ECON 5337

Business & Economic Forecasting

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Project Report

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Submitted by:

Team Members:	UTA ID
1. Abhishek Kumar Jha	1001844104
2. Pallav Das	1002118965
3. Sushmitha Doke	1002116447

INTRODUCTION

Investment in the financial markets is an interesting medium to create wealth. However, the financial markets are unpredictable and are impacted by so many things. In the ever-changing world of finance, the relationship between macroeconomic indicators and the financial market is compelling. Inflation, interest rates, unemployment rate, GDP Growth rate and GDP are a few macroeconomic indicators. These indicators give information about in which direction the economy is moving and the market's stability. Thus indicators serve as guiding light for investors and influence their decision to invest in the stock market and gold by influencing how the financial market moves.

The objective of this project is to estimate the relationship between macroeconomic indicators and financial markets such as the stock market, commodity, and cryptocurrency market, with the prime focus on identifying the substantial macro indicator, the relationship between GDP Growth and Stock Market Performance, and comparing different forecasting Methods. The methodologies that we used to achieve these objectives are the Exponential Smoothing (ETS) model, Time Series Regression, and Autoregressive Integrated Moving Average (ARIMA).

By having a better understanding of the macroeconomic indicator investors can align their financial goals with risk tolerance which can lead to better investment returns and they can have better financial plans and safeguard their financial well-being. Companies can take advantage of this analysis and can make better strategic decisions such as allocating capital, risk management, and cost-cutting.

Overall, We performed Linear Regression to explore the influence of macroeconomic indicators and establish relationships on long-term trends. We also performed ARIMA and ETS forecasting. Because we performed so many transformations on ARIMA, we believe, it performed really well. However, we did not perform model evaluation using training and testing sets because our goal was not to find what model is the best rather to explore what these models suggest.

OBJECTIVE OF THE PROJECT:

1. Which specific macroeconomic indicators significantly influence different financial markets, such as stock markets, commodity, and cryptocurrency markets?

2. How do changes in GDP growth rates affect stock market performance, and can this relationship be used to predict market trends?

3. What is the relationship between interest rate changes by central banks and the financial markets?

4. Can we predict the next financial crisis? Are there any hidden patterns?

5. What are the strengths and limitations of different forecasting methods, such as time series analysis, regression models and machine learning algorithms in predicting financial market movements based on macroeconomic indicators?

Literature review:

In the article "Forecasting Stock Price Trends by Analyzing Economic Reports With Analyst Profiles" written by Suzuki et al.(Masahiro Suzuki, Hiroki Sakaji, Kiyoshi Izumi, and Yasushi Ishikawa) uses natural language processing and neural networks to analyze analyst reports and forecast stock price trends. Analyst reports consist of financial results and stock prices, as well as analyst forecasts of future earnings and stock price performance. The model achieved a Macro-F1 score of 0.811 for opinion sentence extraction, with a recall of 0.848 and a precision of 0.733.

In another paper " Research of the Influence of Macro-Economic Factors on the Price of Gold" by Li Lili, Diao Chengmei.The paper investigates the impact of macroeconomic factors on gold prices, using a dataset that includes global macroeconomic indicators, financial market indices, quantities, and prices of gold. The effect of financial market indices and global macroeconomic indicators on gold prices is negative. This implies that purely financial data and macroeconomic factors have a negative impact on gold prices. The study employs various methods such as the

ADF test, Granger causality test, VAR model construction, generalized impulse response function, and empirical analysis to analyze the factors' impact on gold prices.

The other paper explores Bitcoin price prediction with new machine learning methods, considering both macroeconomic and microeconomic theories. It compares ordinary least squares (OLS), Ensemble learning, support vector regression (SVR), and multilayer perceptron (MLP) on economic, technical, and blockchain indicators. The findings confirm the significance of technical indicators for short-term predictions and macroeconomic and blockchain indicators for long-term predictions, substantiating the relevance of supply, demand, and cost-based pricing theories. SVR outperformed other methods, enhancing the understanding of Bitcoin price predictions theoretically and practically.

DATA DESCRIPTION:

For this project, we have gathered datasets from Yahoo Finance, for the S&P 500 index, daily gold prices, and Bitcoin prices. Then these datasets are integrated with relevant macroeconomic indicators, including inflation, unemployment, GDP growth rate, GDP, interest rate, and CPI parameters. The data for the economic indicators were taken from the world bank. The World bank provides annual data for all the countries. All the transformations are made in excel.

The data for the asset price is daily while the data for the economic indicators are annually. Some of these indicators are reported annually, while some are reported quarterly. We could also find monthly data for some. To maintain consistency, we chose annual data to be the length of our economic indicators. We also choose annual data as the length because we wanted to capture long term trend and effect and dismiss the short term noise which we would have got if we had chosen monthly and quarterly data. The third reason to go for annual data is because the effect of these parameters are not sudden and it takes time for these to take effect for example interest rates. The effects are not immediate. So by taking annual data, we have taken enough time to account for these effects on the markets.

Inflation(GDP Deflator):

Inflation is defined as a prolonged increase in the general price level of goods and services that erodes money's purchasing power. This might be caused by excessive aggregate demand, increased production costs (cost-push inflation), or central bank policy.

Inflation can erode purchasing power, cause economic instability, and amplify income inequality. Central banks combat inflation by raising interest rates, selling government bonds, and increasing reserve requirements. Understanding inflation is critical for making informed decisions about saving and investing.

