Silver ETFs Price Forecast

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Introduction

Project Scope

The scope of this project is focused on SILVER weekly commodity pricing forecasting. The goal of this project is to understand and apply time-series models like ARIMA, SARIMA in forecasting the price of silver.

What is the Problem?

Many investors buy silver both as a cheaper alternative to gold and also as a good way to diversify and counterbalance your portfolio and hedge against inflation.
However, with the rapidly changing economic landscape, does this still hold true? Is silver a good commodity to buy for later profits?.
Is Silver a Good Investment? Outlook, Risks, Comparison to Gold (businessinsider.com)[1]

1. Description of the Data Set

The data was downloaded from the historical prices of silver Silver Mar 22 (SI=F) Stock Historical Prices & Data - Yahoo Finance.
The price selected for the analysis was the closing in a range of 10 years every week from 2010 to 2021.

2. EDA (Exploratory Data Analysis)

The first column of the data set corresponds to the Date and the second column the closing price of silver.
A total of 575 entries, 2010-11-22 to 2021-11-22
No of rows: 575
No of Columns: 1
There were no missing or NAN values.

- ## Data Visualization

  Figure 1 shows the Closing prices of the Silver for the last 10 years and Figure 2 is the density plot.

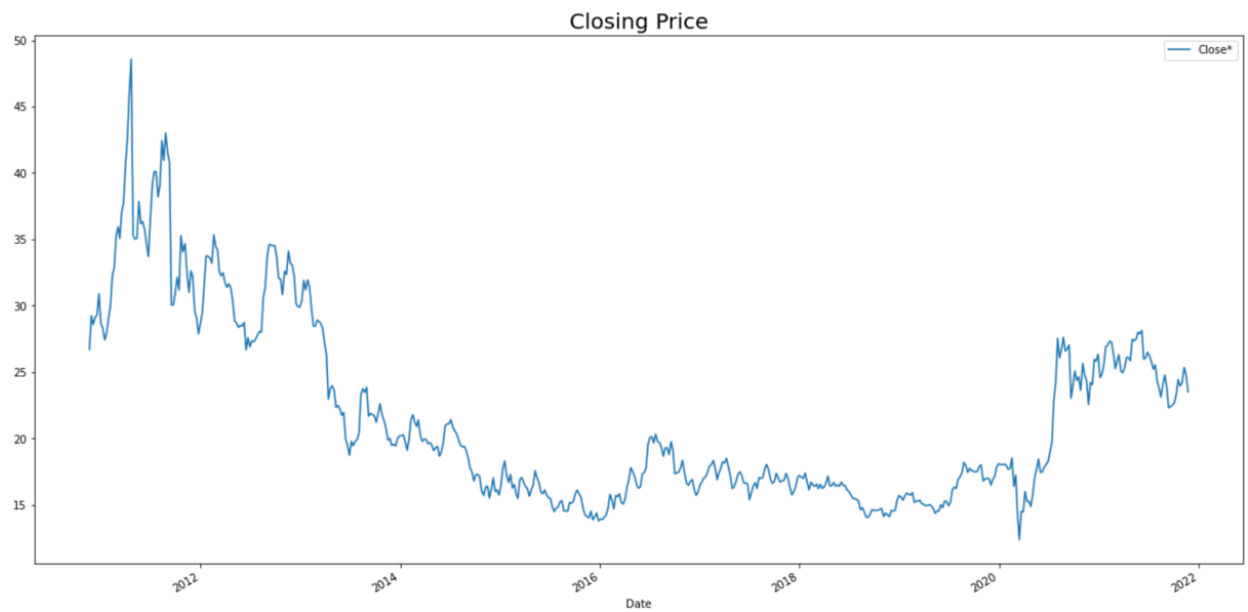

Figure 1: Silver Closing Price for 10 years weekly

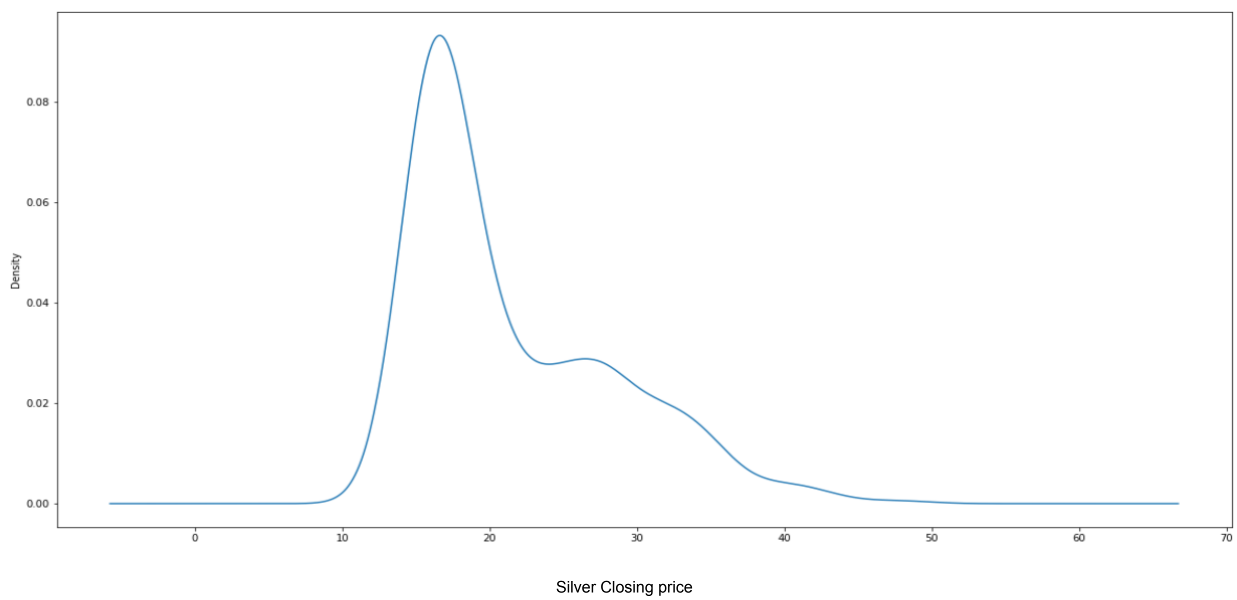

Figure 2: Silver Closing Price density plot

The Density plot shows that the price of silver fluctuates around 10-45 closing price , with higher frequency between 13-18

- ## Stationary Series

Because time series analysis only works with stationary data, we must first determine whether a series is stationary.

For this analysis we used two methods

Rolling statistics

Figure 3: Rolling Mean and Standard Deviation

The graph of rolling mean and rolling standard deviation is not constant, this shows that our dataset is not stationary.

