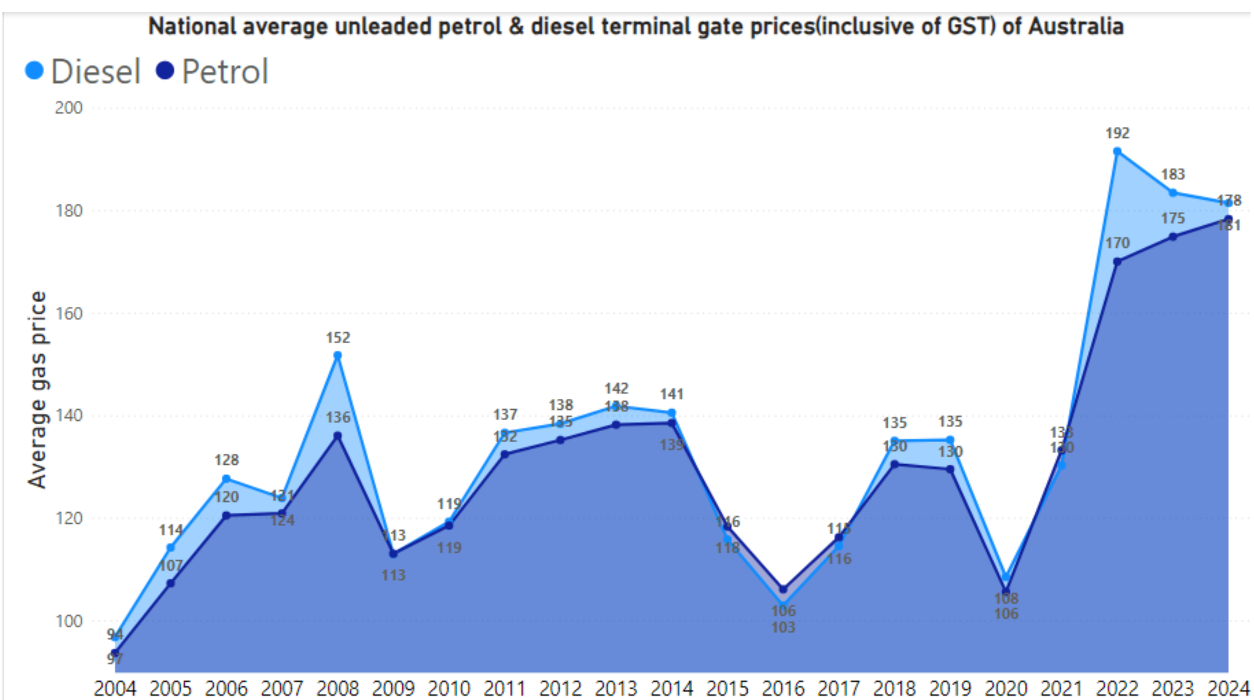

Figure 11: Average fuel terminal gate prices in Australia from 2004 -2024

4.2 Model Evaluation

4.2.1 Forecasting Model Evaluation

To analyse and interpret the accuracy as well as the fit of the forecasting models, the below metrics can be utilised(Omane-Adjepong et al. 2013, Chicco et al. 2021):

- Root Mean Square Error (RMSE) which considers the average of errors between actual and predicted values.
- Mean Absolute Percentage Error (MAPE) which consider the average of the absolute percentage error for each prediction, can be used
- R-Squared is representing the statistical significance of the fit and suitability of the model's ability to explain the variance in the target variance.

Model	RMSE			MAPE			R Squared		
	Ni	Co	Li	Ni	Co	Li	Ni	Co	Li
VAR	1,530.90	3,686.30	11,519.00	6.90%	7.00%	7.10%	0.961	0.955	0.983
ARIMA	1,395.93	3,326.55	9,535.60	5.87%	6.65%	5.23%	0.967	0.963	0.988
Prophet	4,921.35	14,482.21	49,694.43	25.29%	43.25%	44.30%	0.59	0.31	0.69
Holt-Winter's	1,856.00	4,902.00	24,438.00	7.70%	7.90%	6.20%	N/A*	N/A*	N/A*

Table 03: Forecasting model output evaluation

*Tableau was used for Holt-Winter's model, which did not have R-Squared figures in the model output.

From the above evaluation, ARIMA model shows the lowest RMSE, MAPE and the highest R-Squared values, thus becoming the most suitable model.

When analysing the PACF graphs, sudden decreases in values of lags after the initial lag can be an indication of an AR process, where Autoregressive model would perform better(Box et al. 1994).

Earlier analysis shows that the dataset had no significant seasonality which can explain the relatively poor performance of Prophet and Holt-Winter's models.

4.2.2 Regression Model Evaluation

Adjusted R Square explains ability of the overall regression model in explaining the variance in the target variance using the selected independent variables.

The ability of the combined independent variables in explaining the variance in the target variable will be explained by the model p-value and F-score (P value <0.05 will be considered as significant) (Nimon & Oswald 2013).

Cobalt			**Lithium**			**Nickel**		
Adj R Squared	F Value	P Value	Adj R Squared	F Value	P Value	Adj R Squared	F Value	P Value
42%	100.34	1.02E-48	45%	114.15	9.58E-54	53%	154.62	4.98E-67

Table 04: Regression model output evaluation

Adjusted R Squared is spread around 42% - 53%, indicating that the variables of fuel prices and solar installations has a moderate influence on the price of the minerals.