Unemployment rate:

The unemployment rate is defined as the percentage of the labor force that is actively looking for work but is unable to find it, representing the state of the economy and job availability.The unemployment rate has a substantial impact on financial markets such as stocks, gold, and Bitcoin.High unemployment can lead to lower stock prices as consumer spending and corporate profits decline. Gold often shines in such times due to its safe-haven appeal, while Bitcoin can rise as an alternative investment amidst turmoil.

Low unemployment, on the other hand, could prop up stock prices thanks to increased consumer spending and stronger corporate profits. Gold might lose its luster as economic strength reduces the need for safe havens, while Bitcoin's fate could be mixed based on investor risk appetite and its adoption potential.

GDP growth rate:

The gross domestic product (GDP) growth rate, which measures the percentage change in the total market value of goods and services produced within a country over a specific period, serves as a crucial indicator of economic health and activity. Its influence on the financial market is significant.

Increased economic activity leads to better business earnings, which drives up stock prices and boosts investor confidence. High-growth periods can raise risk appetite, thereby undermining gold's appeal as a haven asset. The link between GDP growth and cryptocurrency prices is complicated and changing.

GDP:

Gross domestic product (GDP) represents the total monetary value of all final goods and services produced within a country during a specific period. This critical economic indicator influences a wide range of financial markets, including stocks, gold, and even Bitcoin.

Economic growth fuels stock prices as corporate profits rise, while stagnant economies can lead to downturns. Gold is a safe investment during times of uncertainty, but its demand may wane during strong economic periods. Bitcoin's relationship with GDP is complex and requires further investigation. Understanding these dynamics empowers informed decision-making in the financial market.

Interest rate:

Interest rates, or the cost of borrowing money, are a significant influence in the financial landscape, having enormous effects across a wide range of asset classes. Interest rates influence investment decisions, economic activity, and, ultimately, the functioning of financial markets by changing the cost of lending.

Lower interest rates encourage borrowing and investment, potentially leading to higher business valuations and higher stock prices. Higher rates, on the other hand, discourage borrowing and investment, putting downward pressure on stock prices and necessitating a reconsideration of business values.

Gold is sometimes used as an edge against inflation, with higher interest rates potentially benefiting from inflationary periods. Higher interest rates, on the other hand, promote investment in other asset types, thereby undermining gold's appeal.

CPI:

The Consumer Price Index (CPI) tracks price fluctuations in a basket of products and services commonly purchased by urban consumers. This critical indicator serves as an inflation measure, influencing numerous areas of the financial market.

Rising CPI means increased inflation, which may reduce company profits and discourage investment, potentially resulting in lower stock prices. Gold has traditionally been used to limit inflation, typically profiting from periods of rising CPI because its price rises in accordance with inflation.

Closing Price:

The actual dataset had the opening, closing, low and high prices for each record. However we decided to move forward with the closing price instead. The closing price is the value of the last transacted price before the market officially closes for trading. However for Bitcoin, closing price generally refers to the price at 11:59 PM UTC of any given day.

Below, you will find the link to our dataset:

S & P 500:

https://drive.google.com/file/d/1f2C1N6oljg7LKvG47UvyJwX-yPiNmewC/view?usp=sharing

Bitcoin:

https://drive.google.com/file/d/1sDTvOQzfO4GNlKhmhdAHKkp-nODz42Qi/view?usp=sharing

Gold:

https://drive.google.com/file/d/1IZgk4Ektf6E6tySOKRMrVecyaWzTmO2Y/view?usp=sharing

Data Cleaning

Before using R to build a model that predicts the closing prices of financial markets based on macroeconomic indicators, we cleaned up our data in Excel. We went through each piece of information to make sure it was accurate and consistent. This involved fixing missing or strange values and adjusting the format of the data. We paid special attention to variables like economic indicators and time-related data, ensuring everything was in a standardized and usable form. After cleaning, we imported the refined data into R for analysis.

Methodology:

In this study, we employ Linear Regression, and ARIMA & ETS models to forecast the closing prices of a stock, gold, and Bitcoin. The S&P 500 represents the stock market, the Gold represents the commodity market and Bitcoin represents the cryptocurrency market. Overall, they represent the majority of the financial markets.

Linear Regression

The first model we ran was linear regression. One of the main advantages of linear regression is feature selection. We can see the effect of various independent variables on the target variable (Close) using the Linear Regression. Out of Open, high, close, adjacent close prices, we chose Close price as it is the standard in the financial industry. Below is the analysis of linear regression for various markets:

Linear Regression Results & Findings

We used the forward stepwise regression technique to predict prices. This approach commences with an empty model, gradually incorporating predictor variables while rigorously evaluating their impact on the model's performance. We prioritize the selection of variables that enhance the model while concurrently minimizing the cross-validation (CV)value.