Augmented Dickey-Fuller Test (ADF)

The Dickey-Fuller Test is another more statistically rigorous method to determine stationarity. A p-value < .05 would indicate that we could reject the null hypothesis that the data is not stationary.

Results of Dickey-Fuller Test:

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Test Statistic	-1.662797
p-value	0.450375
#lags Used	10.000000
Number of Observations Used	564.000000
Critical Value (1%)	-3.441998
Critical Value (5%)	-2.866678
Critical Value (10%)	-2.569506

The test statistic is (-1.66) .

The obtained p-value (0.45) is greater than the significance level of 0.05 and the ADF statistic is higher than any of the critical values. Clearly, there is no reason to reject the null hypothesis. So, the ADF test agrees with what we see in the rolling mean chart, that the time series is in fact non-stationary.

● Making the Time Series Stationary

To make the data stationary three methods were tested:

- The difference method: This is where from each value in our time series we subtract the previous
- The square root method: It transforms the time-series by taking the square root of the values in the given interval.
- Difference twice method: method to see which is a best way to make the data stationary

Method	ADF Statistic	p-value
Difference	-6.47	1.35e-08
Square Root	-1.83	0.37
Twice Difference	-11.56	3.18e-21

The Square Root methods didn't produce a p-value less than 0.05. So we should eliminate it. Both Differencing once and twice methods produced a p-value less than 0.05 but Differencing Twice produced a much more negative ADF Statistic. That's what we want, the more negative the better.

● Train-Test Split

Because we are dealing with time series data, the earlier data has to be the training data and the later data the test set.

The range for our training data is from 2010-11-22 to 2018-12-03 and for the test data is from 2018-12-03 to 2021-11-22.

Figure 4 shows the training and test data distribution.