Which indicates a moderate fit, and more research and data will be required to identify other factors that impact the mineral prices and include them into the model.

The small model p-values (P value <0.05) for the F-tests indicate the overall statistical significance of the model & the variables together have a significant influence on the mineral prices.

p-value less than 0.05 (95%CI), is considered statistically significant.

Finally, each independent variable will be analysed for their impact and significance on the target variable through the Coefficient Tables(Nimon & Oswald 2013).

Variable	**Cobalt**	**Lithium**	**Nickel**
	P Value	P Value	P Value
Diesel Price	0.08	6.17E-11	0.06
Petrol Price	0.96	5.73E-09	0.78
Solar Installations	0.01	1.01E-14	8.84E-03

Table 05: Coefficient table output evaluation

The factors analysed and their significance on the mineral prices can be summarized as below:

Independent variable	Lithium	Cobalt	Nickel
Adoption rate of clean energy	Significant	Significant	Significant
Price of alternate fuel: Petrol	Significant	Not-significant	Not-significant
Price of alternate fuel: Diesel	Significant	Not-significant	Not-significant

Table 06: Coefficient table output interpretation

4.3 Forecasting Insights

After identifying ARIMA as the most suitable forecasting model, prices of minerals were forecasted into the 2nd quarter of 2025.

Date	Cobalt	Nickel	Lithium
Jan-25	32,006	16,614	119,753
Feb-25	32,827	16,723	120,288
Mar-25	33,608	16,875	120,319
Apr-25	34,323	16,782	119,940
May-25	34,975	16,903	120,017
Jun-25	35,569	17,178	120,255