Coefficient Analysis:

S&P 500:

```
Call:
tslm(formula = Close ~ Inflation + Unemployment + Interest_rate +
    GDP_Growth_Rate + GDP + CPI, data = df)

Residuals:
    Min      1Q  Median      3Q     Max
-719.69 -198.58  -46.33  138.88 1406.38

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)     -1.703e+03  5.484e+01 -31.060  < 2e-16 ***
Inflation        1.512e+02  1.052e+01  14.380  < 2e-16 ***
Unemployment    -3.383e+01  3.750e+00  -9.021  < 2e-16 ***
Interest_rate    8.149e+01  3.771e+00  21.609  < 2e-16 ***
GDP_Growth_Rate  5.847e+01  2.613e+00  22.375  < 2e-16 ***
GDP              1.960e-10  1.437e-12 136.352  < 2e-16 ***
CPI             -2.094e+01  7.634e+00  -2.742  0.00611 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 317.8 on 7548 degrees of freedom
Multiple R-squared:  0.8943,	Adjusted R-squared:  0.8942
F-statistic: 1.064e+04 on 6 and 7548 DF,  p-value: < 2.2e-16
```

Linear Regression Model Summary: S&P 500

Impact on Stock Price (S&P500):

Equation:

$$\textbf{Closing} = \beta 0 + \beta 1\ \textbf{Inflation} + \beta 2\ \textbf{Unemployment} + \beta 2\ \textbf{Interest rate} + \beta 3\ \textbf{GDP growth rate} + \beta 4\textbf{GDP} + \beta 5\textbf{CPI}$$

$$\text{Closing} = -1703.29 + 151.22\ \text{Inflation} - 33.83\ \text{Unemployment} + 81.49\ \text{Interest rate} + 58.47\ \text{GDP growth rate} + 0.0000000001959955\ \text{GDP} - 20.94\ \text{CPI}$$

The intercept of -1703.29 is the expected stock price when all other factors are zero. Each unit increase in inflation, interest rate, and GDP growth rate is associated with a respective change in the stock price of +151.22, +81.49, and +58.47. GDP's impact is negligible with a coefficient of +0.0000000001959955. A unit increase in unemployment and CPI leads to a decrease in stock price of -33.83 and -20.94, respectively. Inflation, interest rate, and GDP growth rate have positive relationships with the stock price, while unemployment and CPI have negative relationships.

Bitcoin

```
Call:
tslm(formula = Close ~ Inflation + Unemployment + CPI + GDP_Growth_Rate +
    GDP, data = df)

Residuals:
     Min       1Q   Median       3Q      Max
-18051.4  -1982.4   -286.2    951.3  20141.2

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)     -1.405e+05  2.460e+03  -57.09   <2e-16 ***
Inflation       -6.550e+03  4.643e+02  -14.11   <2e-16 ***
Unemployment     7.279e+03  1.117e+02   65.17   <2e-16 ***
CPI              5.681e+03  3.821e+02   14.87   <2e-16 ***
GDP_Growth_Rate  5.263e+03  6.974e+01   75.46   <2e-16 ***
GDP              5.167e-09  1.382e-10   37.38   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5567 on 2916 degrees of freedom
Multiple R-squared:  0.8835,    Adjusted R-squared:  0.8833
F-statistic:  4423 on 5 and 2916 DF,  p-value: < 2.2e-16
```

Linear Regression Model Summary: Bitcoin

Impact on Bitcoin Price:

Equation

Closing = -140500.00 -6550.00 Inflation+ 7279.00 Unemployment+ +5263.0 GDP growth rate+ 0.000000005167 GDP+ 5681.00 CPI

The intercept of -140500.00 represents the expected Bitcoin price when all other factors are zero. Each unit increase in unemployment, GDP growth rate, and CPI is associated with a respective change in Bitcoin price of +7279.0, +5263.0, and +5681.0. GDP's impact is negligible with a coefficient of +0.000000005167. A unit increase in inflation leads to a -6550.0 decrease in Bitcoin price. Unemployment, GDP growth rate, and CPI have positive relationships with Bitcoin price, while inflation has a negative relationship.

Gold

```
Call:
tslm(formula = Close ~ Inflation + Unemployment + Interest_rate +
    GDP_Growth_Rate, data = df)

Residuals:
   Min     1Q Median     3Q    Max
-773.7 -268.8  109.3  254.4  699.2

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     2148.154     29.854  71.955  < 2e-16 ***
Inflation       -126.012     10.025 -12.570  < 2e-16 ***
Unemployment     -20.090      3.398  -5.913 3.57e-09 ***
Interest_rate   -225.920      5.471 -41.294  < 2e-16 ***
GDP_Growth_Rate  -93.034      3.260 -28.538  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 357.9 on 5591 degrees of freedom
Multiple R-squared:  0.5042,    Adjusted R-squared:  0.5038
F-statistic:  1421 on 4 and 5591 DF,  p-value: < 2.2e-16
```

Linear Regression Model Summary: Gold Price

Impact on Gold Price:

Equation:

Closing= 2148.15 - 126.00 Unemployment -20.090 Interest rate -93.034 GDP growth rate

The intercept of 2148.15 is the expected gold price when all other factors are zero. A unit increase in Unemployment, Interest rate, and GDP growth rate leads to a decrease in gold price of -126.0, -20.090, and -93.034, respectively. Unemployment, Interest rate, and GDP growth rate negatively correlate with gold price. Inflation, GDP, and CPI don't have an impact on the gold price.

