Comparison Of Effect Of Inflation In Stock Market Indices

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ABSTRACT

This study compares the effect of inflation in Indices of countries, aiming and analyzing to provide the effects of inflation on different stock market indexes. Using data from 2000-2023, the study applies quantitative techniques to examine how inflation affects stock market performance. The analysis considers a variety of stock prices, providing a thorough understanding of the ways in which various industries react to effects from inflation. The study aims to identify patterns, trends, and variances in the behavior of stock market indexes in reaction to inflation by the application of statistical and technical analysis. The results of this study could provide useful insights for financial analysts and investors to understand the relationship between stock market indexes and inflation. Policymakers could grasp and leverage this information for economic strategies.

CHAPTER 1

INTRODUCTION

Inflation is the state in which prices are increasing. The rises in prices are known as inflation, which is also known as the gradual loss of purchasing power. The average price increase of a selected basket of goods and services over a given period of time can be used to determine the rate at which buying power declines. The increase in costs, which is sometimes stated as a percentage, implies that a certain amount of money may now buy less than it did in previous times. Deflation is the opposite of inflation and happens when prices fall and buying power rises. Inflation stems from a rise in the money supply, however this can occur through a variety of economic causes. The money supply of a nation can be by the monetary authorities by:

- Printing and giving away more money to citizens.
- Legally devaluing (reducing the value of) the legal tender currency.
- Loaning new money into existence as reserve account credits through the banking system by purchasing government bonds from banks on the secondary market (the most common method)

All of these situations result in the money's diminished purchasing power. Three categories of mechanisms can be used to categorize inflation: built-in inflation, cost-push inflation, and demand-pull inflation. The stock market is a marketplace where buyers and sellers exchange shares of corporations that are publicly traded. It is a platform that makes it easier to purchase and sell stocks, which are ownership interests in businesses. The stock index, on the other hand, is a fictitious portfolio of investment holdings that symbolizes a certain area of the financial market. The prices of the underlying holdings are used to calculate the index value. An index's function is to monitor the performance of a certain set of equities in standardized way. This selection of stocks may be used to represent a certain sector of the economy, a particular market (such as the US market), or even the whole stock market. These indices are frequently used as standards by which to compare the performance of mutual funds, ETFs, and individual equities.

This study examines how stock market indices are affected by inflation both before and after the COVID-19 pandemic. The gradual increase in prices for goods and services, known as inflation, can have a big effect on the stock market. This is because inflation has the potential to lower money's purchasing power, which can have an impact on both businesses and consumers. greater inflation may result in greater input costs for businesses, which may reduce their profitability. Increased inflation may lower customers' purchasing power unless their earnings increase in line with it, which may have an effect on their shopping decisions.

Prior to the COVID-19 epidemic, some stock kinds frequently performed better during times of excessive inflation. worth stocks, for instance, can provide investors both the possibility of capital growth and a consistent dividend income stream if they trade at a discount to their true worth. Similarly, investments in inflation-resistant industries like consumer staples, healthcare, and energy stocks can provide both prospective capital gains and consistent income, which can help counteract the consequences of rising costs. But the COVID-19 pandemic created a distinct set of economic conditions. Lock downs prompted by the epidemic, significant fiscal and monetary stimulus, and supply chain disruptions caused inflation to soar. The stock markets saw significant volatility as a result of this abrupt rise in inflation.

A few industries performed better than others during the pandemic. In times of severe inflation, the energy and healthcare sectors, for example, were exceptions. With an annualized return of 14% from 1968 to 1981, the energy sector was predicted to have a significant impact on earnings projections. Conversely, the S&P 500 Growth Index, which identifies companies with the strongest sales and profits per share growth over the previous three years, had an almost 15% decline during the epidemic last year.

High inflation has persisted after the conclusion of the COVID-19 pandemic, fueled by things like broken supply chains and rising consumer spending as economies start to recover. The stock market has been affected by this and has continued to do so, with stock values moving in reaction to shifting in inflation rates.

Three main nations are analyzed: the United States, China, and India. Prior to the pandemic, the U.S. stock market often did well during times of steady, low inflation. On the other hand, times of strong inflation frequently led to higher market volatility and lower real returns. The United States saw a very modest decrease in inflation during the COVID-19 epidemic in 2020, but supply chain disruptions and significant monetary and fiscal stimulus caused a sharp spike in prices in early 2021. The American stock market saw significant volatility as a result of this spike in inflation. Additionally, China's stock market and inflation showed a complicated link that was influenced by both local and international commodities prices as well as national economic situations. Due to the nation's response to the epidemic and disruptions in global supply chains, China saw distortions in its inflation during the COVID-19 pandemic. This also had an effect on the stock market in China. The country's inflation was bolstered by rising commodity prices, particularly those of oil, which had an impact on the stock market.

Previously to the pandemic, monetary policy, global influences, and domestic economic conditions all had an impact on India's inflation and stock market link. Like many other nations, India saw economic disruptions during the COVID-19 epidemic, which had an effect on the stock market as well as inflation. Nevertheless, the sources cited do not easily give particular statistics illustrating the relationship between inflation and the Indian stock market during this time.

In conclusion, there is a complicated relationship between inflation and stock market indices, and because of the particular economic circumstances during and after the COVID-19 epidemic, this relationship has been especially active. The kinds of companies and industries that are included, as well as general economic conditions, can all have an impact on how inflation affects stock market indices.

CHAPTER 2

Literature Review

There are a number of ideas that try to explain the dynamics of the complex relationship between inflation and stock market indices. According to a theory put forth by Modigliani and Cohn in 1979, investors experience money illusion and use nominal discount rates to discount actual cash flows, which causes valuation errors brought on by inflation. This theory states that the stock market undervalues during periods of strong inflation and that this undervaluation should be remedied once actual nominal cash flows are disclosed. [10] This argument is consistent with the finding from investopedia.com [14] that increasing inflation can have negative effects on growth and employment by driving up input prices.

An alternative viewpoint was put up by Fama (1981), who suggested that there was a negative correlation between inflation and stock returns.[8] This theory, sometimes referred to as the "stagflation phenomenon," contends that expectations of future actual activity determine both inflation rates and stock values. Investopedia.com[14] reiterates this notion, stating that growth companies will under-perform during periods of high inflation since interest rates will often rise to counteract the inflation.

Additional understanding of these theories is offered by empirical research. According to a study by Alexakis et al. (1996), stock prices are impacted by high rates of inflation because of the unpredictability of inflation. It was discovered that while stock prices are stable in nations with low rates of inflation, this volatility is common in emerging capital markets.

Both established and emerging economies have been significantly impacted by the

Covid-19 pandemic in terms of the stock market and the global economy. Research indicated that tighter immigration laws and budgetary policies have a detrimental effect on the volume of economic activity. The epidemic increased market risk and unpredictability worldwide. This is consistent with the findings of Baker et al.[9] (2020), who demonstrated that, in comparison to the periods of SARS, swine flu, MERS, Ebola, and avian flu, the market fluctuations caused by COVID-19 were exceptionally large. The pandemic has had a major effect on a number of distinct worldwide stock market sectors. Al-Awadhi et al. (2020), for instance, employed a panel regression technique to investigate how the pandemic affected the various segments of the Chinese stock market. They discovered that while the information technology and pharmaceutical industries performed comparably better, big market capitalization stocks suffered.

The 2020 study "Spillover of COVID-19: Impact on the Global Economy" by Peterson K. Ozili and Thankom Arun sought to examine how the COVID-19 pandemic affected the economies of the four continents: Asia, Europe, Africa, and North America.[11] The researchers discovered that the economy and stock values suffered as a result of the social distancing measures put in place to stop the virus from spreading. [13] This was brought on by the limitations placed on economic activity, which also caused a decline in business revenue and productivity as well as higher operational expenses and cash flow issues. The analysis also showed how the epidemic caused a decline in global equities, bond, and oil shares. Since 1987, there has been a significant one-day decline in the Financial Times Stock Exchange 100 index in Europe. In March 2020, the world's largest economy, the US stock market, triggered the circuit breaker mechanism four times in ten days. There were also notable increases in the European and Asian stock markets.

The study "The impact of COVID-19 on the degree of dependence and structure of risk-return relationship: A quantile regression approach" by Asil Azimli examined how the COVID-19 pandemic affected the structure of the risk-return relationship in the US stock market. A statistical technique called quantile regression was applied in the study to examine the association between variables at various quantiles (percentiles) of the distribution. Because it enables the investigation of a variable's impact at various levels of the distribution, this method is especially helpful in the fields of finance and economics. This can yield more subtle insights into the relationships between variables. The study's findings showed that there was a growing degree of dependence between returns and market portfolio.This indicates that at higher distributional levels, there was a larger correlation between risk and return. It is possible to view this increase in dependence at the upper quantiles as a sign of investors become more risk cautious. A reduction in stock market returns may result from investors shifting their holdings toward safer assets when they become more risk averse. This is due to the fact that equities are typically seen as riskier than other asset classes, and investors who are more risk averse have a tendency to steer clear of stocks.

A study by Shehzad et al. from 2020 examined the nonlinear behavior of the US, Italian, Japanese, and Chinese financial markets.[12] For this analysis, the researchers employed a model known as the asymmetric power GARCH model. One kind of statistical model that is used in time series analysis to simulate the volatility of financial assets is the GARCH model.[6] A version of the GARCH model known as "asymmetric power" permits distinct volatility patterns for positive and negative shocks. According to the study, the S&P 500, a significant stock market index in the US, saw lower stock returns as a result of the COVID-19 epidemic. On the other hand, the epidemic had negligible effect on the Nasdaq composite index, another important stock market measure.[4] This implies that different financial markets and industries were affected by the epidemic in different ways. Put differently, certain markets and industries were significantly impacted by the pandemic, while others were not. There are several possible reasons for this, including variations in market and sector structures, the makeup of the sectors, and the ways in which the markets and sectors have responded to the epidemic.

Cepoi conducted study in 2020 that examined the connection between news connected to COVID-19 and stock market returns in the nations most impacted by the epidemic.[5] A scenario known as "asymmetry dependence" occurs when the stock market responds to news, both favorable and bad, in distinct ways. This indicates that when unfavorable news about the epidemic breaks, investors are more likely to respond negatively.[7] This is due to the fact that unfavorable news, like a rise in COVID-19 cases or fatalities, can lower investor confidence and, as a result, lower stock market returns. The research revealed that there was an uneven reliance on COVID-19-related data by the stock market. This implies that the news of COVID-19 has a varied effect on the stock market. Both good and negative news regarding the epidemic have different effects on the market. Numerous factors, including the news's specificity, timeliness, and general market emotion, could be to blame for this. The study's conclusions have major implications for comprehending how the stock market behaves during a pandemic. They advise investors to be mindful of the possibility of asymmetry in the way the market reacts to COVID-19 news. This might enable them to make better decisions and possibly lessen the dangers brought on by the pandemic.

A 2020 study by Osagie et al. suggested various legislative changes to strengthen the financial system in light of the COVID-19 pandemic.[1] The initial suggestion was for a politically stable atmosphere. Stable political conditions can aid in lowering financial market volatility and uncertainty, which can enhance investor confidence and market performance. The second suggestion was to provide incentives to domestic businesses. Businesses that are indigenous or that are controlled or held locally can support economic expansion and diversification. The government can encourage these businesses to increase their market investments by offering incentives, which will boost the economy and enhance market performance. Increasing economic diversification was the next piece of advice. Spreading production and investment throughout a number of industries and geographical areas is known as economic diversification. By doing this, the hazards brought on by economic shocks like the COVID-19 epidemic can be lessened. The government can avert a market collapse in the case of a shock by diversifying the economy to ensure that the market is not unduly dependent on any one sector or location. The establishment of a flexible exchange rate regime was the final recommendation. A regime with a variable exchange rate permits the currency's value to alter in response to supply and demand and other market factors. This may lessen the chance of currency devaluation, which can have a bad effect on the market. The government can contribute to preserving the stability of the currency and, by extension, the market, by putting in place a flexible exchange rate policy. The paper concludes by suggesting that regulatory measures may be able to lessen the detrimental effects of the COVID-19 pandemic on the financial market. The financial market may become more resilient and stable as a result of these actions, which would be advantageous for the economy and investors.

According to Baker's analysis (2020), [3] there has been a notable 70–80% decline in oil prices. When compared to the 2008–2009 financial crisis, this was deemed severe. An important metric for assessing the state of the world economy is the price of oil, and a large decline in this price can have a profound impact on the economy.[2] A drop in oil prices can have a big effect on the economy of the country indicated in the statement because of its heavy reliance on oil revenue. This might result in fewer consumer spending, poorer government revenue, and possibly even greater unemployment rates.

According to Herrero's study (2020), emerging economies were particularly hard hit by the COVID-19 pandemic's third wave.[3] The third wave of the pandemic is the time after a period of decline when cases began to climb once more. For emerging countries, which were already dealing with the pandemic's initial effects, this wave posed special challenges. According to the report, the third wave caused a decline in economic activity, with Latin America suffering the most because of its significant reliance on outside funding. This indicates that these nations were more vulnerable to the pandemic's economic shocks, which may have resulted in higher jobless rates, lower consumer spending, and poorer government revenue.

The COVID-19 outbreak caused a "roller-coaster ride" for the economy of South Korea, one of the top rising countries, according to Hyun-Jung's 2020 report.[3] This indicates that there were times when the economy expanded quickly and contracted quickly, which is normal for an emerging market economy that is still growing and adjusting to new circumstances.

According to Topcu and Gulal's study (2020), emerging markets in Asia were most affected by the COVID-19 pandemic, whilst emerging markets in Europe were least affected. This shows that different regions were affected by the pandemic in different ways. This could be because of a number of things, including the economies' structures, the types of sectors they operate in, and the ways in which markets and sectors responded to the pandemic. In their 2020 study, Goldberg and Reed talked about how COVID-19 hurts commerce between emerging nations. This indicates that the pandemic caused a decline in global trade, which may have a detrimental effect on emerging market economies. Economic activity and growth are largely driven by trade, and a decline in trade can have the opposite effect. According to Raja Ram's 2020 analysis, the COVID-19 pandemic significantly impacted both the Indian and international stock markets. The pandemic caused the world financial market to collapse, which sharply fluctuated the Indian stock market.[3] The decline in outside portfolio investments, which decreased the Indian stock market's return, was the cause of this instability. This implies that the epidemic had a noteworthy effect on the economy of India and the rest of the world, an effect that was mirrored in the stock markets. According to Mandal's research (2020), the BSE Sensex, a significant index of the Indian stock market, saw its largest one-day decline of 13.2%, exceeding the historic April 28, 1992 loss. The Nifty also took a sharp 29% tumble, surpassing the 1992 catastrophe. This implies that the COVID-19 pandemic had a notable effect on the Indian stock market, resulting in a notable decline in the equities' value. The pandemic's effects on the Indian and worldwide economy, which were mirrored in the stock market, were the cause of this decline.