Figure 4 Train and test data split

3. Modeling

For our analysis used two methods : ARIMA and SARIMA methods.

● ARIMA Model with no seasonality

ARIMA, short for 'Auto Regressive Integrated Moving Average', predicts the target variable using a regression based on the prices in previous time steps.
The initial ARIMA model was run with no seasonality.

● SARIMA Model (Arima Model with seasonality)

Seasonal ARIMA, is an extension of ARIMA that explicitly supports univariate time series data with a seasonal component. Below in Figure 8 is shown the time series decomposition of our data set.

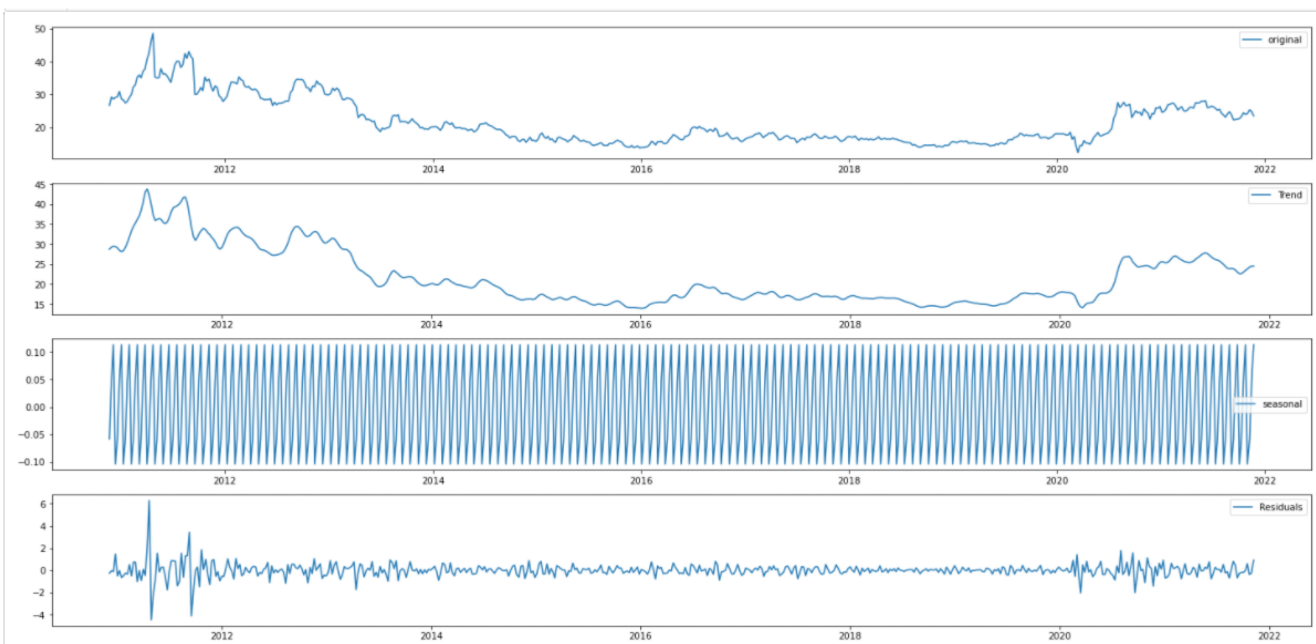

Figure 8 time series decomposition

Sarima adds three new hyperparameters to specify the autoregression (AR), differencing (I) and moving average (MA) for the seasonal component of the series, as well as an additional parameter for the period of the seasonality.

There are four seasonal elements that must be configured; they are:
P: Seasonal autoregressive order.
D: Seasonal difference order.
Q: Seasonal moving average order.
m: The number of time steps for a single seasonal period.

- ## Model Order Selection

For **ARIMA** model order Selection two methods were used: the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) and the auto_arima function.

The model order are determined by the following parameters:

d is the minimum number of differencing needed

p is the order of the 'Auto Regressive' (AR) term. It refers to the number of lags of Y to be used as predictors

q is the order of the 'Moving Average' (MA) term. It refers to the number of lagged forecast errors that should go into the ARIMA Model.

Below Fig 5 is the display using the ACF and PACF Method.