Table 07: ARIMA model forecasting results for 2025

Figure 12: ARIMA model Cobalt price forecast

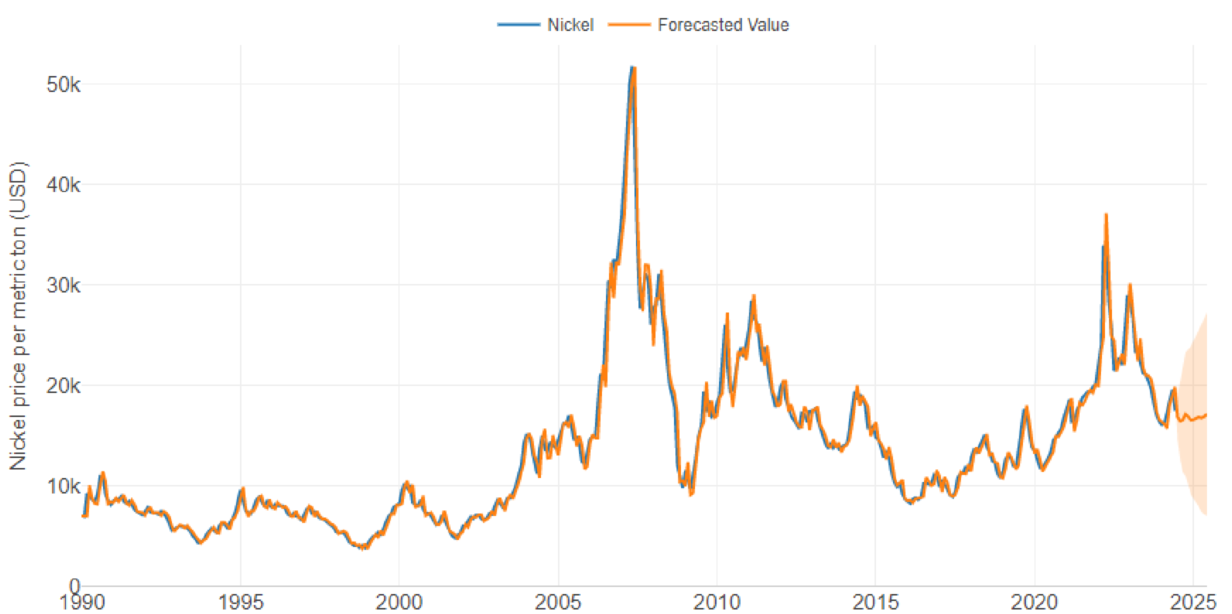

Figure 13: ARIMA model Nickel price forecast

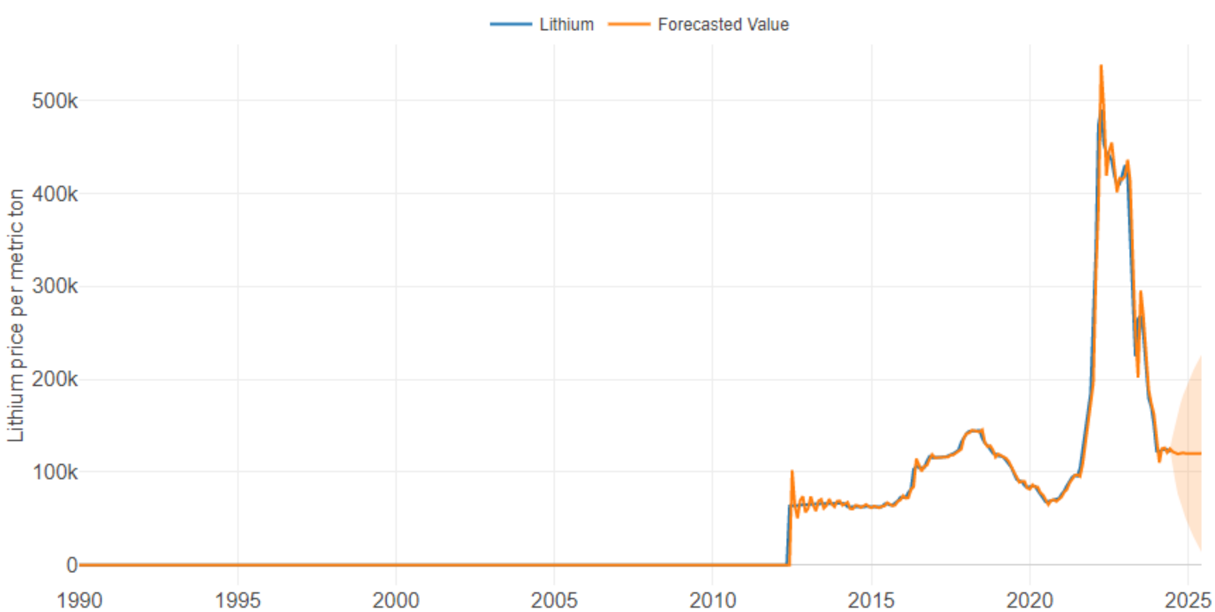

Figure 14: ARIMA model Lithium price forecast

Lithium global trading prices were available from Q2 of 2012

5.0 Recommendations

5.1 Insights from the predictive analysis

From analysing the forecasting results of the ARIMA model, it was evident that Cobalt has a significant price increase predicted while Nickel has a slight increase and Lithium staying within the same levels of price.

It can be recommended that the prices of these clean energy transition minerals will not exhibit strong seasonal fluctuations during the year, evident from the seasonality analysis as well as the relatively poor performance on forecasting model prophet that is better equipped for accommodating datasets with seasonality.

From the regression analysis it was identified that all 3 mineral prices are significantly correlated to the rate of adopting clean energy, which means with the growth is use of solar and wind energy, demand for these minerals will also increase.

Furthermore, it was identified that only lithium prices were affected by price of petrol and diesel, this could be due to the fact that electric-powered cars that are replacing petroleum-powered cars, predominantly use lithium-ion batteries for their power storage.

5.2 Limitations of the study

The overall study was designed and executed within the parameters a limited time horizon which was 12 weeks and thus the study was limited to analyse three minerals and analysing the factors which were identified in previous literature, so that the execution can be done within the deadlines imposed.

The data for the study was limited to the open-access data sources available, which limited the level of analysis performed into the prediction of future mineral prices and the factors identified to explain the volatility in the price of minerals.