The BSE Sensex, a significant measure of the Indian stock market, saw the most single day decline of 13.2%, according to Mandal's study (2020). This indicates a large decline in the stock market as the BSE Sensex's value dropped by 13.2% in a single day. This incident broke the previous record, which was set on April 28, 1992. Another important Indian stock market index, the Nifty, too saw a sharp decline of 29%, surpassing the catastrophic events of 1992 in another record-breaking occurrence. Of the 300 businesses listed on the National Stock Exchange of India (NSE), 50 are included in the free-float market capitalization-weighted index known as the Nifty. The COVID-19 epidemic, which has caused anxiety about the state of the global economy and fear of a potential recession, is to blame for these large declines in the BSE Sensex and Nifty.[3] As a result, investors have left the market, which has caused the value of the equities to drop.

The COVID-19 pandemic has had a significant impact on the global economy and stock markets, leading to a sharp decline in economic activity and stock prices. This pandemic has led to more risk-averse behavior among investors, increasing the dependence between risk and return in the stock market and reducing the benefits of diversification. The pandemic has particularly affected countries heavily dependent on oil revenue and those with economies more vulnerable to economic shocks. To lessen the detrimental effects of the epidemic on their economies, these nations could need to enact policy changes. The report emphasizes the need for more investigation to comprehend the pandemic's long-term effects on the world economy and stock markets. Theoretical and empirical research indicate that unforeseen occurrences, such as the pandemic, and inflation can have a major effect on stock market indices. These factors include the level of inflation, the health of the economy, investor expectations, and external influences.

CHAPTER 3

Data and Methodology

3.1 Data

The study aims to find the impact of inflation in stock markets based on selected stocks and indices of certain countries. Stock prices were taken from the Rapidapi.com and Investing.com databases. We have inflation rate and share price data to compare with stocks and indices data from USA, China, and India, these three countries were selected on bases of there title of developed and developing countries. And the indices S&P500, Shanghai Composite and Nifty50 are selected respectively. Nifty 50 is the flagship benchmark of the National Stock Exchange (NSE) in India. The top 50 companies in terms of free-float market capitalization that are traded on the exchange are included in this well-diversified index. The Nifty 50 aims to represent, under all market factors, the state of the listed Indian company universe and, by extension, the whole economy. The free float market capitalization method—basically, the number of shares in active circulation in the market at any given time—is used to calculate the index. The financial services sector accounted for 35.73% of Nifty's components, followed by the energy sector (14%), the information technology sector (11.46%), the automotive sector (10.64%), and the consumer goods sector (10.13%). It should be understood that these percentages are subject to change based on market capitalization. Top constituents by weight-age which are selected for the analysis:

HDFC Bank Ltd.	13.24%
Reliance Industries Ltd.	9.25%
ICICI Bank Ltd.	7.66%
Infosys Ltd.	5.84%
ITC Ltd.	4.53%
Larsen & Toubro Ltd.	4.23%
Tata Consultancy Services Ltd.	4.12%

Table 3.1: Nifty50 Stocks weight-age.

The primary stock market index in China is the Shanghai Composite Index, or SHCOMP. It is determined by the Shanghai Stock Exchange (SSE) and serves as a standard for investments in stock markets in China. All of the equities listed on the Shanghai Stock Exchange, which comprise businesses from a variety of industries including technology, manufacturing, services, and finance, make up the Shanghai Composite Index. Since the index is weighted by the market capitalization of the constituent companies, the impact of larger market capitalization companies on the index is greater. And in this indices all the stock hold the same weight-age. we have considered the below stocks for the analysis:
The 500 largest publicly traded firms in the United States make up the S&P 500, often referred to as the S&P 500 Index, which is a stock market index. One of the most popular equity indices, it is frequently used as a standard for the US stock market. S&P Dow Jones Indices, an S&P Global affiliate, is in charge of maintaining it. The index's constituent companies are chosen according to specific qualifying standards, such as market size, liquidity, and profitability. The index is re-balanced on a quarterly basis. Businesses from a variety of industries, including technology, healthcare, banking, consumer goods, and more, are represented in the S&P 500. Some of the largest companies which we have selected for the analysis in the S&P 500 include Apple Inc., Microsoft Corporation, Amazon.com Inc., Alphabet Inc. (Google), Berkshire Hathaway Inc. The weight of each company in the index is

Inner Mongolia BaoTou Steel Union Co., Ltd
China Petroleum & Chemical corporation
CITIC Securities
Sany Heavy Industries Co.
China Merchant Bank Co.
Poly Developments and Holdings group Co.
SAIC Motor corp.

Table 3.2: Shanghai Composite Index Stocks.

determined by its market capitalization. Below is the list of how many percent each company weight:

Apple (AAPL)	7.10%
Microsoft (MSFT)	6.51%
Amazon (AMZN)	3.24%
NVIDIA (NVDA)	2.84%
Alphabet Class A (GOOGL)	2.14%
Tesla (TSLA)	1.87%
Meta Platforms Class A (META)	1.84%

Table 3.3: S&P500 Stocks weightage.

CHAPTER 4

Methodology

Worldwide occurrences might impact stocks both directly and indirectly. One such event that we have considered is inflation. Inflation has the ability to lower the purchasing power of money, which in turn causes a decline in consumer spending, disruptions in market cash flow, growth in company investment, and market volatility. As a result, countries such as the United States, China, and India are used for comparison. The Consumer Price Index is the most widely used method for calculating inflation rate (CPI).

Inflation rate = (FP – IP) / IP * 100

Where, FP – Final price

IP - Initial price

There are two types of GDP. Nominal GDP and Real GDP, nominal GDP is calculated using current prices. It does not deduct inflation or the rate of price increases, which can artificially exaggerate the growth estimate.

Nominal GDP = consumer spending + Investment + Government Spending + (Exports - Imports)

Real GDP, on the other hand, is for inflation and is also referred to as "constant-price" or "inflation-corrected" GDP. It provides the most accurate representation of how a nation’s economy is either contracting or expanding.

Real GDP = Nominal GDP / GDP Reflector

Is there any effect on inflation by share prices? How are they co-related to each other and how do we find the relation between these anomalies, is all calculated by the correlation coefficient which indicates the relationship between two variables, the formula is as follows:

$$r_{xy} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$$

Figure 4.1: Correlation Coefficient

Where:
rxy – the cor-coefficient of the linear relationship between the variables x and y
xi – the values of the x-variable in a sample
x-bar – the mean of the values of the x-variable
yi – the values of the y-variable in a sample
ȳ – the mean of the values of the y-variable

A statistical method known as Time series is involved in analyzing a sequence of data points collected at regular intervals over a period of time. The data points in a time series are usually recorded at consistent intervals, such as daily, weekly, monthly, or annually. The time series data can be used to forecast future trends based on historical data. Time series analysis is a powerful statistical method that involves analyzing a sequence of data points collected at regular intervals over a period. It is used to uncover underlying patterns, trends, and seasonality in the data.
There are also other types of time series analysis methods such as ARIMA, STL, and ETS, each with their own strengths and drawbacks. Here we will take SARIMA (SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODEL) is the combination of simpler models that create a complex model that can present a time series exhibiting non-stationary properties and seasonality. Seasonality - It's a repeating pattern that occurs or is found at consistent levels such as, daily, weekly, monthly, or yearly. For our comparison we have taken apple stock from S&P500 which are one of stock indices from USA, here the stock data is grouped by year and compared it to the inflation rate of US and the charts have been observed with no

patterns. Thus, it confirms that our data have no seasonality. Since our data doesn't have seasonality, we are not opting for SARIMA model.
Next, we have the ARIMA model. The ARIMA model is a form of regression analysis that gauges the strength of one dependent variable relative to other changing variables. In simple the "I" in the ARIMA model is used when there is upward or downward trend, for example in a correlation trend of the series instead of through actual values. Since there is no trend in our data, we are using the ARIMA model. There are some scenarios where the volatility of the data is high, since we do not need that and want it to be closer to zero and around zero, this the aim proposed through stationarity, which means in time series analysis it refers to the statistical properties of a time series do not change over time. In other words, a time series is considered stationary if its statistical properties remain constant over time. In simple words stationarity means your reducing the scale and bringing all points to a constant Ness between certain scales. We have minus the stationarity so moving forward to volatility.
Being done with the Seasonality and stationarity we are left with volatility. Volatility relates to standard deviation so how deviated each point is from zero. So for example wherever the price range is less it will have a small deviation around zero and some prices which are more will have a large deviation, therefore we need to reduce the peak and scale it down to a range of constant environment where the model finds it easy to identify the pattern or understand the data so to achieve this we have grouped by every year data points and calculated the standard deviation and mapped that standard deviation to all the data points and divided individual points with respective year standard deviation so by doing this process and again plotting the chart we show that the volatility has also decreased and now the data is ready for the model to analyze and understand. Thus, the time series analysis steps have been completed and we will be moving forward with time series prediction with the ARMA model.
ARMA model, Autoregressive Moving Average (ARMA) model is a statistical model used to analyze time series data. It is a combination of two other models: an autoregressive (AR) model and a moving average (MA) model. An AR model uses past values of the series to predict future values, while an MA model uses past errors to predict future values. An ARMA model combines these two approaches to make

predictions. We will be using this model to train and predict the values for future data. The notation ARMA (p, q) refers to the model with p autoregressive terms and q moving-average terms. This model contains the AR(p) and MA(q) models.

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}.$$

Figure 4.2: ARMA Model

CHAPTER 5

Results

5.1 Comparison Between Three Countries

The below graph and charts represent the comparison done between three countries of inflation rate, share price and GDP.

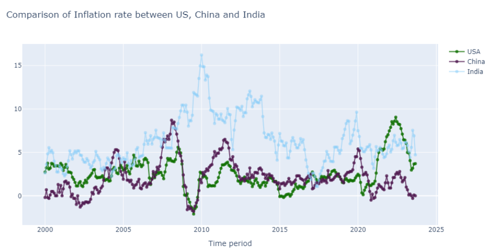

Figure 5.1: Comparison of Inflation

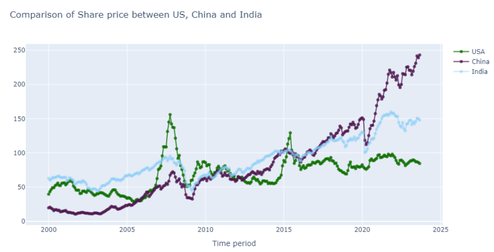

Figure 5.2: Comparison of Share Price

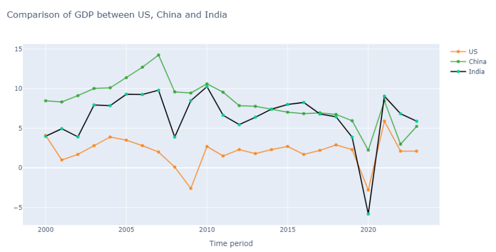

Figure 5.3: Comparison of GDP

From the charts we can see that in comparison of inflation India has had a every high inflation since 2000 than US and china, But the recent years India rate has come down. And a steady growth in the Share price which shows the development of

companies in country, which is also reflected in the GDP growth expect in the year 2020 because of the Covid-19 hit there is a down fall in the GDP.
In comparison of inflation with US, it has had a every high inflation in recent years than India and China, But in the last 2 decades US rate has maintained a steady flow. And sudden spike in the share price in since 2005-2010 and between 2015-2017, which is also reflected in the GDP growth expect in the year 2020 because of the Covid-19 hit there is a down fall in the GDP.
As of china shows a huge rise in inflation rate between 2005-2010 but then it has been a steady flow. And the share price have been upwards with a steady flow which shows the development of economy resulting in the growth of country.

5.2 Correlation Analysis

Find the heatmap for the Correlation between selected sectors of the countries. From

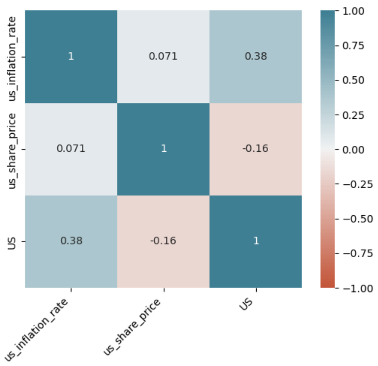

Figure 5.4: Correlation between inflation rate, share price and gdp for US

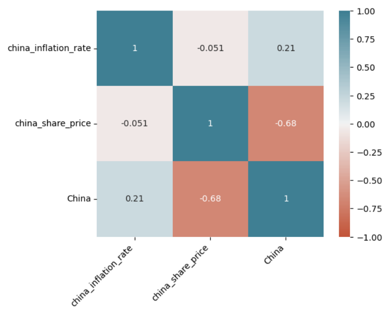

Figure 5.5: correlation between inflation rate, share price and gdp for China

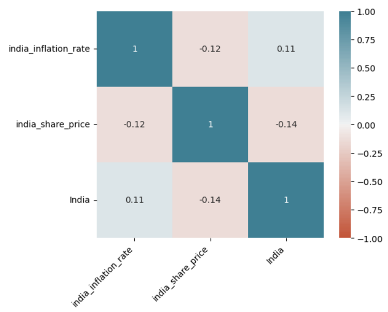

Figure 5.6: correlation between inflation rate, share price and GDP for India

the heatmap fig:5.4 we can see that for US there is a high correlation between inflation rate and share price but not so much with respect between US GDP and inflation rate and the correlation is negative between share price and GDP which indicates that they are so much dependent on each other.
Fig:5.5 is the heatmap of China. In this we can observe that Inflation rate and GDP correlation shows a slight positive outcome which means there is slight dependency of each other, on the other hand inflation rate and share price along with share price

and GDP has a negative correlation.

Fig:5.6 shows the correlation of India, in which it is observed inflation and GDP has a very slight positive correlation but share price and inflation rate along with share price and GDP has a negative correlation of the factors.

5.3 Regression Analysis

Here we have made observation from plotting a regression based on GDP for inflation rate and share price.

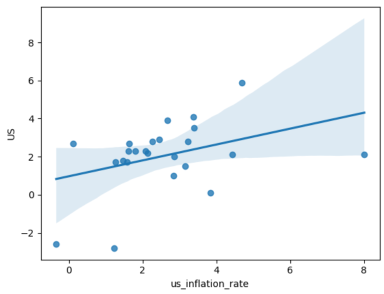

Figure 5.7: Regression for US between Inflation and GDP

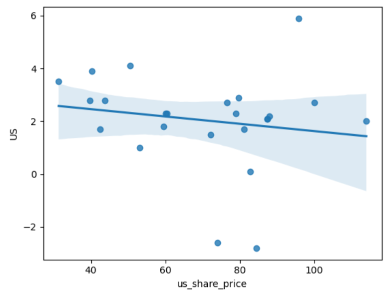

Figure 5.8: Regression for US between Share price and GDP

The above fig:5.7 and fig:5.8 shows the correlation between inflation rate and GDP of US. From the first fig we can see that there is slight growth as the inflation and GDP moves upwards. And from the second fig as the GDP goes higher there is a slight is downward trend which shows there are not so correlated.