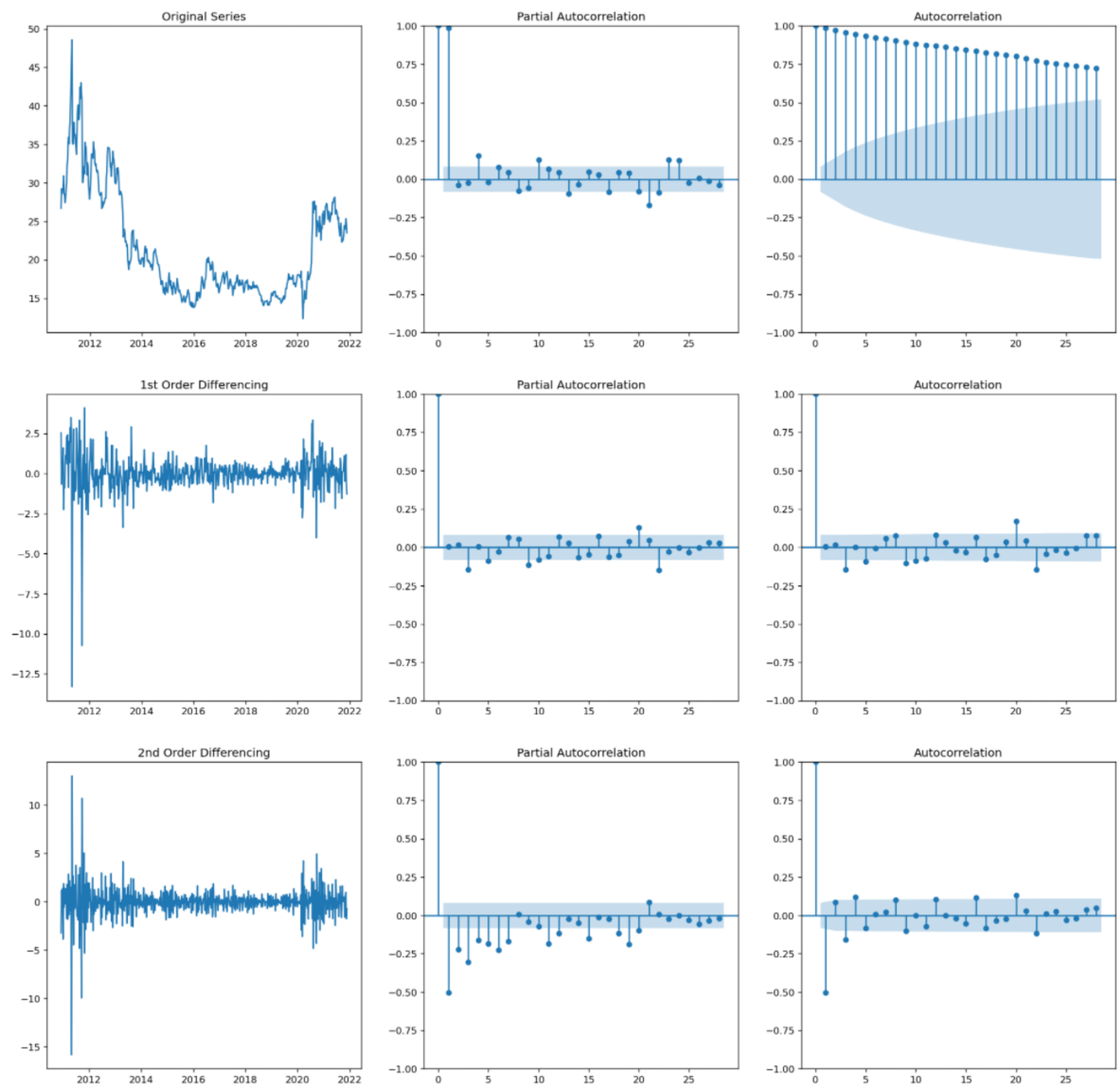

Figure 5 Display of the ACF and PACF for model order selection

The ACF cuts off after lag 1 and the PACF tails off. This may indicate that a Moving Average Model with an order of 1 MA might be the best. However, there are limitations to the ACF and PACF method. We are making the judgement based on how the ACF and PACF graphs look. Sometimes it may not be as clear to make a conclusion.