5.3 Future improvements

Future studies can focus on identifying more data sources and volume, such as the availability of daily prices for minerals, could have improved the forecasting model accuracy, while availability of trading prices by country can provide insight into Australia's competition against other countries.

There is need for more analysis on factors that impact the price of minerals, while the two factors analysed in this study - the rate of clean energy adoption and cost of alternate energy, showed statistical significance, they only moderately explained the variance in mineral prices. More factors with relevant data should be taken into consideration to improve the analysis and results.

Deeper analysis of the application of these minerals such as Electric car sales, investment by governments and energy companies into solar and wind energy can provide wider insights of the price volatility as well as future demand.

6.0 Data Privacy, Security and Ethical Considerations

As credited in the study, the data was sourced from open-access government and global agency sources who collected the data and made them publicly available.

Therefore, there is no privacy consent or legal issues such as copyright issues.

Further, the data was received at aggregate level which had no sensitive personal information for anonymise or infringe any data protection laws.

The sole use of the data was for the forecasting model and due to the public-access availability of the data there is no data storage or retention issues as well.

Future analysis would need to update the data sources to receive more accurate and up-to-date insights to maintain the integrity of analysis.

Word Count: 2113

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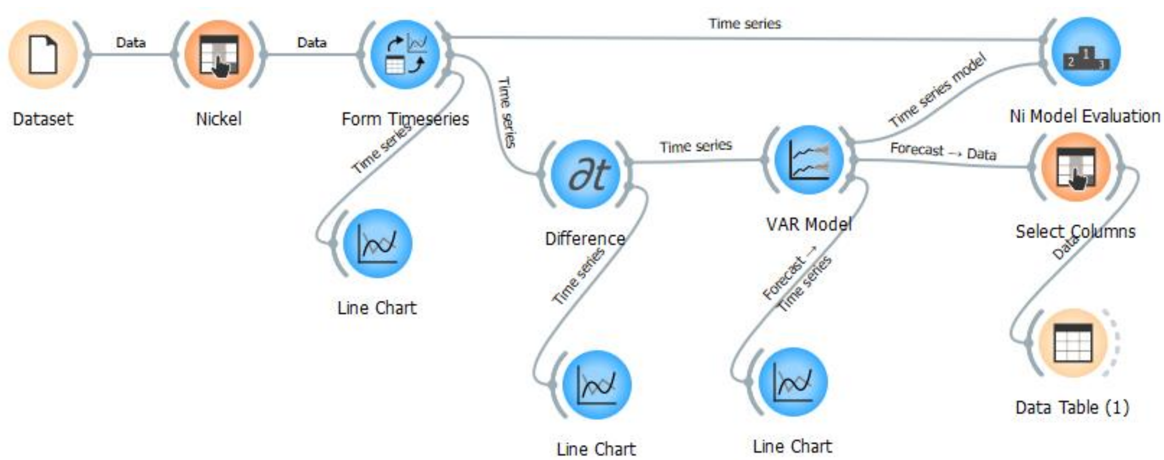
8.0 Appendices