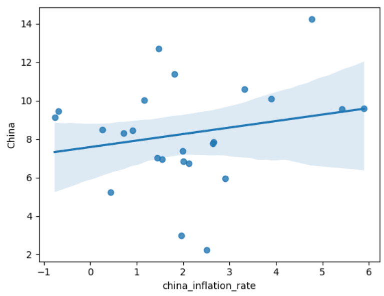

Figure 5.9: Regression for China between Inflation and GDP

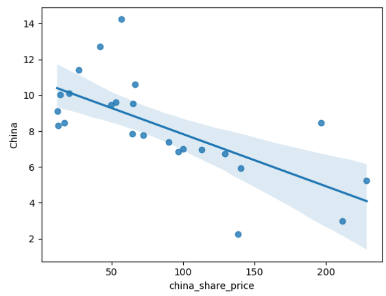

Figure 5.10: Regression for China between Share price and GDP

The above fig:5.9 and fig:5.10 shows the correlation between inflation rate and GDP for China. From the first fig we can see that there is slight growth as the inflation and GDP moves upwards. And from the second fig as the share price has gone downwards with a reflection on negative correlation, resulting that they are not so correlated.

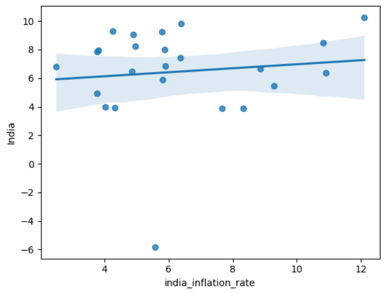

Figure 5.11: Regression for India between Inflation and GDP

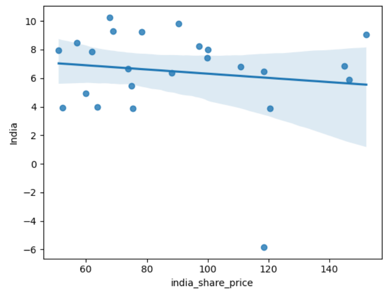

Figure 5.12: Regression for India between Share price and GDP

The above fig:5.11 and fig:5.12 shows the correlation between inflation rate and GDP for India. from the fig we can see that both the charts indicate a no drastic upward movement expect for fig:5.11 indicating it has a slight positive uptrend and correlation between share price and GDP is no so correlated.

5.4 Comparison Of Stocks and Indices

Coming to the main analysis, here we have the comparison of stocks with inflation rate and share price. The indicators such as 'open', 'high', 'low', 'close', 'volume' from all the stocks mentioned from the data. Below image showcases the head of the data from Apple company which is a stock of S&P500 indices from US.
This process has been carried on with all the stock and indices dataset which we have taken for the analysis with respect to US, china and India.

Below we have the head of dataset from inflation rate and share price from US, China and India.

Date	open	high	low	close	volume
1999-12-01	101.00	118.00	91.06	102.81	84091200
2000-01-01	104.87	121.50	86.50	103.75	112099800
2000-02-01	104.00	119.94	97.00	114.62	65355200
2000-03-01	118.56	150.38	114.00	135.81	77663900
2000-04-01	135.50	139.50	104.87	124.06	77342900

Figure 5.13: Columns of AAPL Data

Inflation data

Date	us_inflation_rate	us_share_price	china_inflation_rate \
2000-01-01	2.738892	39.55779	-0.2
2000-02-01	3.221884	43.48396	0.7
2000-03-01	3.757576	46.61248	-0.2
2000-04-01	3.068592	49.17913	-0.3
2000-05-01	3.188929	49.00218	0.1

Date	china_share_price	india_inflation_rate	india_share_price
2000-01-01	19.75834	2.619048	62.86602
2000-02-01	20.65533	3.614458	59.92387
2000-03-01	19.18312	4.830918	61.62468
2000-04-01	17.93419	5.542169	64.01819
2000-05-01	15.61101	5.011933	63.33833

Figure 5.14: Columns of Inflation Data

5.4.1 U.S.A

The description here on forth is about all the dataset of Stocks and Indices which has been selected from US for the analysis.

5.4.1.1 AAPL

We have created charts using the points from each corresponding column in the AAPL dataset. The date is shown on the x-axis, while the values are shown on the y-axis. The stock price fluctuation from 2000 to the present can be seen in the charts below.

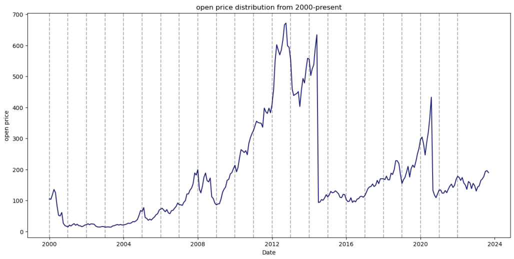

Figure 5.15: Open Price

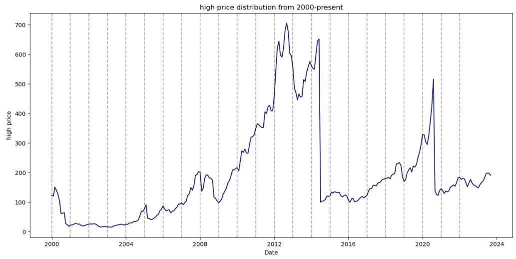

Figure 5.16: High Price

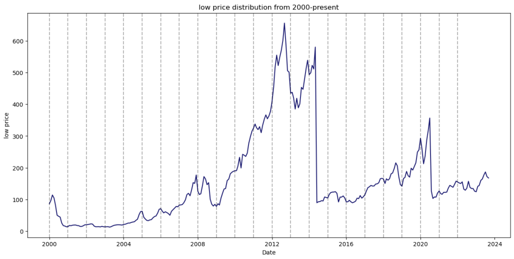

Figure 5.17: Low Price

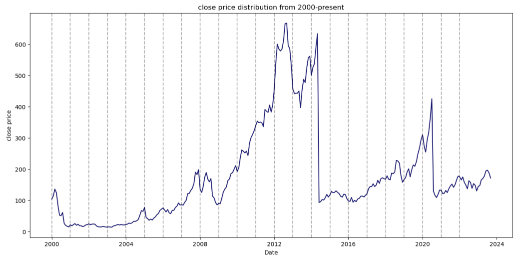

Figure 5.18: Close Price

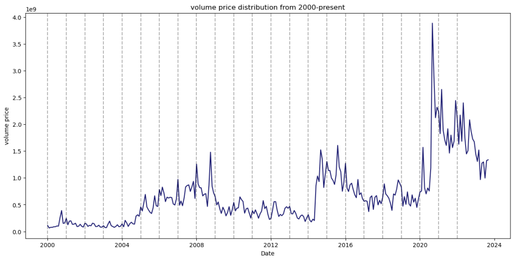

Figure 5.19: Volume

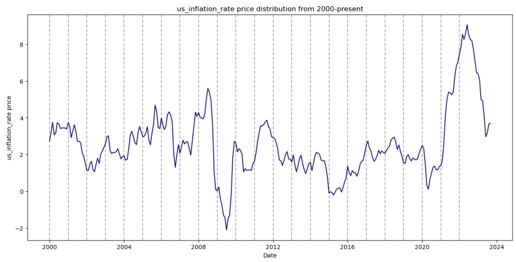

Figure 5.20: Inflation Rate

Figure 5.21: Share Price

Here we are calculating the difference between the current and previous value of each values in the dataframe. This is done by using the diff() function, then we use the dropna() function to remove any rows with missing values i.e (NaN) from the dataframe.

This is done for all the columns in the dataframe. In the next step we are calculating the standard deviation (std) for all the values from each year. Standard deviation means its a measure of variation or dispersion of certain set of values. A low standard

deviation means the values are most likely to be close to the mean of set, where as higher standard deviation means the values are in wider range.
Then we are mapping the standard deviation of each year to the corresponding values. This is done using a lambda function. After this then we normalize the values or data by dividing it by the corresponding standard deviation, this is done to reduce the impact of outliers and make the dataset more easier for the machine to learn.
Below is the result of the process:

	open	high	low	close	volume	us_inflation_rate	us_share_price
Date							
2000-01-01	104.870	121.50	86.5000	103.75	112099800	2.738892	39.55779
2000-02-01	104.000	119.94	97.0000	114.62	65355200	3.221884	43.48396
2000-03-01	118.560	150.38	114.0000	135.81	77663900	3.757576	46.61248
2000-04-01	135.500	139.50	104.8700	124.06	77342900	3.068592	49.17913
2000-05-01	124.870	126.25	81.7500	84.00	87569200	3.188929	49.00218
...	...	...	...	...	...	...	...
2023-05-01	169.280	179.35	164.3100	177.25	1275052503	4.047609	88.91565
2023-06-01	177.700	194.48	176.9306	193.97	1297863403	2.969178	86.98043
2023-07-01	193.780	198.23	186.6000	196.45	996368613	3.177780	87.03687
2023-08-01	196.235	196.73	171.9600	187.87	1323817340	3.665112	85.95383
2023-09-01	189.485	189.98	167.6200	171.21	1337873796	3.699698	84.55810

Figure 5.22: Columns from the Dataset

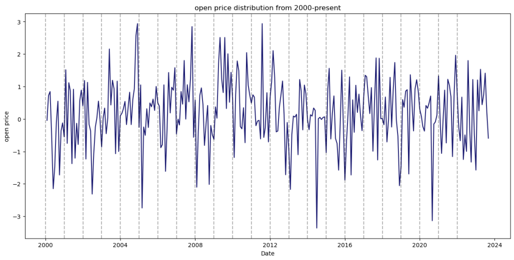

Figure 5.23: Normalised Open Price

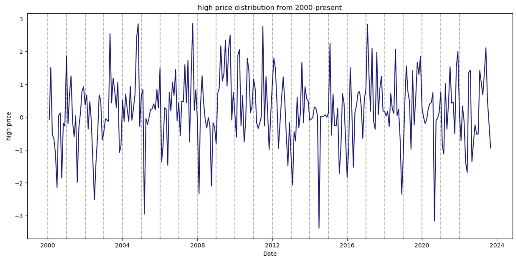

Figure 5.24: Normalised High Price

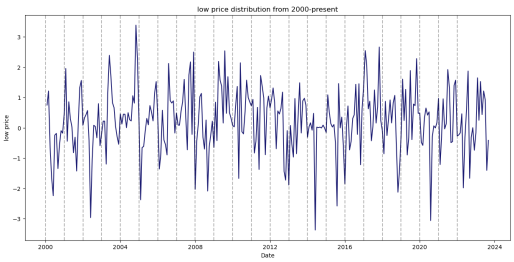

Figure 5.25: Normalised Low Price

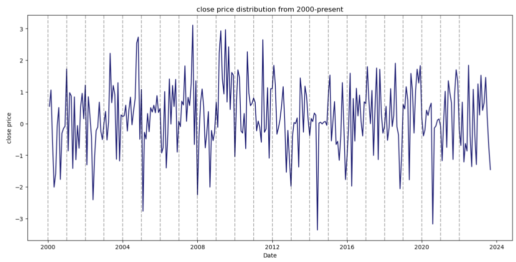

Figure 5.26: Normalised Close Price

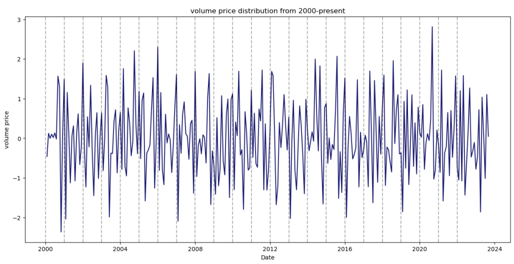

Figure 5.27: Normalised Volume

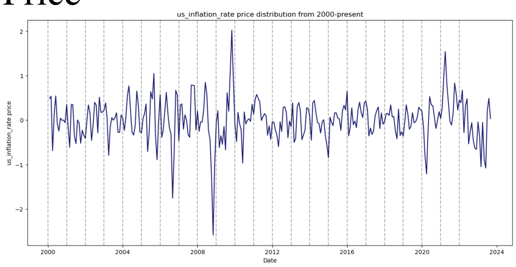

Figure 5.28: Normalised Inflation Rate

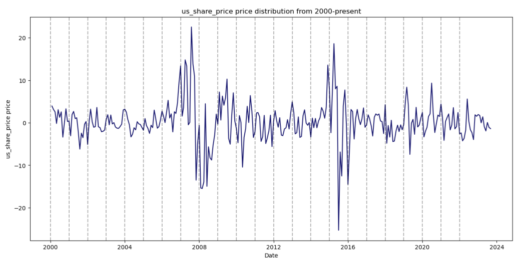

Figure 5.29: Normalised Share Price

Below is the summary of **ARIMA Model**, which has been used here because there was no observation of any upward or downward trend and no seasonality was found.Therefore we are using **ARIMA** model with order (p, d, q) as (1, 0, 1).

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                  close   No. Observations:                  279
Model:                 ARIMA(1, 0, 1)   Log Likelihood                -247.402
Date:                Wed, 22 Nov 2023   AIC                            514.804
Time:                        00:10:33   BIC                            551.116
Sample:                    02-01-2000   HQIC                           529.370
                         - 04-01-2023
Covariance Type:                  opg
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                 0.0451      0.030      1.498      0.134      -0.014       0.104
open                 -0.4887      0.053     -9.306      0.000      -0.592      -0.386
high                  0.6235      0.052     11.950      0.000       0.521       0.726
low                   0.5770      0.037     15.596      0.000       0.505       0.650
volume                0.0416      0.046      0.902      0.367      -0.049       0.132
us_inflation_rate     0.0207      0.058      0.355      0.723      -0.094       0.135
us_share_price        0.0153      0.005      2.791      0.005       0.005       0.026
ar.L1                -0.2861      0.146     -1.956      0.050      -0.573       0.001
ma.L1                -0.1027      0.163     -0.630      0.529      -0.423       0.217
sigma2                0.3447      0.025     13.879      0.000       0.296       0.393
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                11.36
Prob(Q):                              0.96   Prob(JB):                         0.00
Heteroskedasticity (H):               1.33   Skew:                             0.08
Prob(H) (two-sided):                  0.18   Kurtosis:                         3.97
===================================================================================
```

Figure 5.30: Normalised Open Price

- Dep. Variable: This is the dependent variable that the model is trying to predict. Here it is Close price
- Log Likelihood: This is a measure of how well the model fits the data.
- Covariance Type: This is the type of covariance used in the model.
- coef: Represent the relationship between the dependent variable and the independent variables.
- z: This is the z-score of the coefficients.
- P>|z|: This is the p-value of the z-score.
- 0.025 & 0.975: This is the confidence intervals for the coefficients.
- Prob(Q): The p-value of the Ljung-Box test. A value of 0.96 indicates that the residuals are independently distributed.

- Jarque-Bera (JB): The value of 11.36 indicates that the residuals are normally distributed.
- Prob(JB): The value of 0.00 indicates that the residuals are normally distributed.
- Heteroskedasticity (H): The value of 1.33 indicates that the residuals are heteroskedastic.
- Prob(H) (two-sided): A value of 0.18 indicates that the residuals are not heteroskedastic.
- Skew: The value of 0.08 indicates that the residuals are slightly skewed to the right.
- Kurtosis: The value of 3.97 indicates that the residuals have a kurtosis of 3.97.

Now using fitted **ARIMA** model to make the prediction on the test data and calculating the Root Mean Square Error **RMSE** of those prediction. The RMSE is a measure of the differences between the actual and predicted values. It's the square root of the mean of the squared differences. A lower **RMSE** indicates a better fit of the model to the data.