The second method used was the auto arima function that selects the parameters automatically based on the results of the test, in this case the Augmented Dickey-Fuller test.
We Use AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) results to pick the Optimal Model Order.Lower AIC indicates a better model AIC is ideal for simple models with lower order.Lower BIC indicates a better model BIC penalizes complex models.

We chose AIC to choose the model order.

Best Model Arima	**(0,1,0)(0,0,0)[0]**	**AIC=1793**
Best Model Sarima	**(1,0,0)(1,1,1)[4]**	**AIC=1784**

- ## Fit to Prediction on Training data

Based on our non seasonal and seasonal with the correspondent order we create a fit to predict the closing price of Silver for the last year (52 weeks) of the training data and then we compare the prediction against the real values of the last 52 weeks of the training data set.

Below in Figures 6 and 7 the display of the prediction on the training data

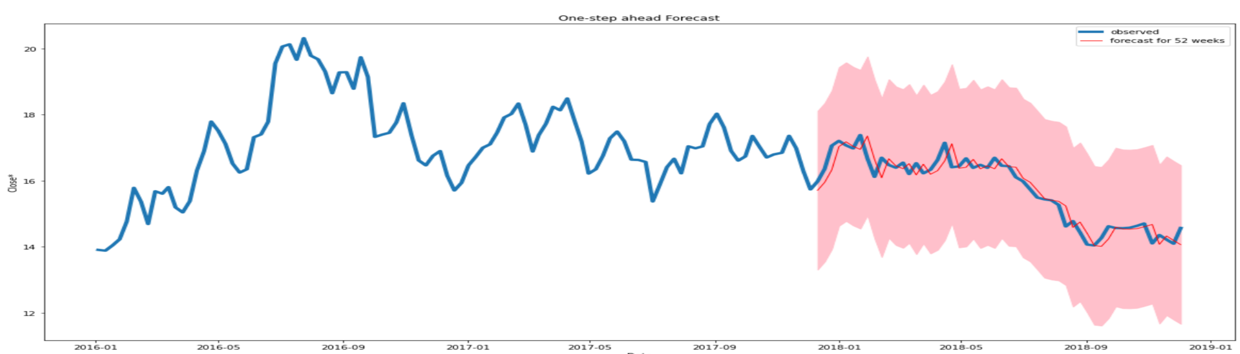

Figure 6 Observed and training prediction for ARIMA model

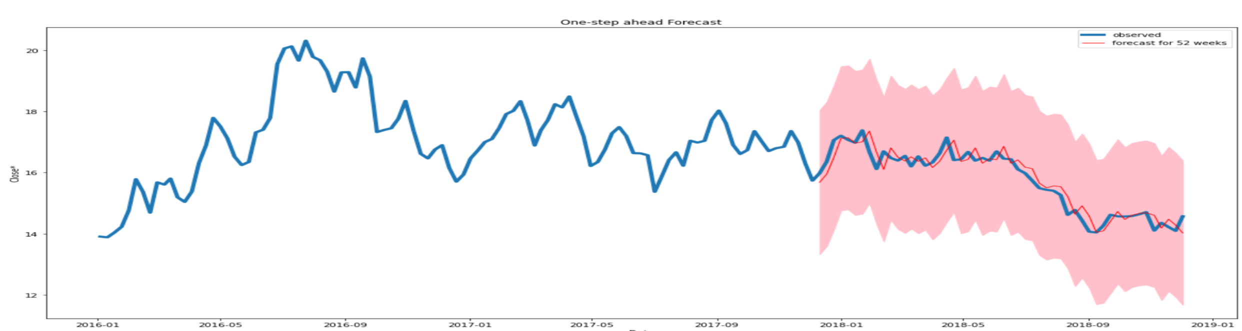

Figure 7 Observed and training prediction for SARIMA model

The Figures 6-7 shows that the prediction for the last 52 weeks of the training data aligns close to the real data in both Arima and Sarima Models.