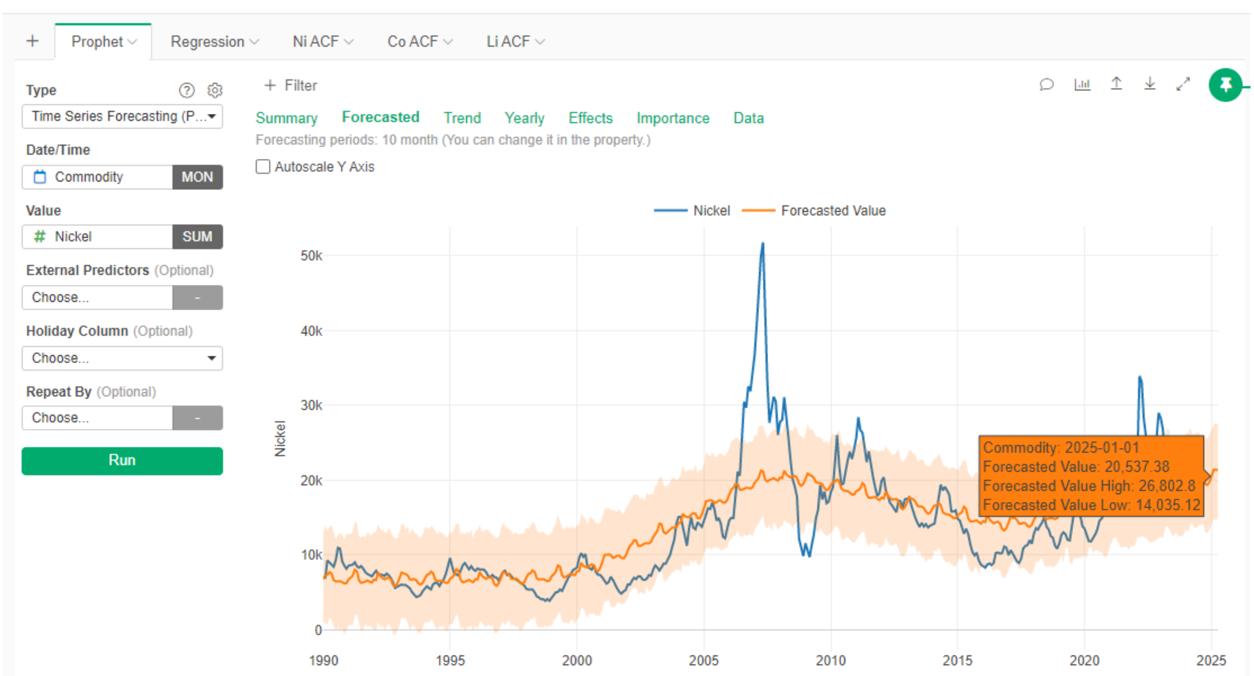
Appendix 1: Forecasting models in software

- ARIMA (Exploratory)

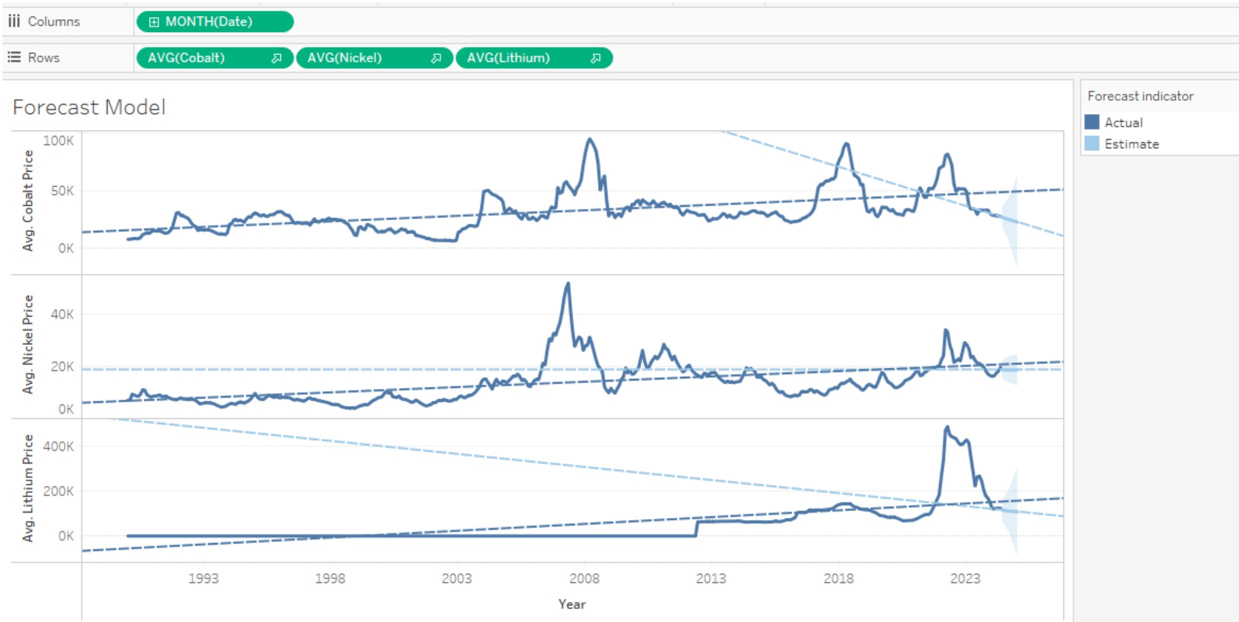
- VAR (Orange)