```
Root Mean Square Error: 0.4577151214442902
```

Figure 5.31: RMSE

Coming to the final part, here is the prediction of the actual and predicted charts by the model.

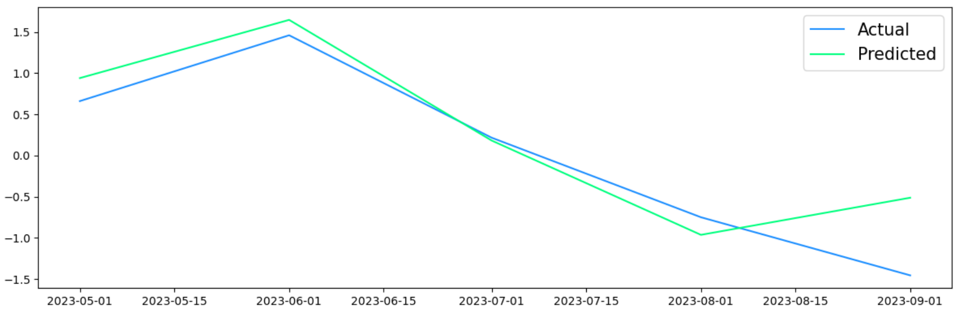

Figure 5.32: Predicted Model

5.4.1.2 S&P500

Similarly from the above explanation we have further taken S&P500 indices and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

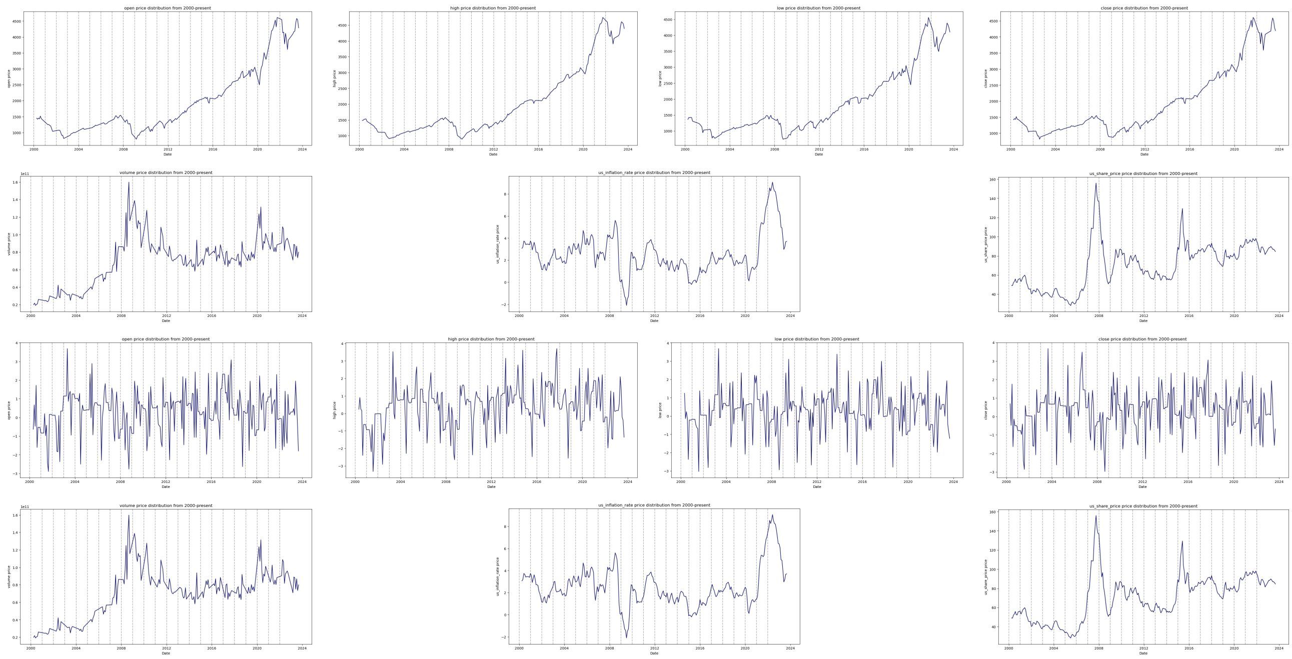

Figure 5.33: Analysis of S&P500

Below is the chart of Actual data and Predicted Data:

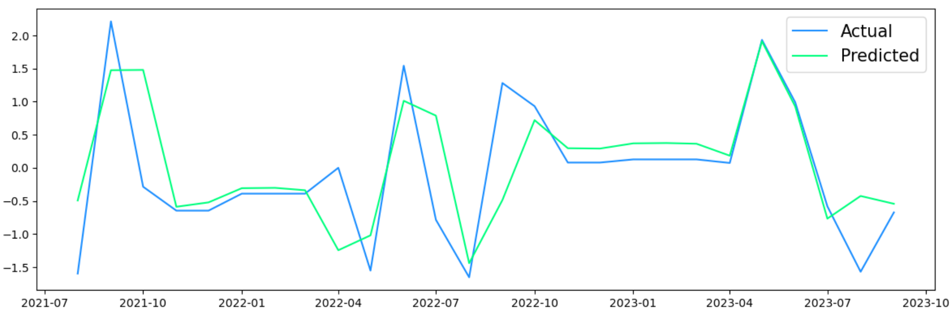

Figure 5.34: Predicted Model for S&P500

5.4.1.3 AMZN

Similarly from the above explanation we have further taken AMZN stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

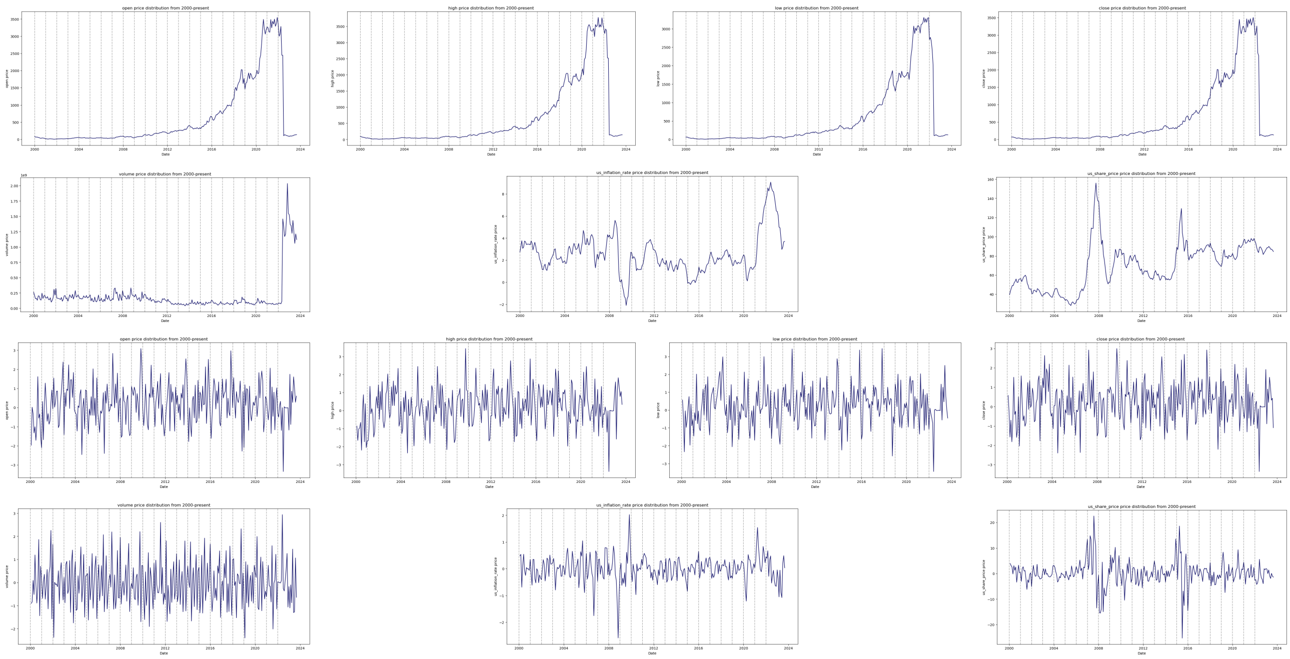

Figure 5.35: Analysis of AMZN

Below is the chart of Actual data and Predicted Data:

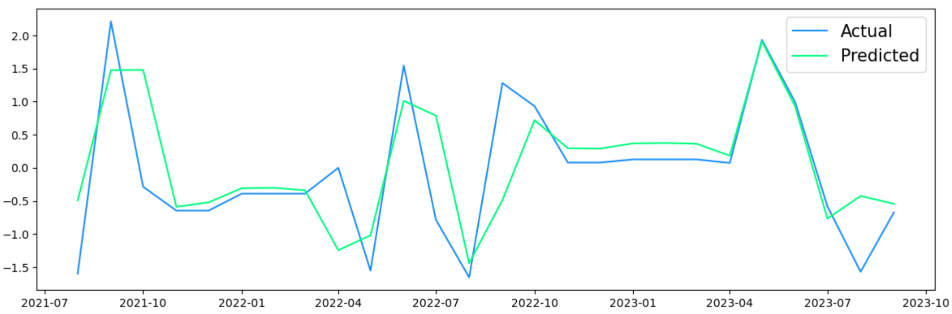

Figure 5.36: Predicted Model for AMZN

5.4.1.4 GOOGL

Similarly from the above explanation we have further taken GOOGL stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

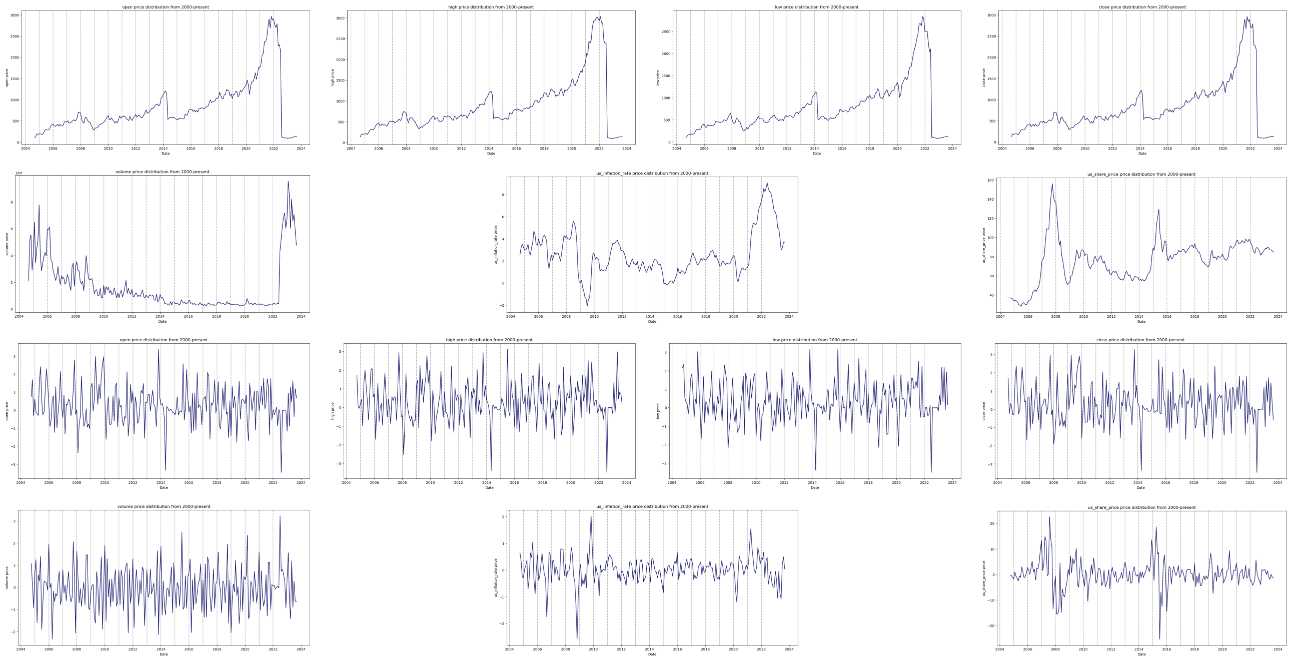

Figure 5.37: Analysis of GOOGL

Below is the chart of Actual data and Predicted Data:

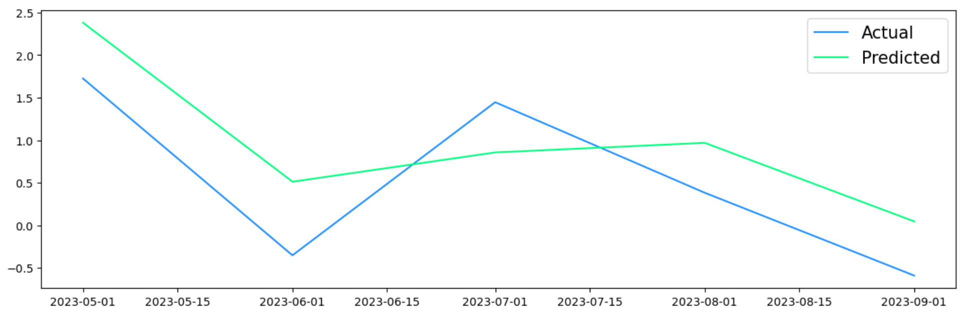

Figure 5.38: Predicted Model for GOOGL

5.4.1.5 META

Similarly from the above explanation we have further taken META stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

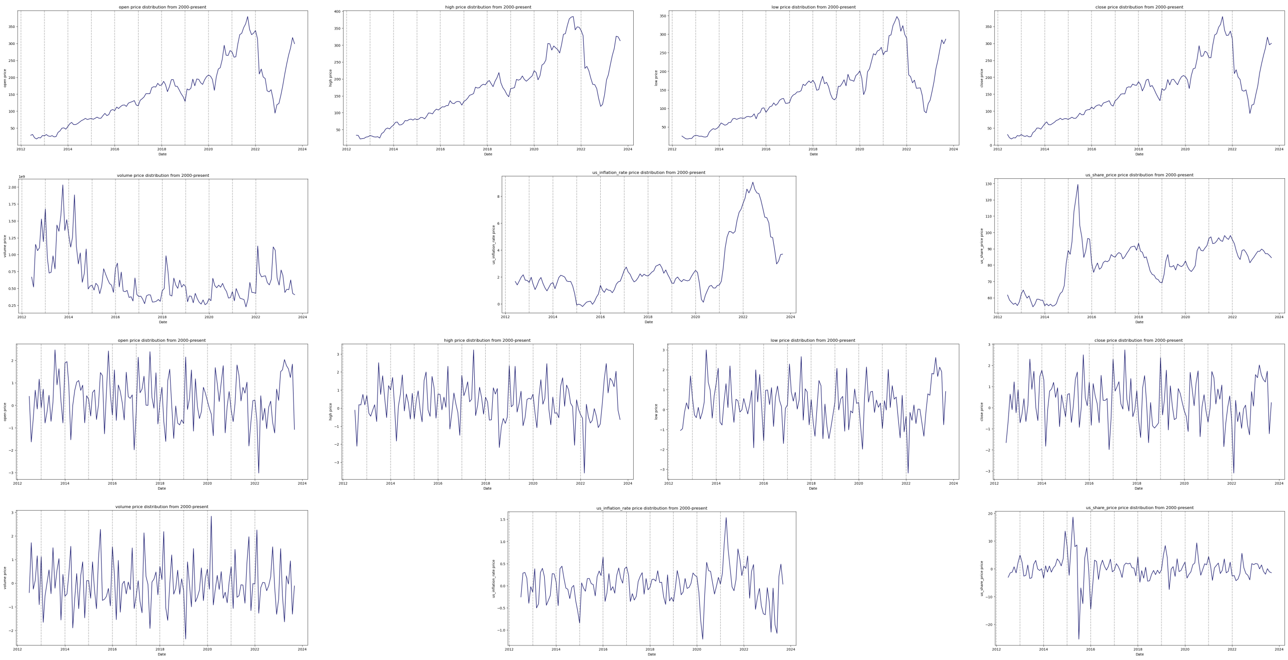

Figure 5.39: Analysis of META

Below is the chart of Actual data and Predicted Data:

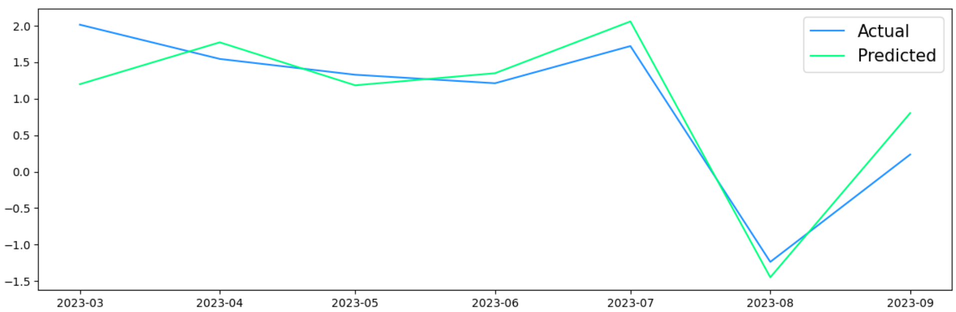

Figure 5.40: Predicted Model for META