In summary:

	Stock Price	Bitcoin	Gold
Intercept	-1703.29	-140500.00	2148.15
Inflation	151.22	-6550.0	0
Unemployment	-33.83	+7279.0	-126.00
Interest_rate	81.49	0	-20.090
GDP_Growth_Rate	58.47	+5263.0	-93.034
GDP	0.0000000001959955	+0.000000005167	0
CPI	-20.94	+5681.0	0

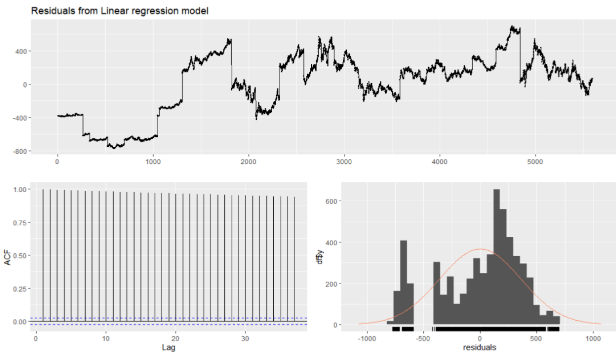
Model Coefficients and Intercept of SnP500, Bitcoin and Gold

Residual Analysis

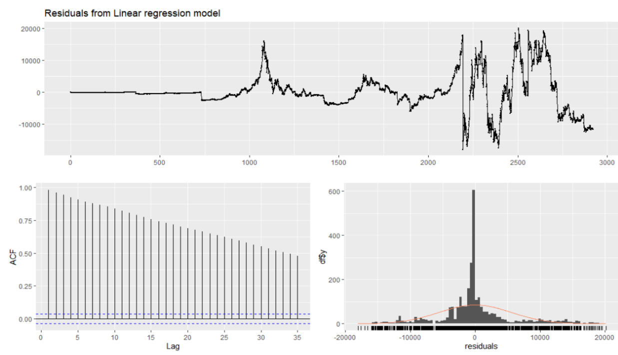
We also performed a Residual analysis. Below we will look at the result of the Breusch Godfrey test. The result was similar for all 3 of them:

```
	Breusch-Godfrey test for serial correlation of order up to 10

data:  Residuals from Linear regression model
LM test = 7480.9, df = 10, p-value < 2.2e-16
```

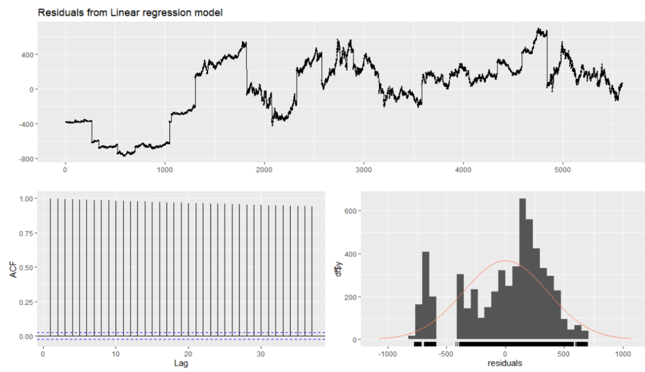
Breusch-Godfrey test for SnP500



Breusch-Godfrey test for SnP500



Breusch-Godfrey test for Bitcoin



Breusch-Godfrey test for Gold

Markets	p values
Stock price	p- value <2.2e-16
Bitcoin price	p- value <2.2e-16
Gold price	p-value <2.2e-16

P-values from the Breusch-Godfrey test for SnP500, Bitcoin & Gold

The p-value from the Breusch-Godfrey test for stock price, bitcoin price, and gold price is the same. A p-value of less than 2.2e-16 in the Breusch-Godfrey test strongly suggests that we can reject the null hypothesis of no autocorrelation in the error term of the model. In simpler terms, this implies strong evidence of autocorrelation in the residuals of our model.

While autocorrelation raises concerns about the validity of the model's statistical inferences and predictions, it does not necessarily negate the existence of a linear relationship between the variables. Therefore, linear regression can still be valuable for exploring and identifying this relationship.

This linear relationship model provides insights into how the macroeconomic indicators influence the stock price, even though it may require further adjustments to address the issue of autocorrelation. These adjustments are made later using the ARIMA model.

Time Series Regression- ARIMA:

A time series is a collection of data items indexed in time order. Time series regression is a statistical technique used to forecast and analyze time series. It simulates the relationship over time between one or more independent variables—the variables you are using to generate the prediction—and a dependent variable, the variable you are trying to predict. These variables may include historical values of the dependent variable, other pertinent time series, or even extraneous variables such as meteorological or holiday conditions.