- Prophet (Exploratory)



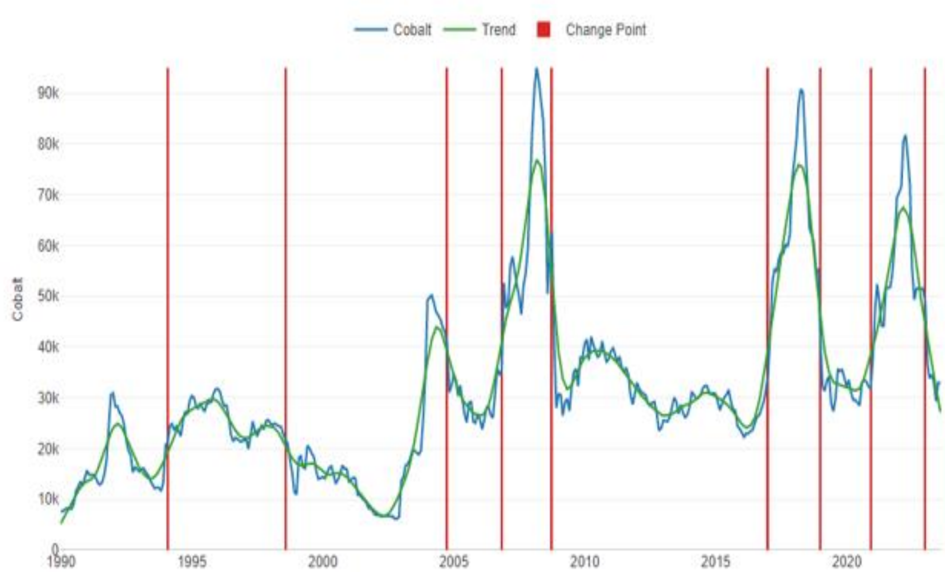
- Holt-Winter's (Tableau)



Appendix 2: Trend and Seasonality analysis

- Visual analysis

Upon analysis, an additive trend was present in Cobalt and Lithium prices while no significant seasonal properties were identified in all 3 mineral prices.



Avg. Cobalt

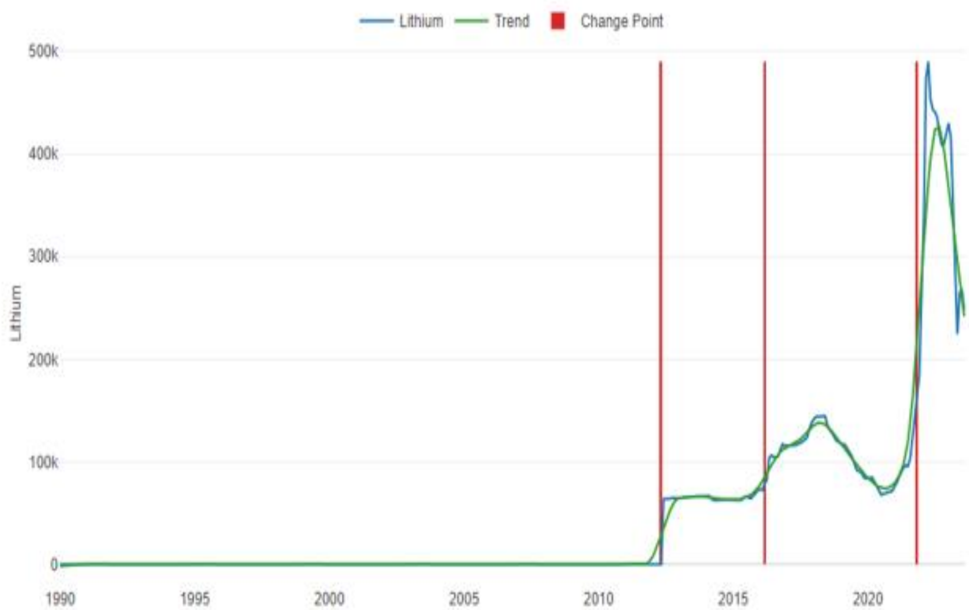
Model		
Level	Trend	Season
Additive	Additive	None

Avg. Lithium

Model		
Level	Trend	Season
Additive	Additive	None

Avg. Nickel

Model		
Level	Trend	Season
Additive	None	None



Avg. Cobalt

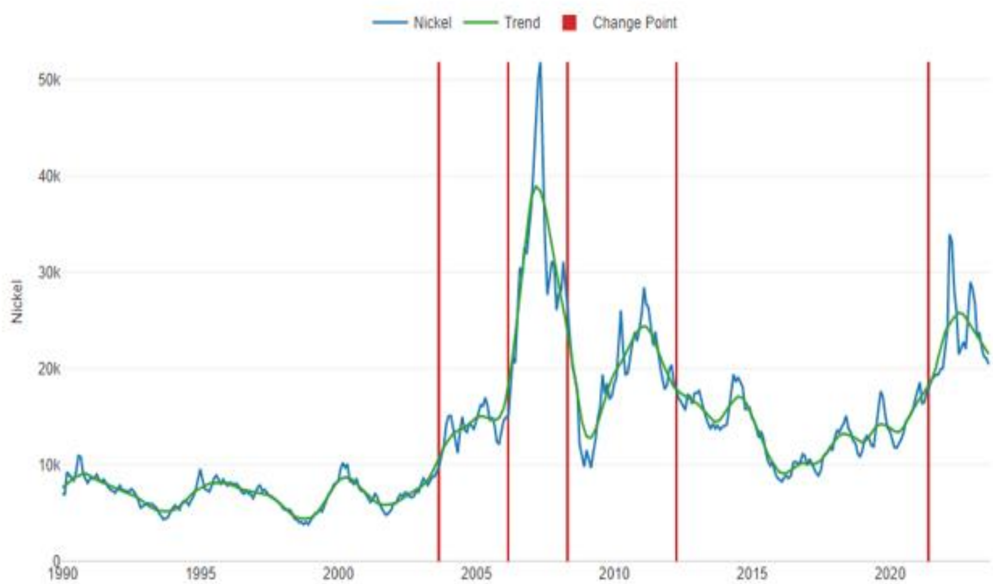
Model		
Level	Trend	Season
Additive	Additive	None