5.4.1.6 MSFT

Similarly from the above explanation we have further taken MSFT stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

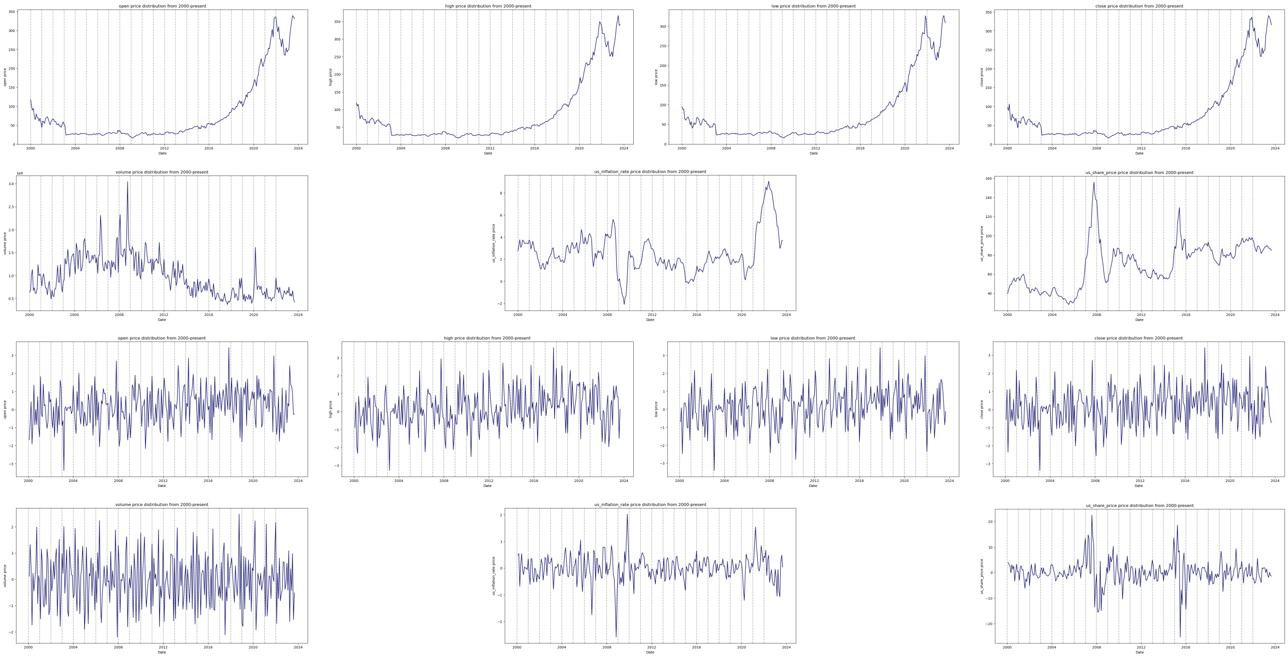

Figure 5.41: Analysis of MSFT

Below is the chart of Actual data and Predicted Data:

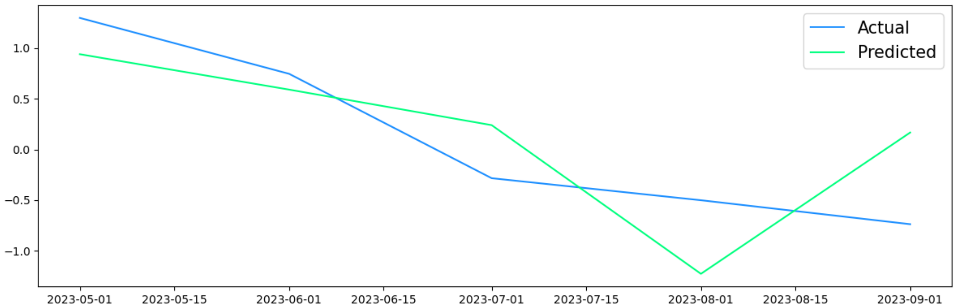

Figure 5.42: Predicted Model for MSFT

5.4.1.7 NVDA

Similarly from the above explanation we have further taken NVDA stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

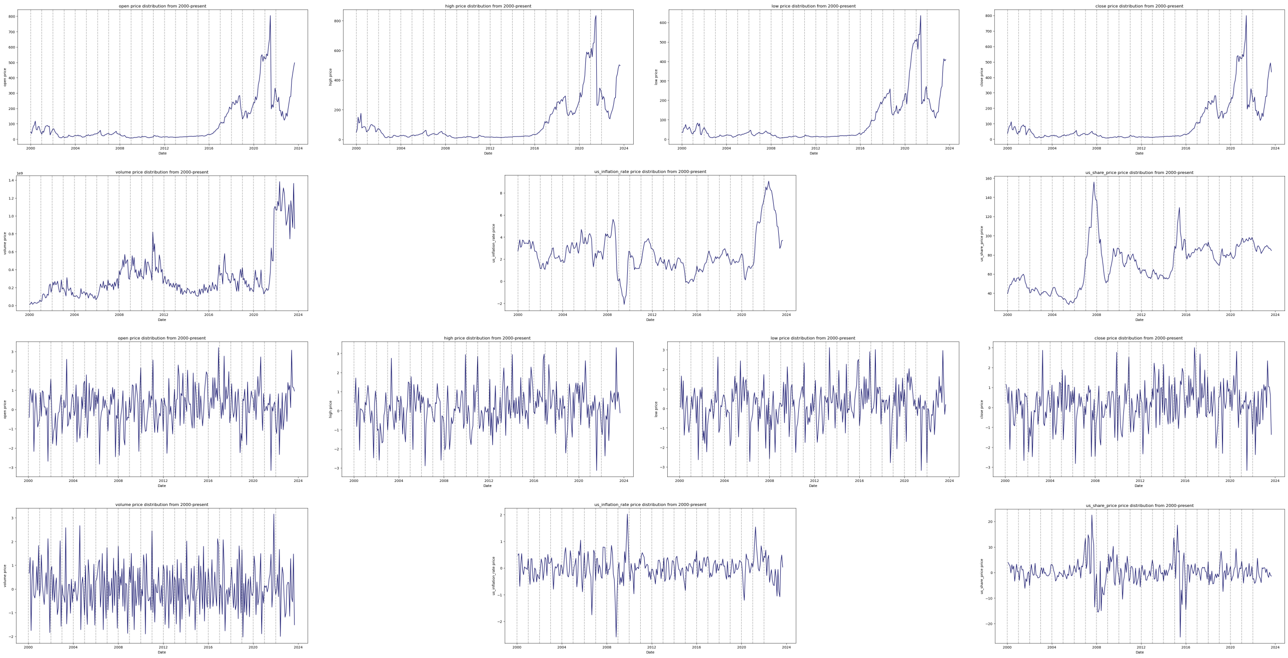

Figure 5.43: Analysis of NVDA

Below is the chart of Actual data and Predicted Data:

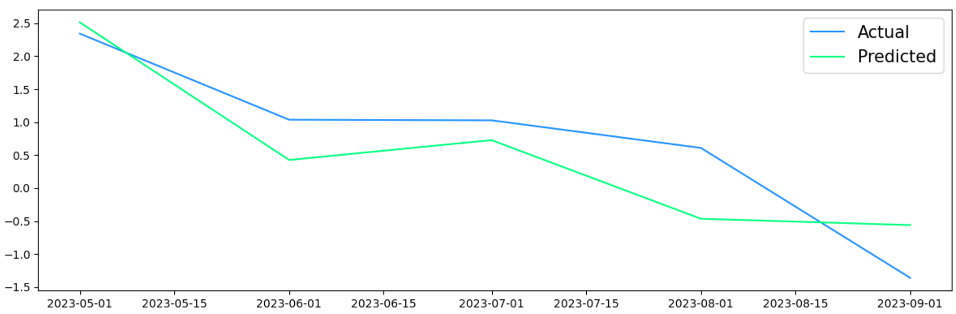

Figure 5.44: Predicted Model for NVDA

5.4.1.8 TSLA

Similarly from the above explanation we have further taken TSLA stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

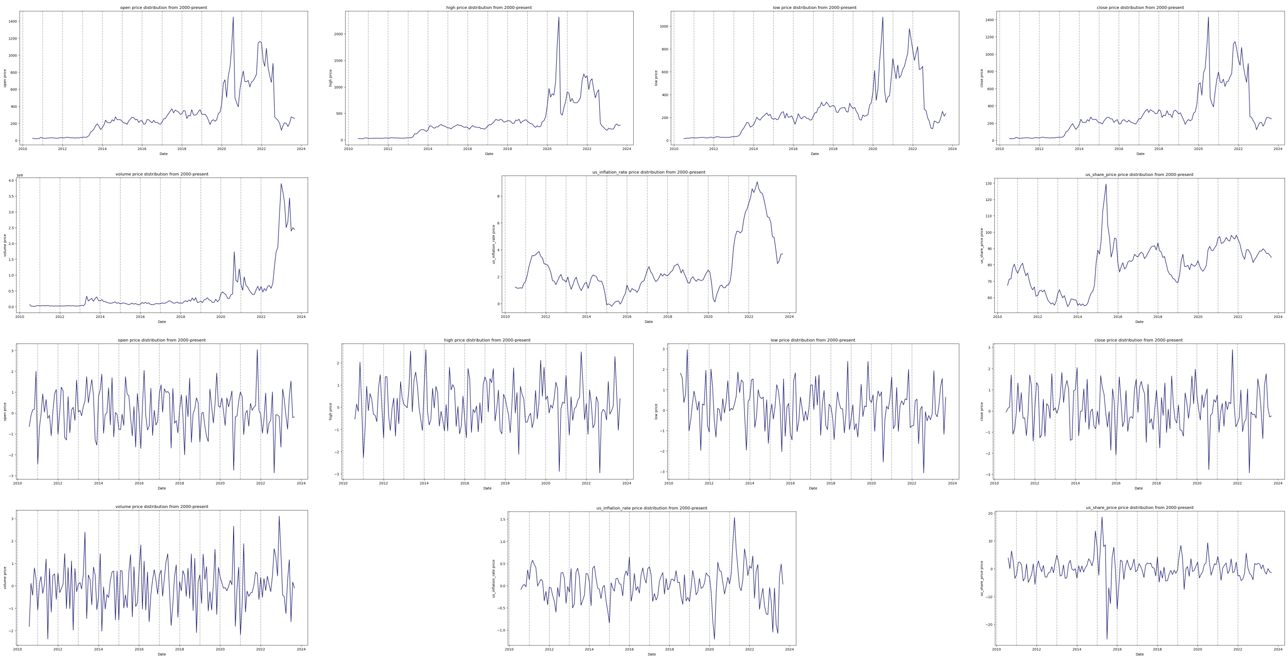

Figure 5.45: Analysis of TSLA

Below is the chart of Actual data and Predicted Data:

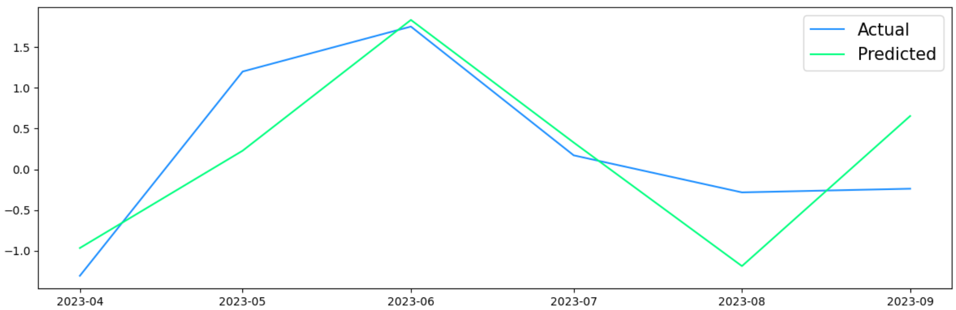

Figure 5.46: Predicted Model for TSLA

5.4.1.9 Results for USA:

From the graph we can observe that, even though there has been a huge volatility in the data from time to time in all the stocks and indices there has been a steady growth in the inflation rate in USA, than compared to other countries, these might been because of the cash flow in the nation or economic uncertainty or the consumer spending.

5.4.2 CHINA

The description here on forth is about all the dataset of Stocks and Indices which has been selected from CHINA for the analysis.

5.4.2.1 SHI co