- ## Forecast of the Silver price and compare to the test data

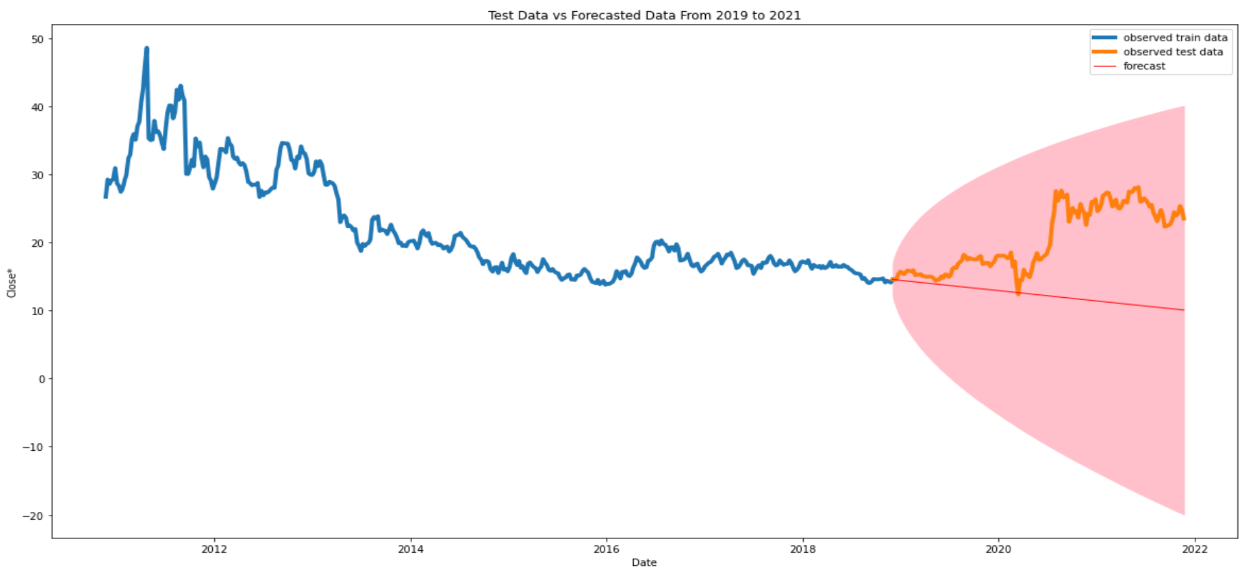

Figure 8 Test Data Vs Forecasted Arima model

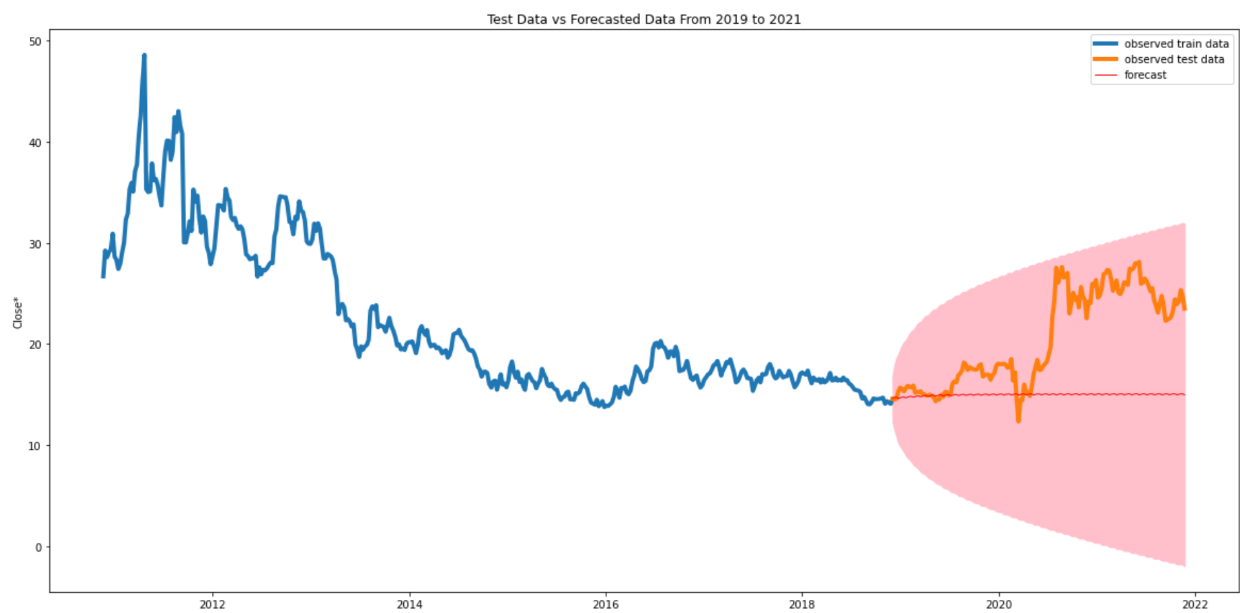

Figure 9 Test Data Vs Forecasted Sarima model

In figures 8-9 we observed that for the Arima model the trend is downward while the Sarima model is almost flat but closer to the actual trend and the confidence interval appears narrower for Sarima than for Arima.