Avg. Lithium

Model		
Level	Trend	Season
Additive	Additive	None

Avg. Nickel

Model		
Level	Trend	Season
Additive	None	None



Avg. Cobalt

Model		
Level	Trend	Season
Additive	Additive	None

Avg. Lithium

Model		
Level	Trend	Season
Additive	Additive	None

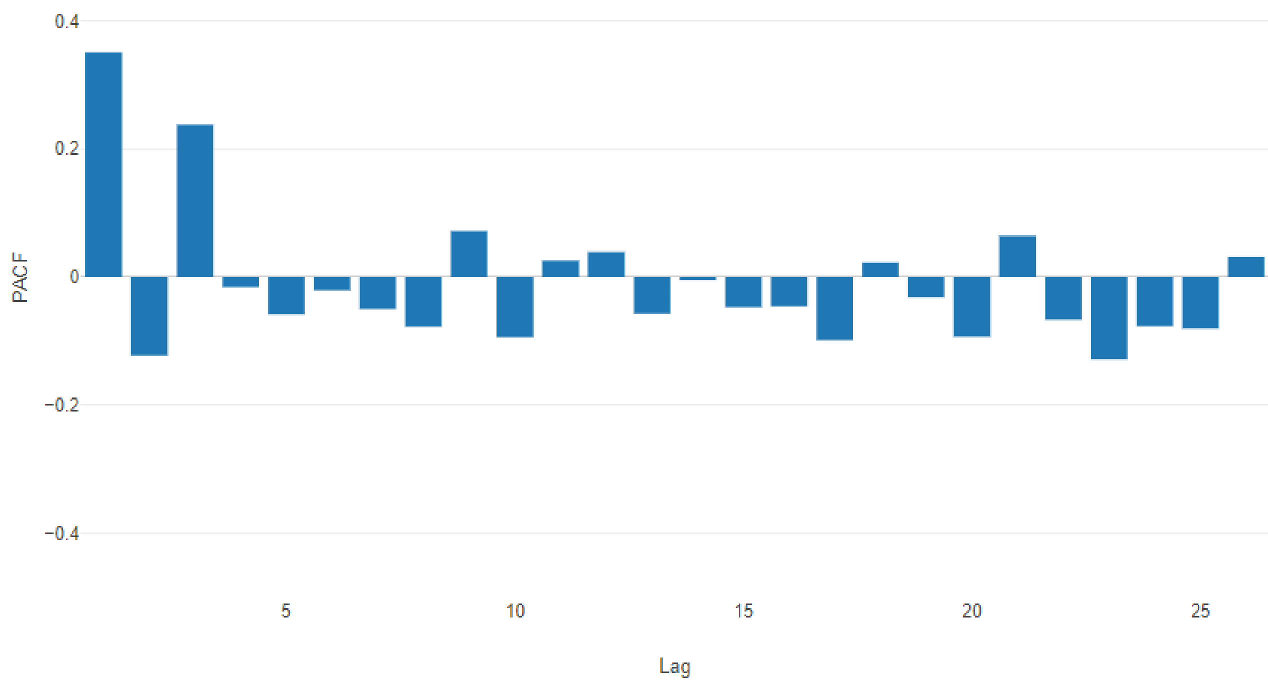
Avg. Nickel

Model		
Level	Trend	Season
Additive	None	None

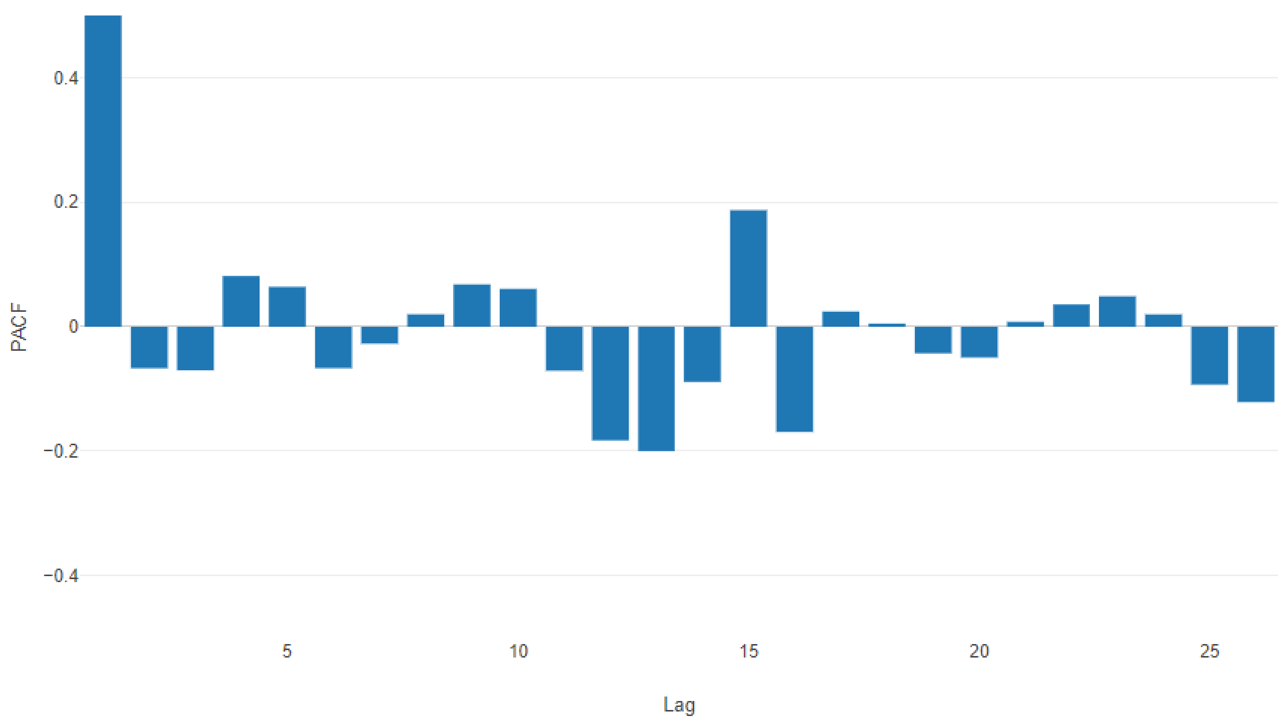
- Partial ACF plot analysis

No significant seasonality identified through visual inspection and analysed through ACF & Partial ACF graphs.