Similarly from the above explanation we have further taken SHI co stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

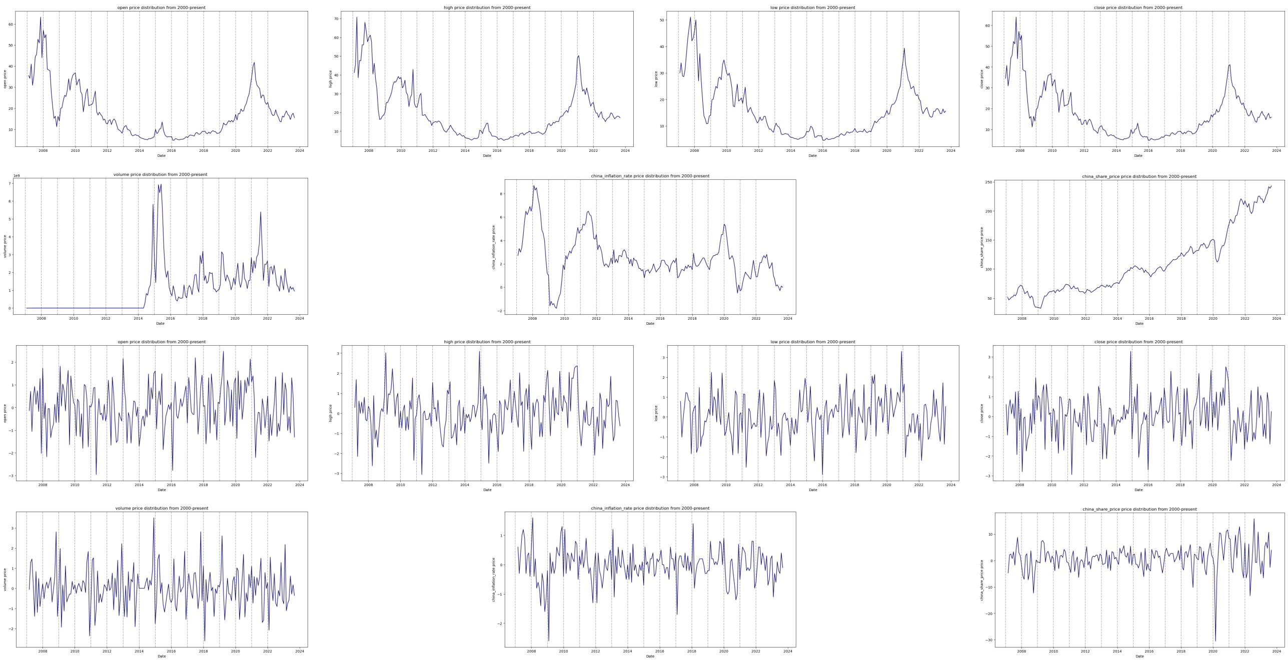

Figure 5.47: Analysis of SHI co

Below is the chart of Actual data and Predicted Data:

Figure 5.48: Predicted Model for SHI co

5.4.2.2 SHANGHAI COMPOSITE

Similarly from the above explanation we have further taken SHANGHAI COMPOSITE indices and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

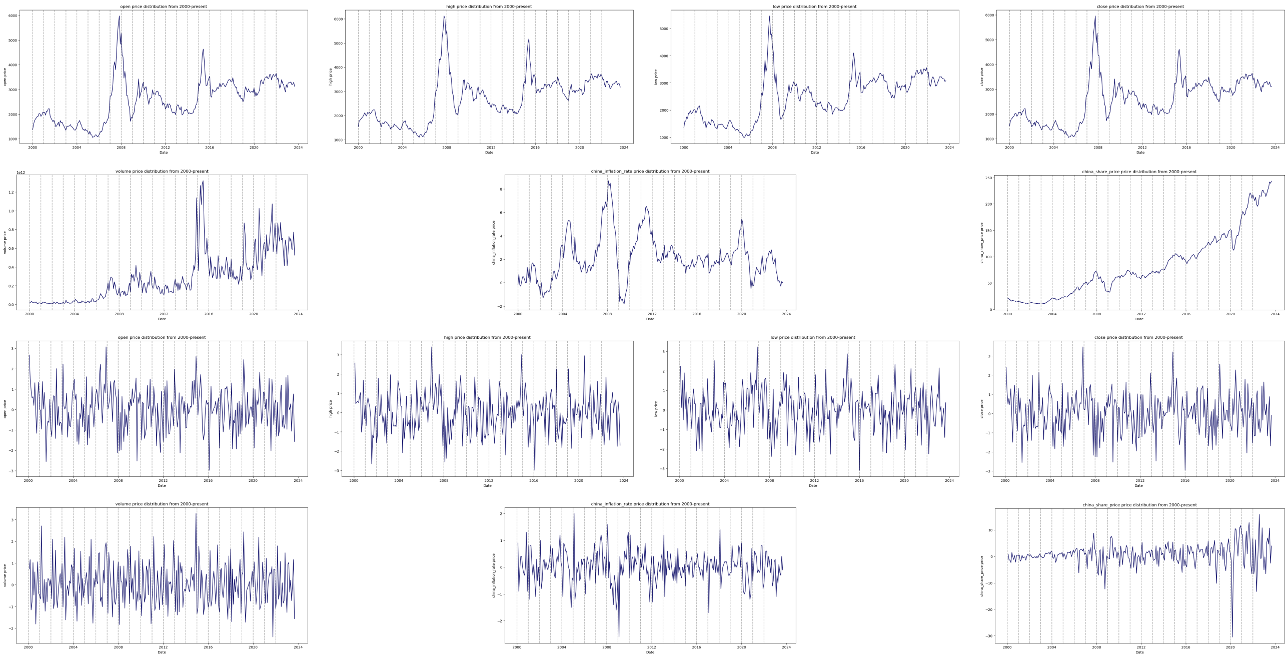

Figure 5.49: Analysis of SHANGHAI COMPOSITE

Below is the chart of Actual data and Predicted Data:

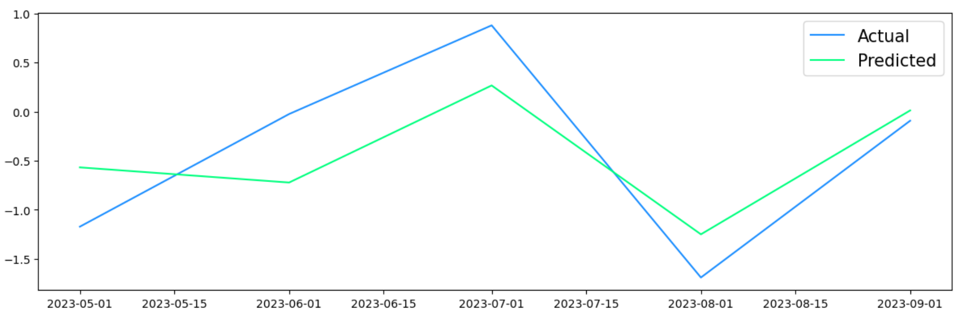

Figure 5.50: Predicted Model for SHANGHAI COMPOSITE

5.4.2.3 CITI Securities

Similarly from the above explanation we have further taken CITI Securities stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

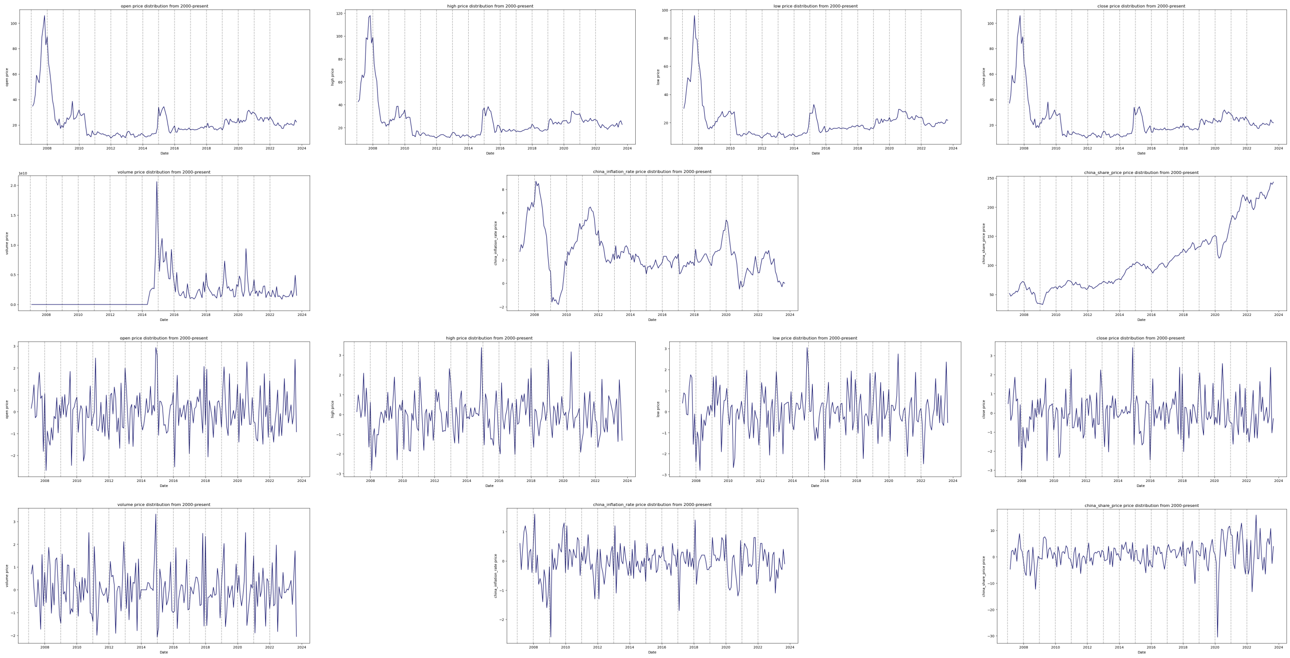

Figure 5.51: Analysis of CITI Securities

Below is the chart of Actual data and Predicted Data:

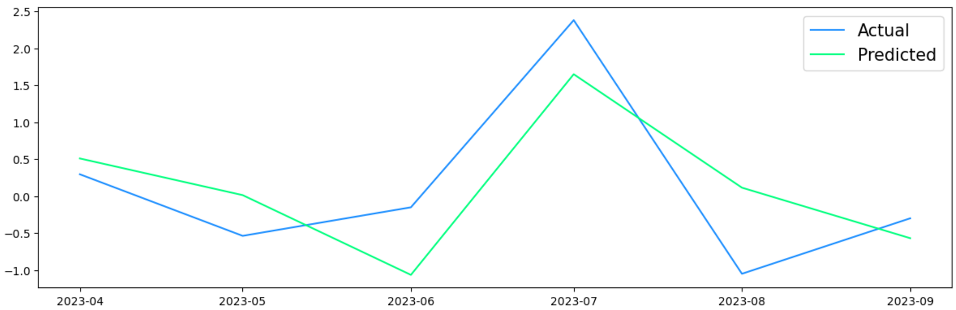

Figure 5.52: Predicted Model for CITI Securities

5.4.2.4 CMB co

Similarly from the above explanation we have further taken CMB co stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

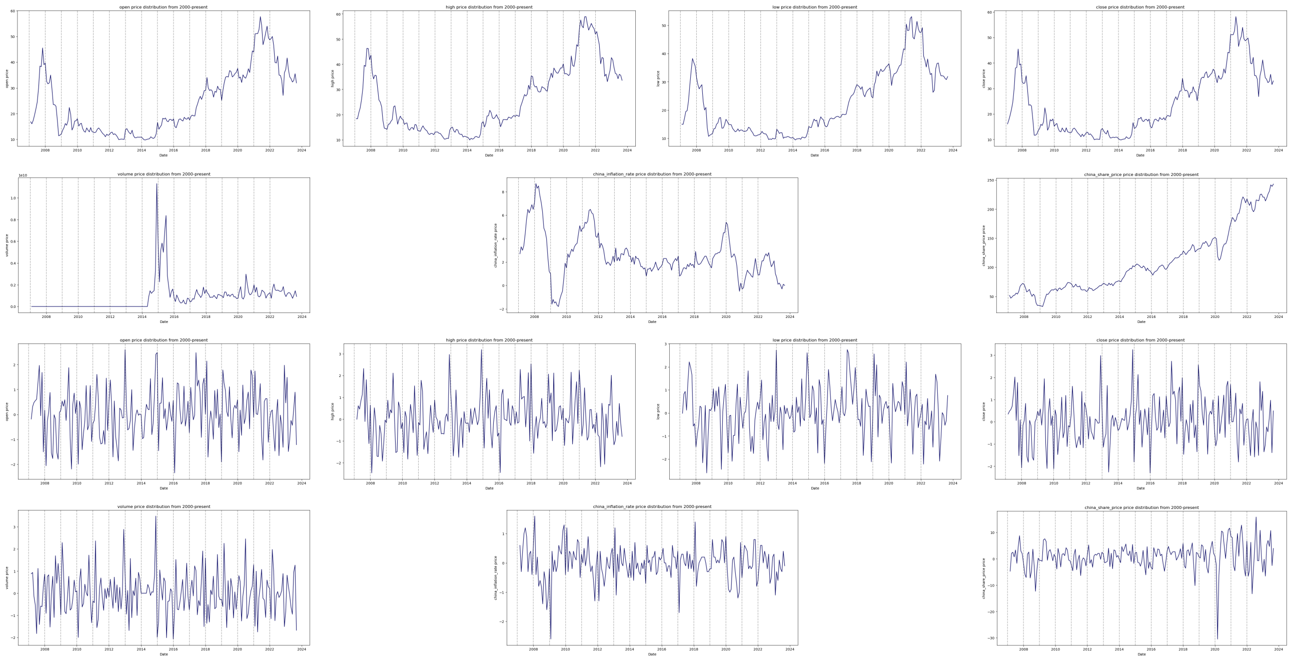

Figure 5.53: Analysis of CMB co

Below is the chart of Actual data and Predicted Data:

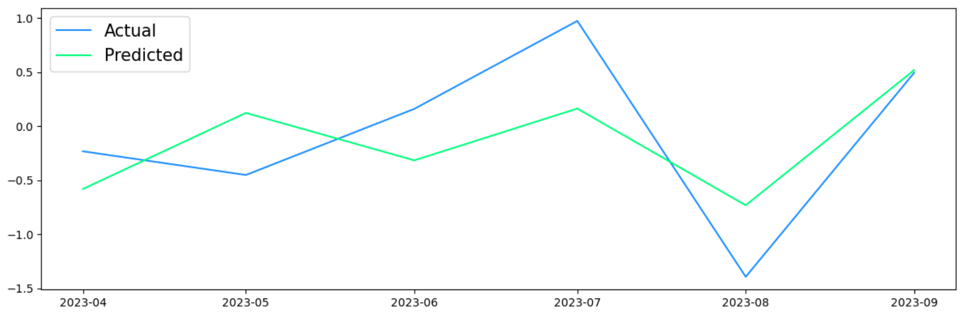

Figure 5.54: Predicted Model for CMB co

5.4.2.5 CP&C co

Similarly from the above explanation we have further taken CP&C co stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

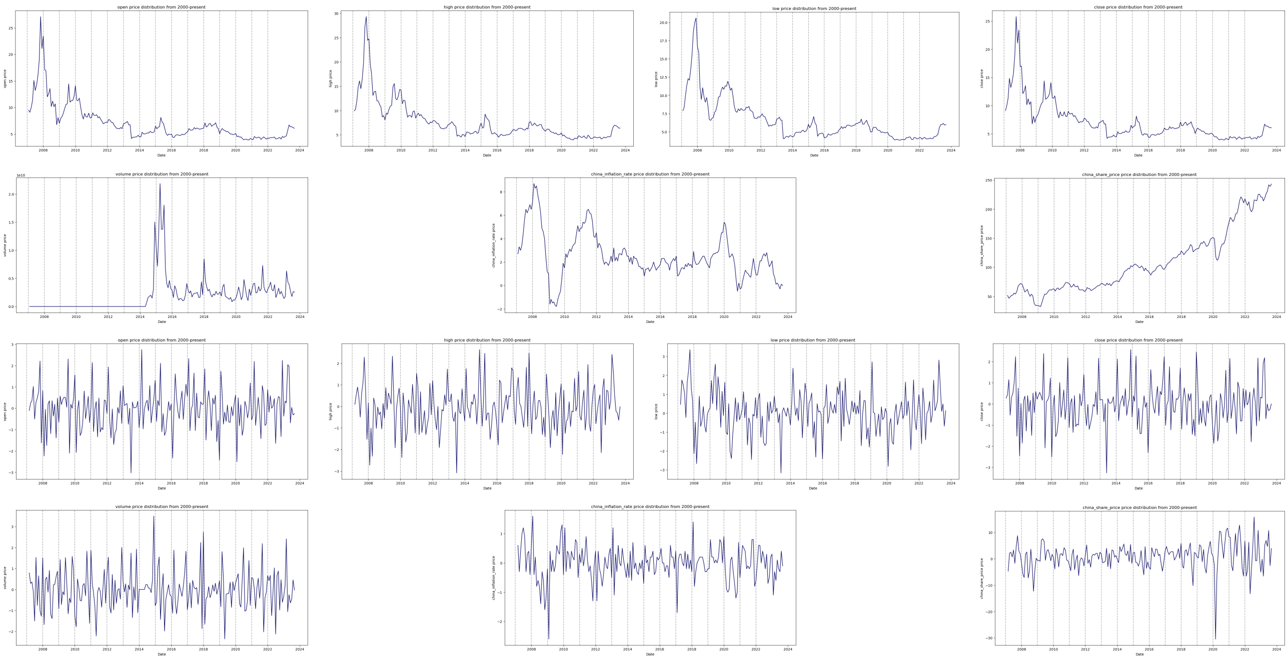

Figure 5.55: Analysis of CP&C co