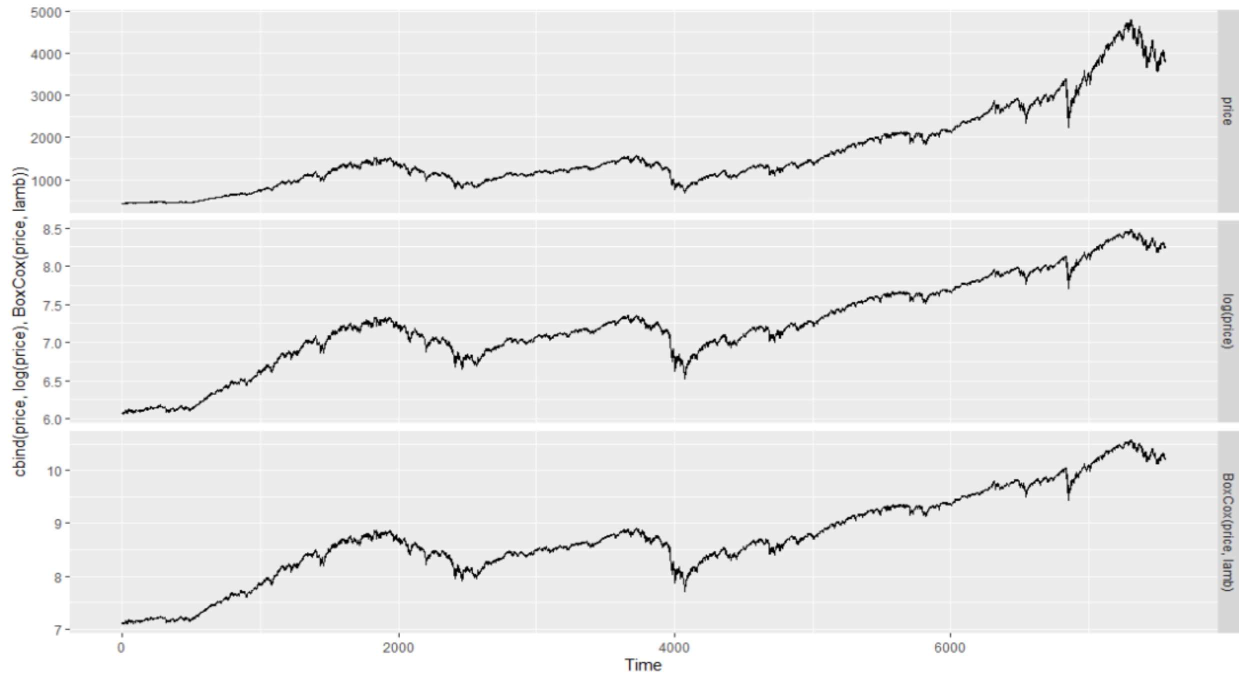
ARIMA Process:

ARIMA stands for Autoregressive Integrated Moving Average. It's a statistical method for analyzing and forecasting time series data

We will now utilize the ARIMA model to analyze and forecast the closing prices of the S&P 500, Gold, and Bitcoin. The processes below have been repeated for all of them: S&P 500, Gold, and Bitcoin. However, the images represent the S & P 500 for reference.

Step 1: Transformations:

In our data analysis process, we applied Box-Cox and log transformations as crucial techniques to address issues related to heteroscedasticity, or unequal variance, which is a common challenge in statistical modeling. The Box-Cox transformation is a power transformation method that optimizes the normality and homoscedasticity of the residuals. By identifying the lambda parameter that maximizes the log-likelihood, Box-Cox ensures that the transformed data exhibit constant variance. Similarly, the log transformation involves taking the natural logarithm of the data, which is particularly effective in stabilizing variance and making it more uniform across the range of observations.



Step 2: Unit Root Test

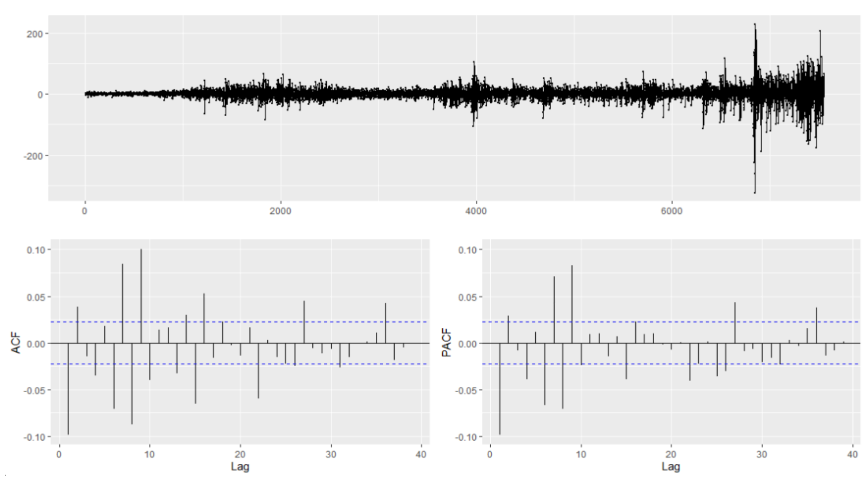
In the Augmented Dickey-Fuller (ADF) test, the null hypothesis posits the presence of a unit root, indicating non-stationarity in time series data. Failure to reject the null suggests the data is likely non-stationary. Conversely, rejecting the null provides evidence of stationarity, indicating the absence of a unit root. Stationarity is crucial in time series analysis, as many statistical methods and models assume or require stationary data. In our case, with one differencing, rejecting the null implies that the differenced data is stationary, facilitating more reliable analyses and model applications.

```
Value of test-statistic is: -18.9359 119.5242 179.2848

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -3.96 -3.41 -3.12
phi2  6.09  4.68  4.03
phi3  8.27  6.25  5.34
```

Step 3: Initial ARIMA models

When building an ARIMA model, a crucial step involves examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to determine the initial model parameters. The ACF plot displays the correlation between a data point and its preceding values, helping identify potential autoregressive (AR) terms. The PACF plot, on the other hand, highlights the direct correlation between a data point and its lag, aiding in the identification of the order of the autoregressive process. Peaks in the ACF and PACF plots guide the selection of the initial values for the ARIMA model, providing insights into the number of autoregressive and moving average terms.