- **Model Diagnostics Results**

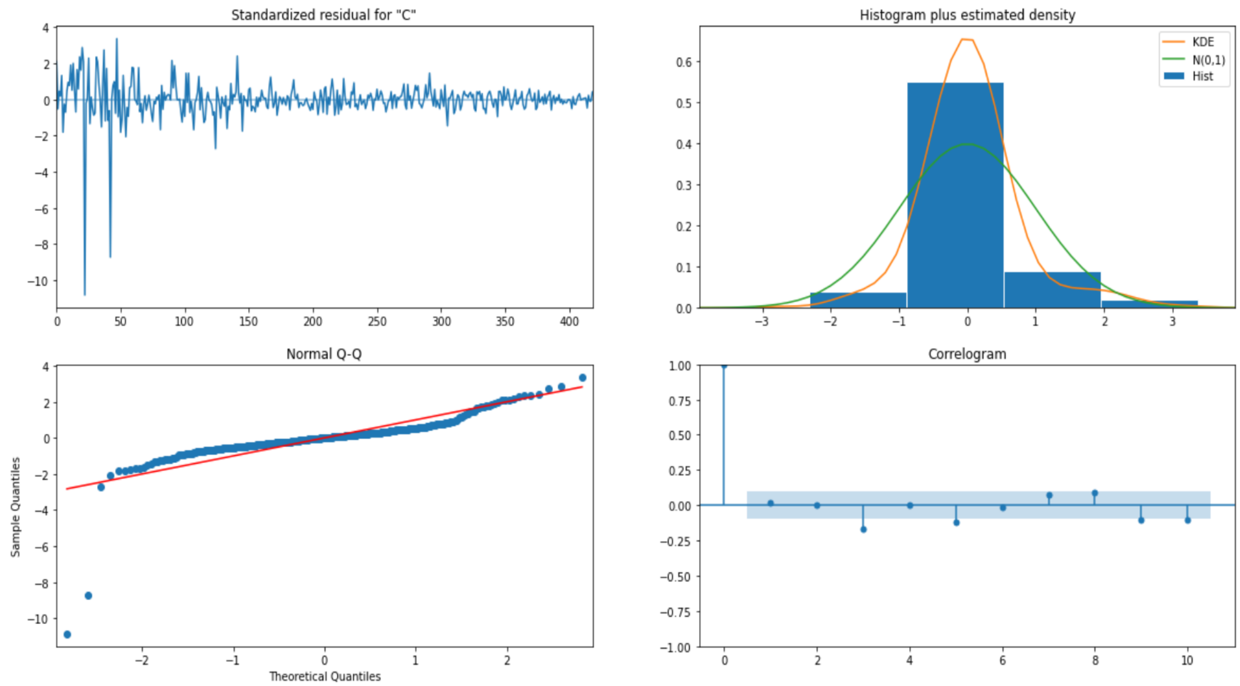

Figure10 Arima Model Diagnostics

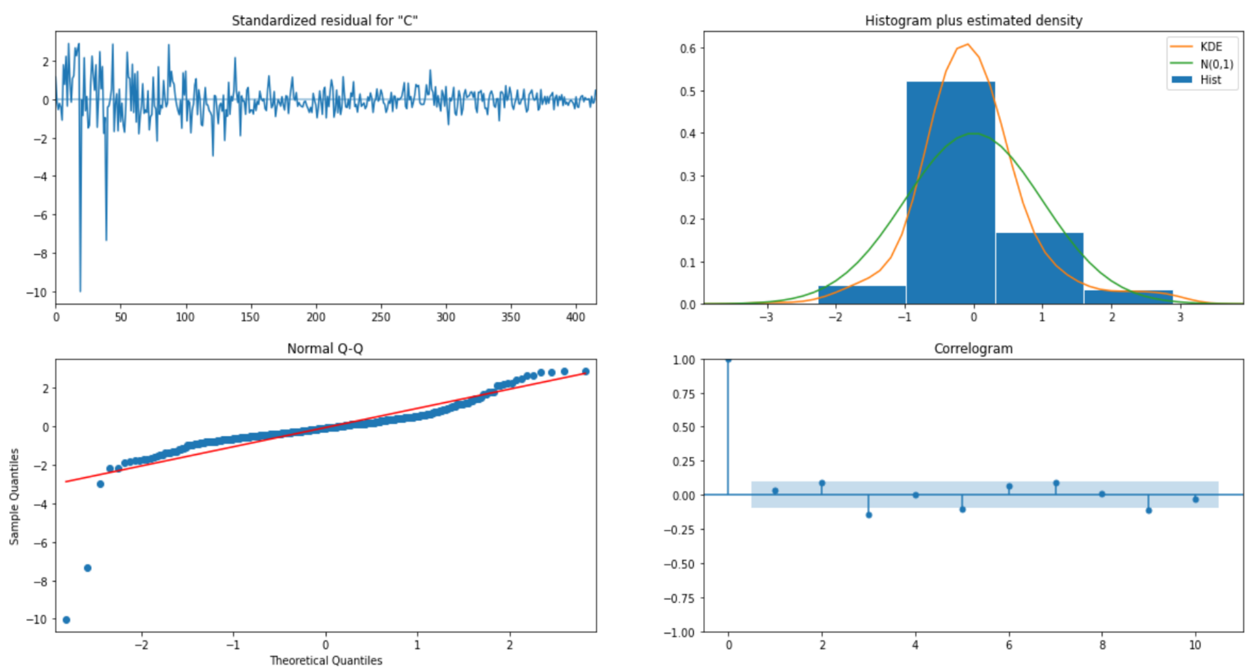

Figure 11 Sarima Model Diagnostics

The diagnostics show:

Standardized Residual Plot: The residual errors seem to fluctuate around a mean of zero and have a uniform variance for both models, although a little closer for Sarima than Arima.

Histogram Plus Estimated Density: The density plot suggests normal distribution. The green line shows a normal distribution of the residuals with mean zero and the orange line should be close to the green line. In this case both models are not close but Sarima is closer than the Arima model.

Normal Q-Q: Shows how the distribution of the residuals compares to a normal distribution. In This case most of the residual for both models are on the line.

Correlogram t: The Correlogram, aka, ACF plot shows the residual errors are not autocorrelated. Any autocorrelation would imply that there is some pattern in the residual errors which are not explained in the model. Overall, it seems to be a good fit.

Model	**Ljung-Box Prob (Q)**	**Jarque-Bera Prob(JB)**
Arima	**0.66**	**0.00**
Sarima	**0.62**	**0.00**

Ljung-Box - the null hypothesis states there are no correlations in the residual. If Prob(Q) <= 0.05,
Since the p-values for both models are bigger than 0.05 , we can't reject the null hypothesis that the errors are white noise.
Jarque-Bera - the null hypothesis states the residuals are normally distributed. If Prob(JB) <= 0.05, in this case for Both Models p-value is equal to 0 then we have to reject the null hypothesis, and the data are not normally distributed. This means that in the next steps for modeling, the reason for this would need to be examined and the model adjusted accordingly to account for it.

- ## Scoring Metrics: MAE, RMSE

Model	MAE	RMSE
ARIMA	8.11	9.99
SARIMA	5.50	7.12

Conclusion

This project focused on SILVER weekly commodity pricing forecasting. The goal for this project is to understand and apply ARIMA, SARIMA time-series models in forecasting the price of silver.
By looking at the plot of the ARIMA Model we can observe a downward trend in the forecast window which is not aligned with the trend of the test data.

The SARIMA model, which is the ARIMA Model that includes seasonality, shows an improved forecast although not the correct trend which is upward. The accuracy metrics confirm that the Sarima Model is more accurate.

Future work would include refining this model (for example to make the residuals normally distributed) and using other modeling tools such as Facebook prophet and LSTM.

References

1. Is Silver a Good Investment? Outlook, Risks, Comparison to Gold (businessinsider.com)