Below is the chart of Actual data and Predicted Data:

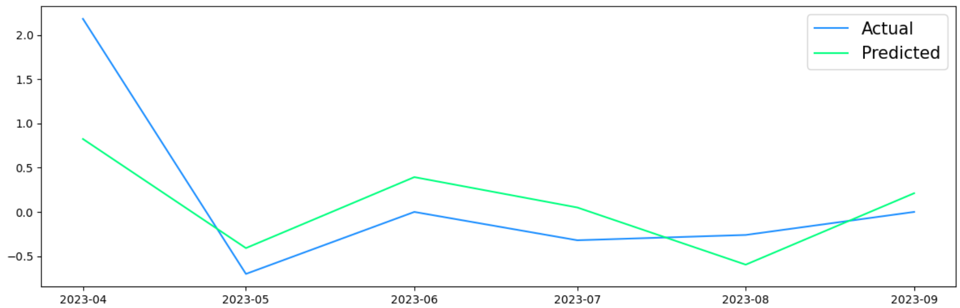

Figure 5.56: Predicted Model for CP&C co

5.4.2.6 IMBSU LTD

Similarly from the above explanation we have further taken IMBSU LTD stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

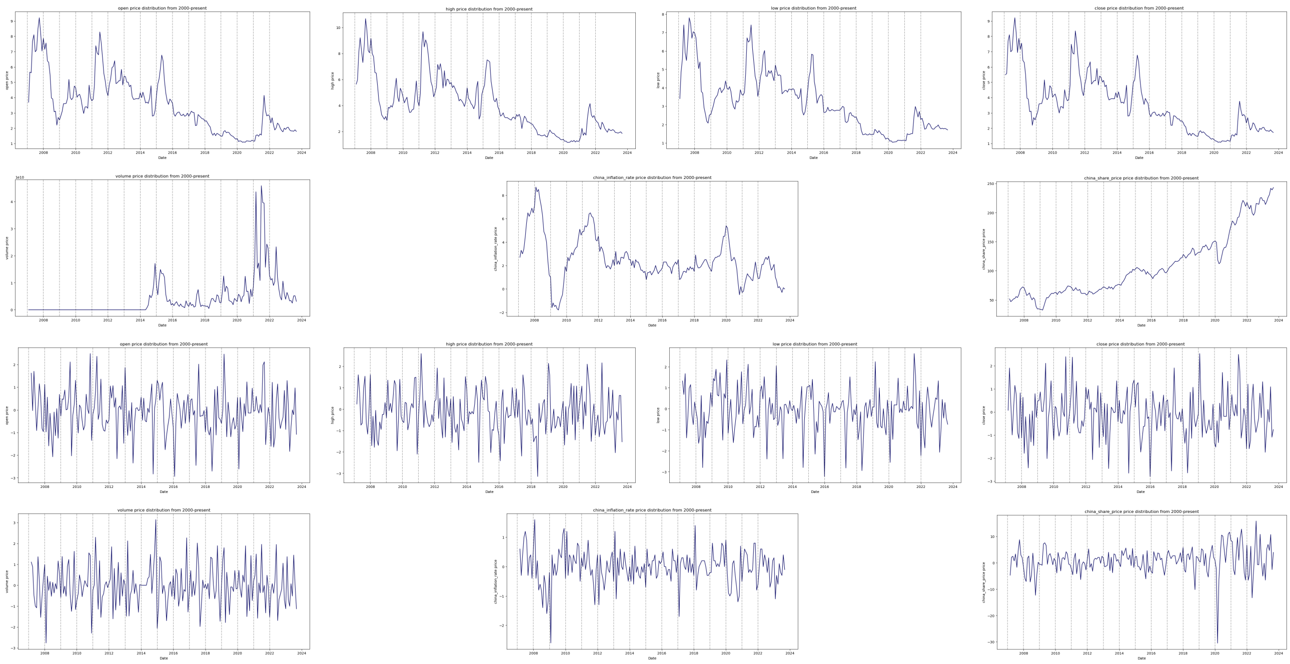

Figure 5.57: Analysis of IMBSU LTD

Below is the chart of Actual data and Predicted Data:

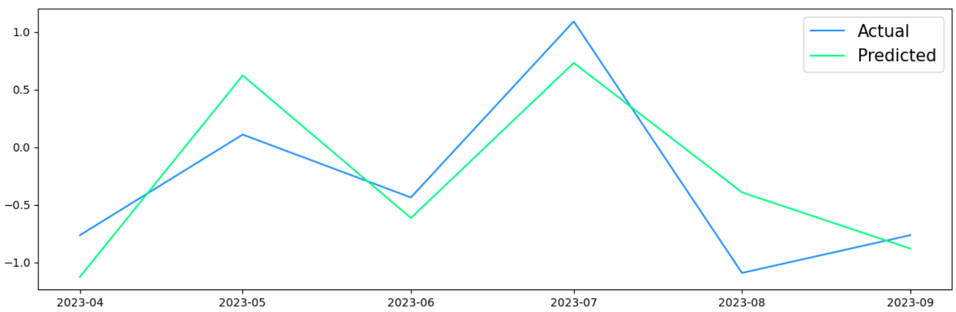

Figure 5.58: Predicted Model for IMBSU LTD

5.4.2.7 PD&HG co

Similarly from the above explanation we have further taken PD&HG co stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

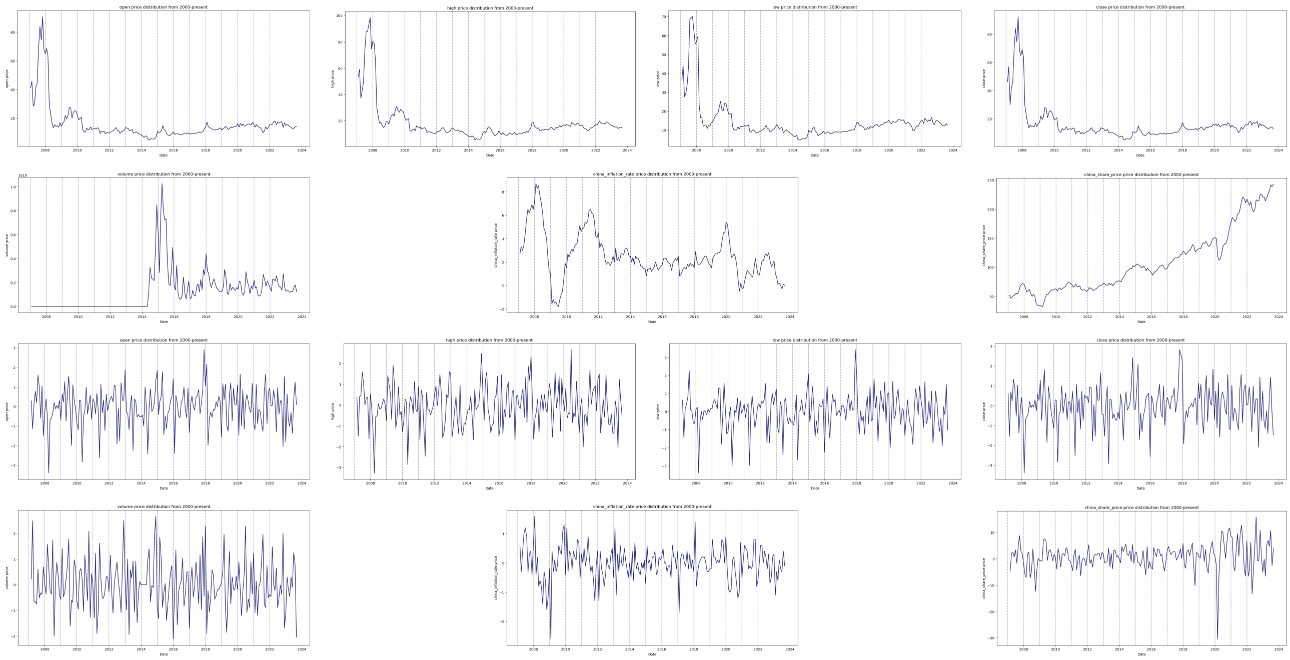

Figure 5.59: Analysis of PD&HG co

Below is the chart of Actual data and Predicted Data:

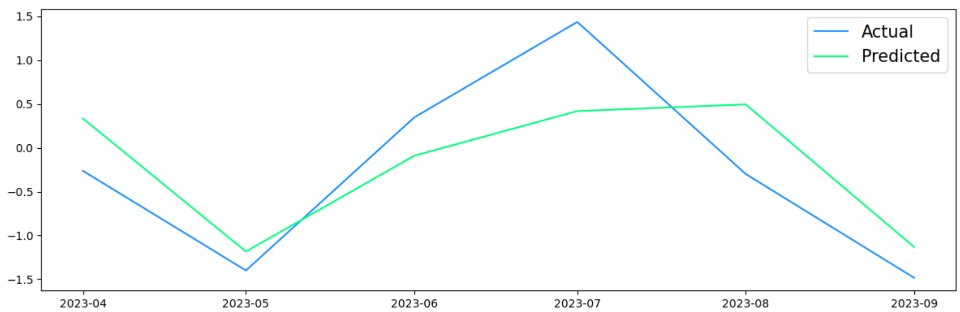

Figure 5.60: Predicted Model for PD&HG co

5.4.2.8 SAIC Motor Corp

Similarly from the above explanation we have further taken SAIC Motor Corp stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

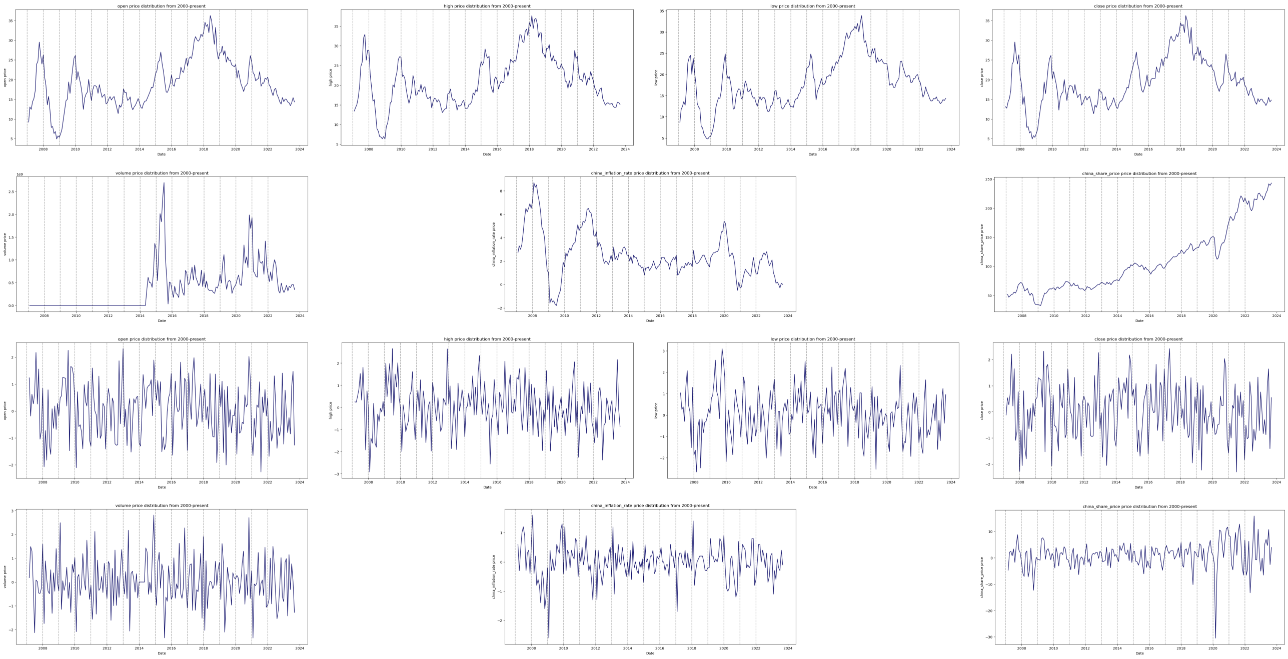

Figure 5.61: Analysis of SAIC Motor Corp

Below is the chart of Actual data and Predicted Data:

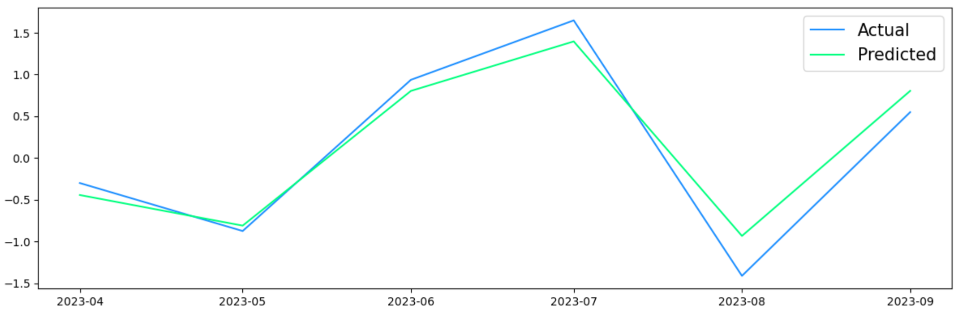

Figure 5.62: Predicted Model for SAIC Motor Corp

5.4.2.9 Results for CHINA:

Covid-19 had a great impact on china and rest of the world, which in response show a huge impact on market indices and though the effect of covid has been covered in a rapid speed, the inflation rate effect has been observed in the analysed stocks.