We used ACF and PACF plots to find our initial ARIMA Model:



Step 4: Finding the best ARIMA model

We found the best ARIMA model based on a lower AICC value in all 3 cases. The image below is a sample image. We also used the Auto ARIMA function to get a recommended model. We chose the model

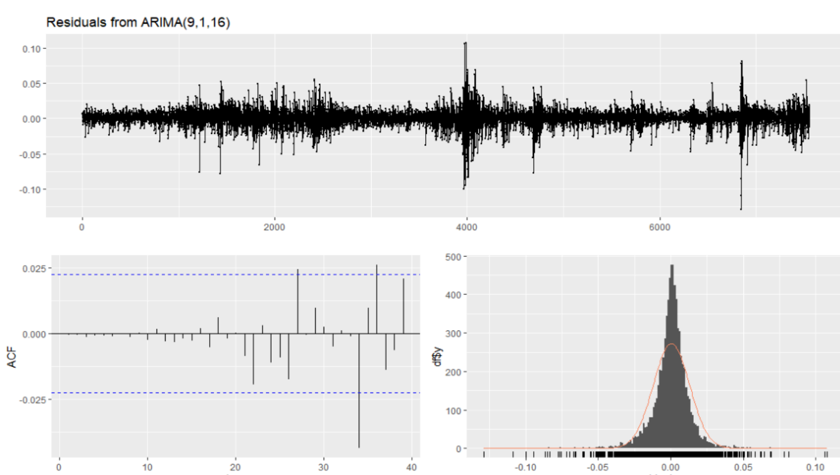
```
sigma^2 = 0.0001567:  log likelihood = 22383.82
AIC=-44715.64   AICc=-44715.45   BIC=-44535.46

Training set error measures:
                    ME    RMSE      MAE        MPE      MAPE     MASE          ACF1
Training set 0.5283078 21.878 12.70054 0.02611325 0.7828142 1.000858 -5.892606e-05
```

The best models for all 3 data:

Financial markets	**ARIMA(p,d,q)**
Stock price	ARIMA(9,1,16)
Bitcoin	ARIMA(6,1,6)
Gold	ARIMA(9,1,9)

Step 5: Checking residual of the ARIMA model

We used the check residual function to check the residual of the ARIMA model to make sure we have white noise residual.



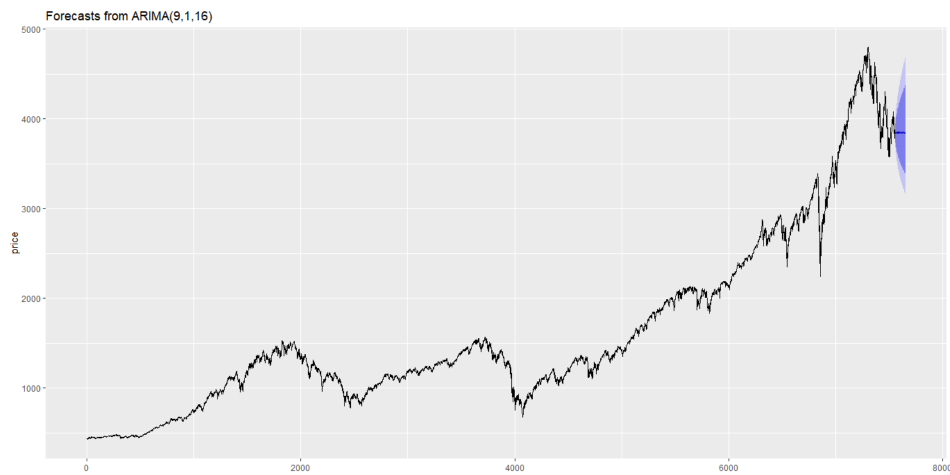
Results - Forecasting:

Forecasting-S&P 500

Forecast using ARIMA:

The graph below displays the S&P 500 stocks, where the price follows an upward trend followed by a recent decline near the end. The model forecasts that the stock price will decrease over time and there's a 95% confidence interval, which suggests the actual price of the stock would fall within the blue band.

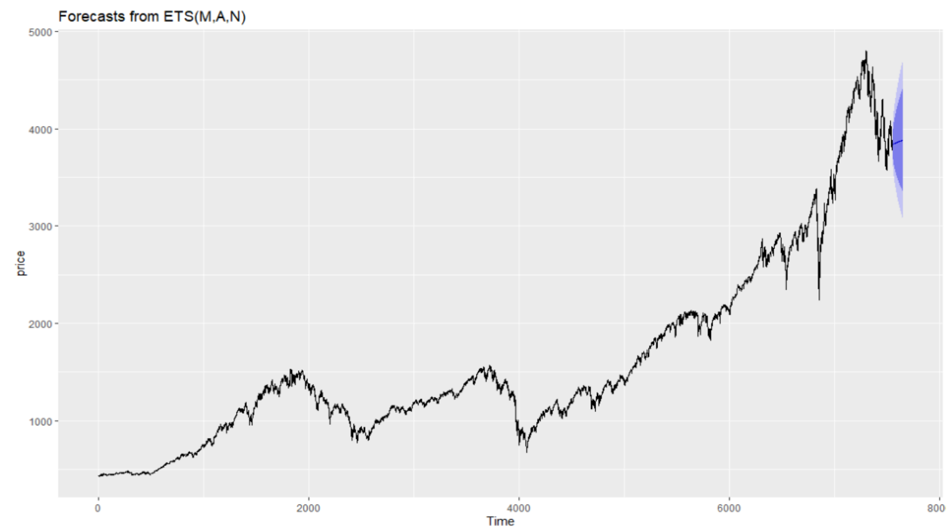
	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
7556	3836.173	3774.333	3899.105	3742.033	3932.869
7557	3833.542	3750.165	3918.919	3706.820	3964.942
7558	3838.437	3738.308	3941.461	3686.444	3997.201



Forecast using ETS:

The ETS model suggests that the S&P 500 price is expected to rise slightly over time. Also the confidence interval suggests that the price is likely to remain within a range of 3,800 and 4,200 points in the coming weeks.