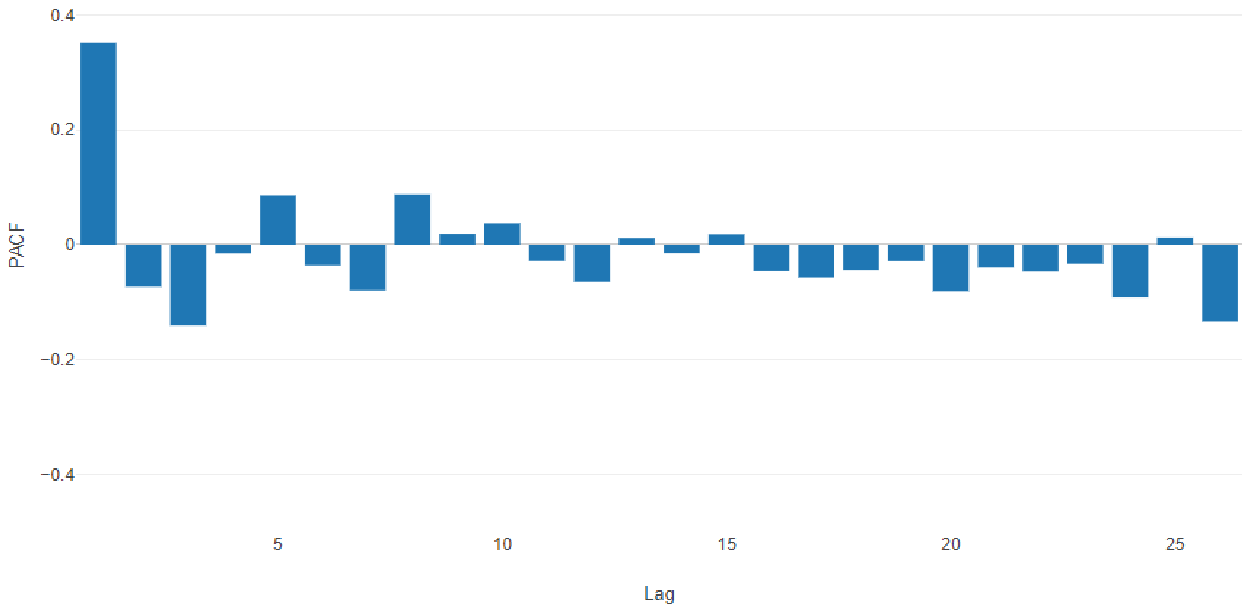
Partial ACF plot for Cobalt



Partial ACF plot for Lithium



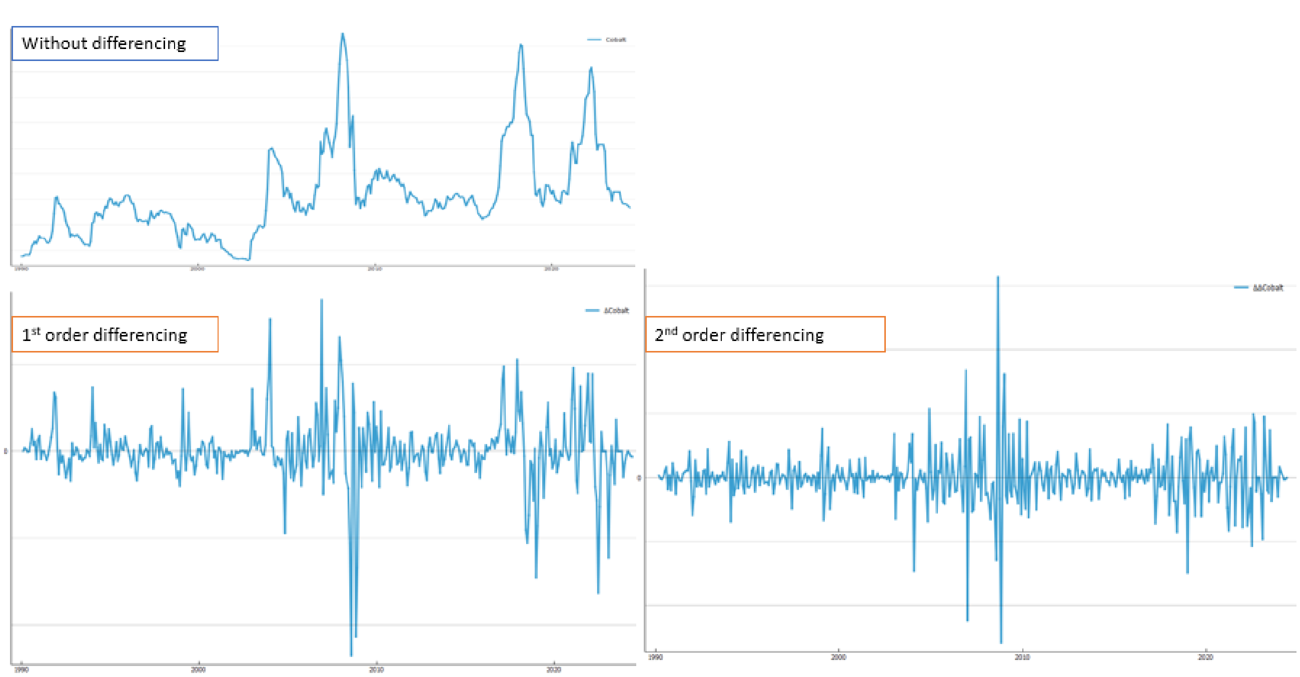
Partial ACF plot for Nickel



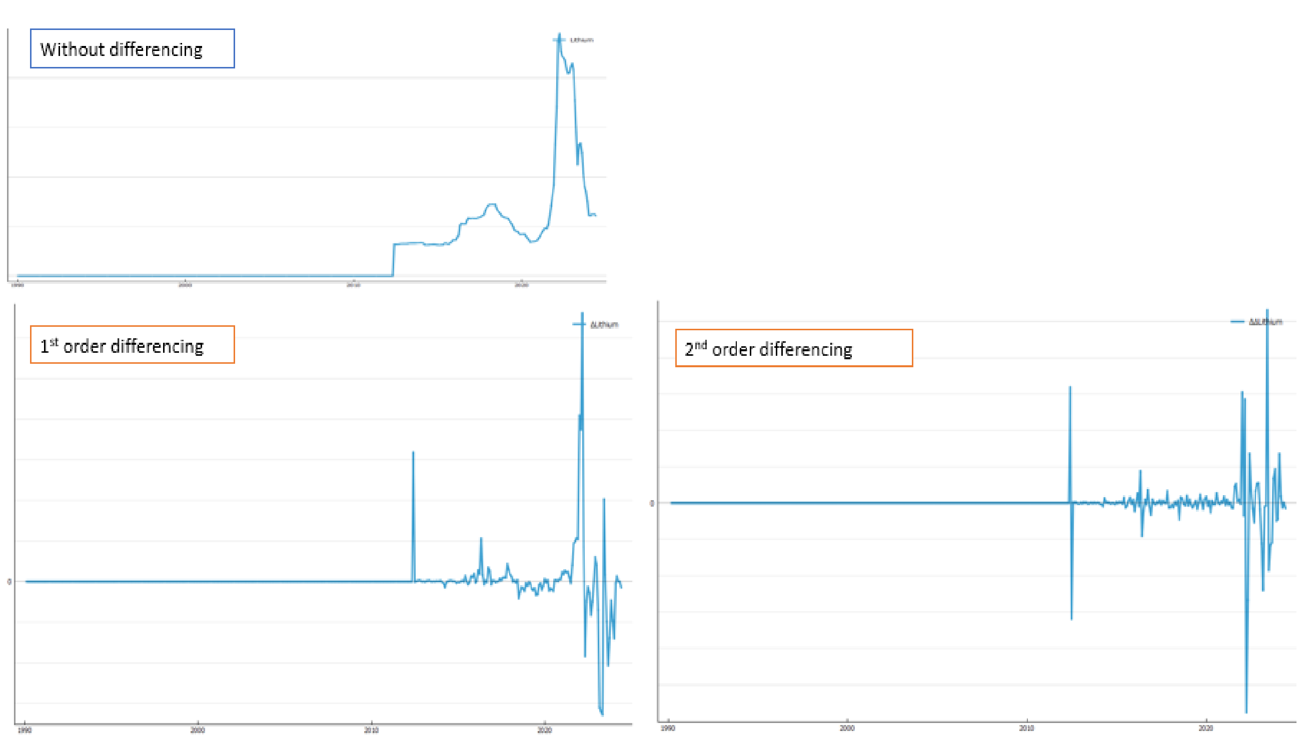
Appendix 3: Stationarity

Stationarity of the data was achieved with 2nd order differencing which is used to decompose the trend and seasonality properties of the data for analysis.

Cobalt



Lithium



Nickel