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
7556	3840.356	3782.644	3898.068	3752.093	3928.619
7557	3840.798	3763.146	3918.450	3722.040	3959.557
7558	3841.241	3747.803	3934.678	3698.341	3984.141

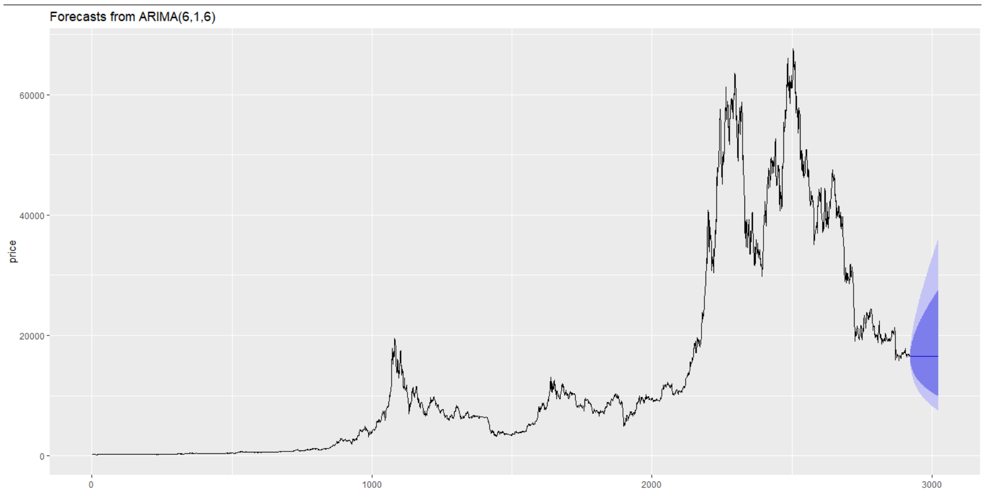


Forecasting- Bitcoin:

Forecast using ARIMA:

This ARIMA model displays the Price Forecast after significant fluctuations over the historical data. The model suggests the price to remain overall stable.

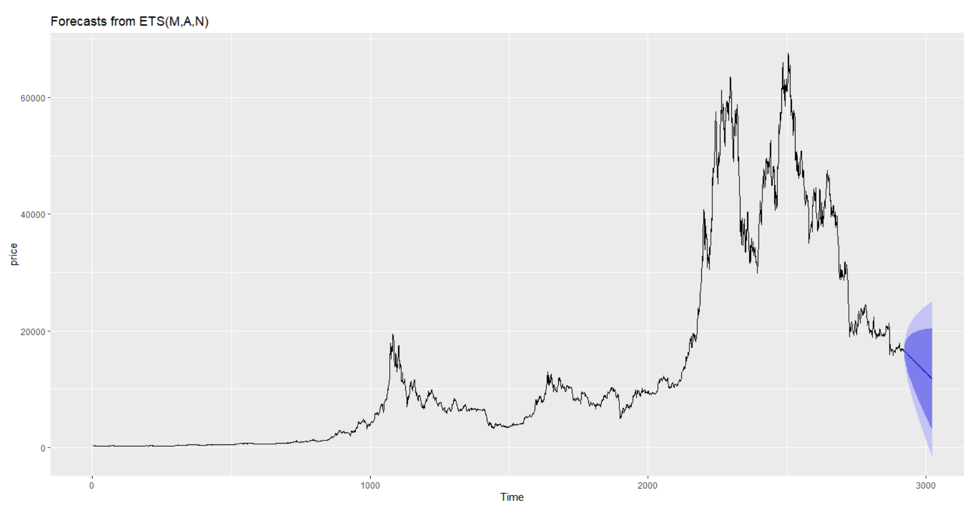
	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2923	16546.52	15750.781	17382.07	15345.012	17841.16
2924	16528.57	15427.788	17707.11	14874.797	18364.31
2925	16528.41	15189.534	17984.10	14524.864	18805.40



Forecast using ETS:

This ETS model forecasts the price to go further lower. The price is forecasted to be in a downward trend for the next foreseeable days and weeks.

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2923	16499.81	15686.807	17312.81	15256.42959	17743.19
2924	16451.84	15325.616	17578.06	14729.42957	18174.25
2925	16403.87	15033.387	17774.35	14307.89903	18499.84

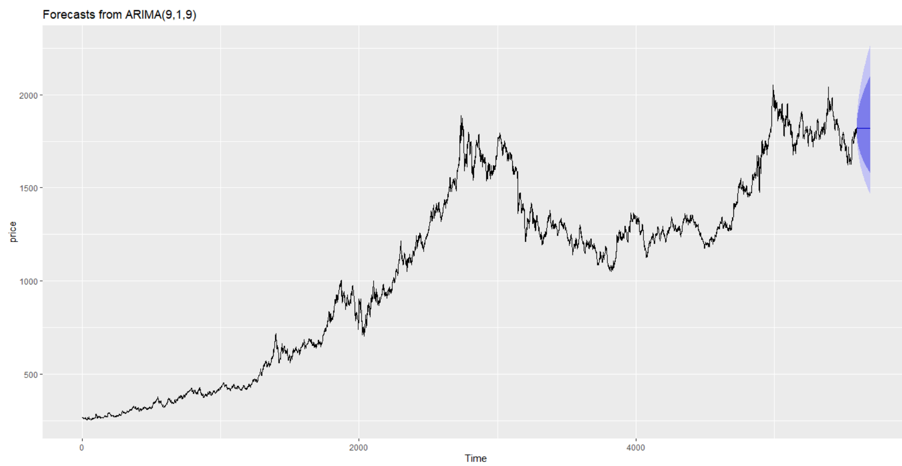


Forecasting- Gold

Forecast using ARIMA:

The ARIMA model of the Gold indicates the price would be following the upward trend in the near future.The model suggests the price will rise slowly towards the upward direction.

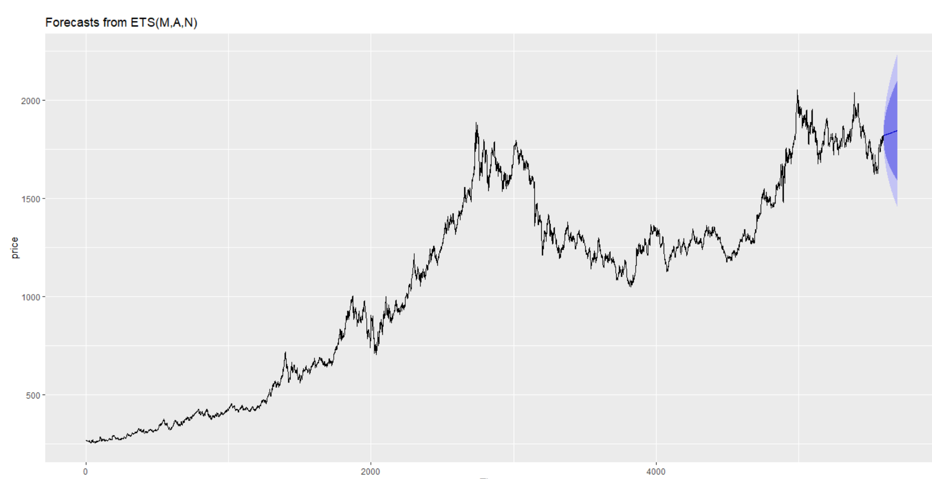
	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
5597	1819.757	1792.970	1846.975	1778.962	1861.561
5598	1821.725	1784.128	1860.177	1764.564	1880.885
5599	1820.414	1774.680	1867.419	1750.972	1892.830



Forecast using ETS:

The ETS model of the Gold also suggests the price would be following the upward trend in the near future. The model suggests the price will rise slowly towards the upward direction.

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
5597	1819.960	1794.309	1845.610	1780.731	1859.189
5598	1820.221	1784.220	1856.223	1765.162	1875.281
5599	1820.483	1776.498	1864.468	1753.214	1887.752



Limitations

Despite our efforts to create a robust model, it's important to acknowledge certain limitations in our project. First and foremost, the accuracy of our predictions heavily relies on the quality of the available data. If there are inaccuracies or missing information in the dataset, it could affect the reliability of our model. Additionally, our linear regression analysis assumes a linear relationship between the macroeconomic indicators and the closing prices of financial markets. However, real-world relationships can be more complex, and our model may not capture all the nuances. Furthermore, unforeseen external factors or events that were not included in our analysis could impact financial markets, leading to deviations from our predictions. Lastly, economic conditions are subject to change, and the stability of the relationships we identify may vary over time. As such, users should interpret the results with an awareness of these limitations and consider them when applying the findings to real-world scenarios.

An additional limitation of our project lies in the choice of using annual data for macroeconomic indicators. While this decision was made to standardize the data and simplify the analysis, it introduces a limitation in terms of temporal granularity. Economic conditions can change more frequently than on an annual basis, and utilizing quarterly or monthly data might better capture the dynamic nature of macroeconomic indicators. The use of annual data may overlook short-term fluctuations and miss critical trends that occur within a year.

Conclusion

In conclusion, our analysis employed both ARIMA (AutoRegressive Integrated Moving Average) and ETS (Error, Trend, Seasonality) models to understand and forecast trends in financial markets. Through rigorous transformations and adjustments, ARIMA emerged as the preferred choice due to its adaptability to the complexities of the dataset. The application of various transformations aimed at optimizing the model's accuracy and ensuring robust predictions. Additionally, we delved into a linear regression analysis to explore the influence of macroeconomic indicators on the closing prices of Bitcoin, S&P 500, and Gold. This multifaceted approach allowed us to capture both short-term patterns with ARIMA and long-term relationships through linear regression. The integration of these techniques offers a comprehensive understanding of the intricate dynamics between macroeconomic factors and financial market performances, enhancing the depth and applicability of our findings.