Through our charts and data points it is observed few stocks related to automobiles has been effected from inflation, this may be by the high volatility of money flow which has caused consumer to spend send less money and has damaged for the growth of the companies resulting in the backlash of market and stocks of the company resulting in the economy.

5.4.3 INDIA

The description here on forth is about all the dataset of Stocks and Indices which has been selected from INDIA for the analysis.

5.4.3.1 HDFC BANK

Similarly from the above explanation we have further taken HDFC BANK stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

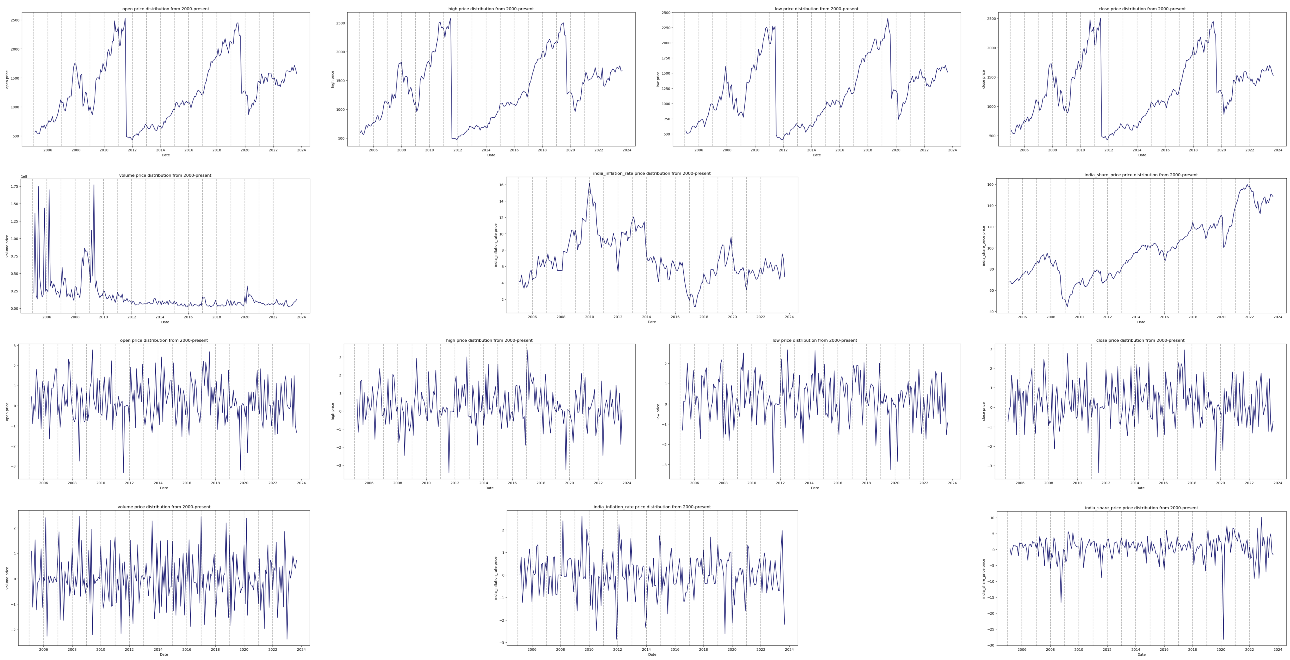

Figure 5.63: Analysis of HDFC BANK

Below is the chart of Actual data and Predicted Data:

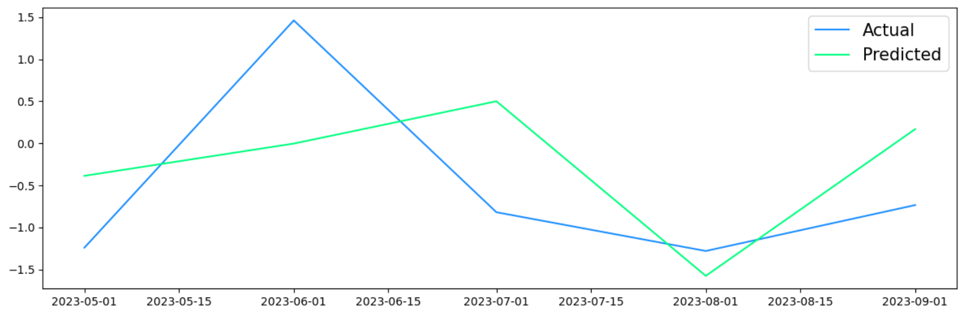

Figure 5.64: Predicted Model for HDFC BANK

5.4.3.2 NIFTY50

Similarly from the above explanation we have further taken NIFTY50 indices and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

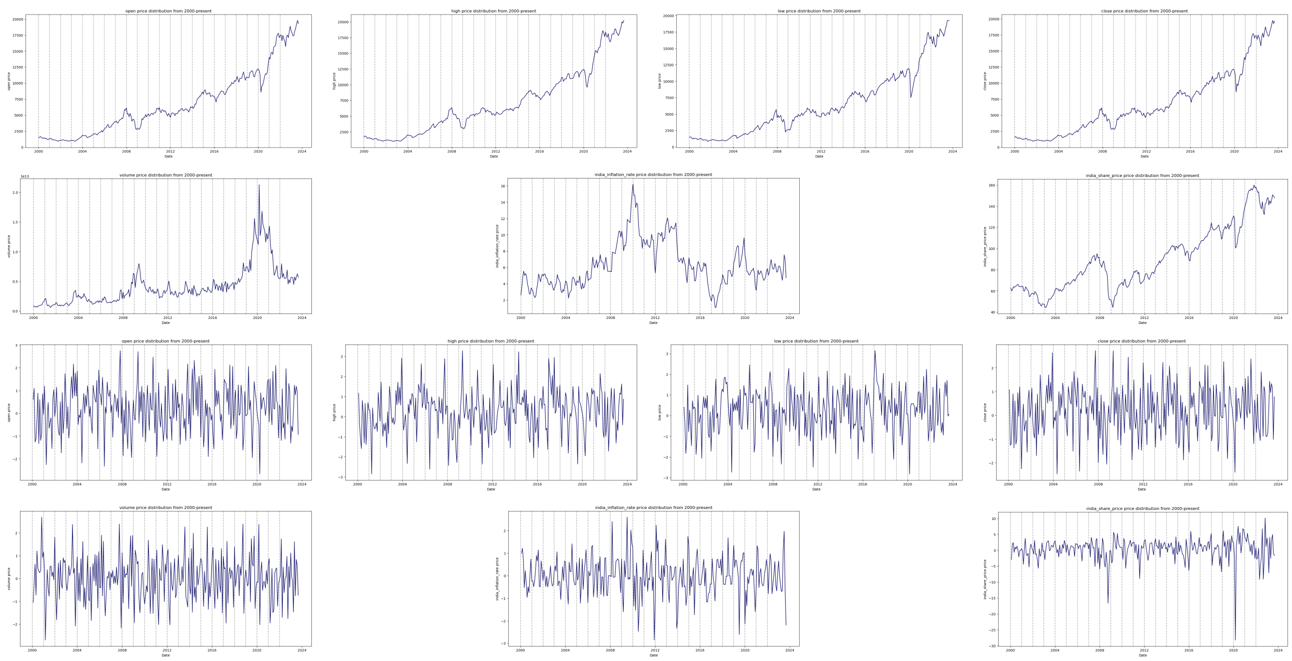

Figure 5.65: Analysis of NIFTY50

Below is the chart of Actual data and Predicted Data:

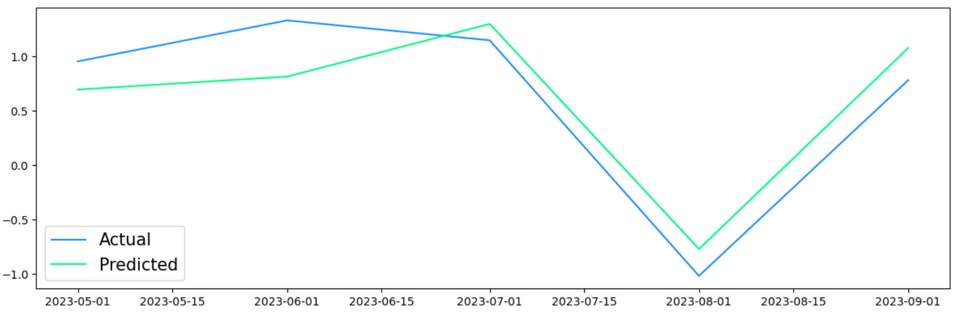

Figure 5.66: Predicted Model for NIFTY50

5.4.3.3 ICICI BANK

Similarly from the above explanation we have further taken ICICI BANK stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

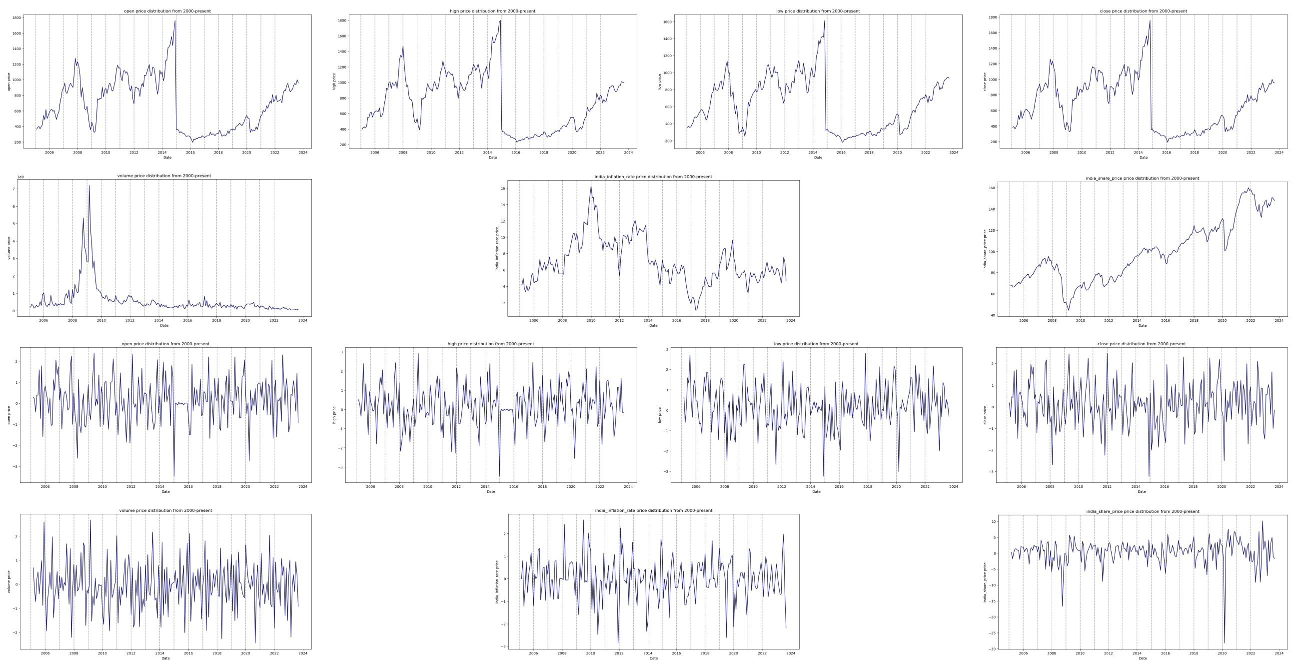

Figure 5.67: Analysis of ICICI BANK

Below is the chart of Actual data and Predicted Data:

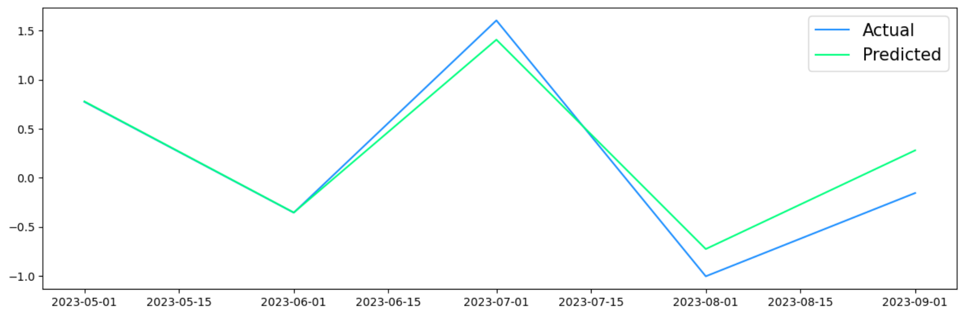

Figure 5.68: Predicted Model for ICICI BANK

5.4.3.4 INFY

Similarly from the above explanation we have further taken INFY stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

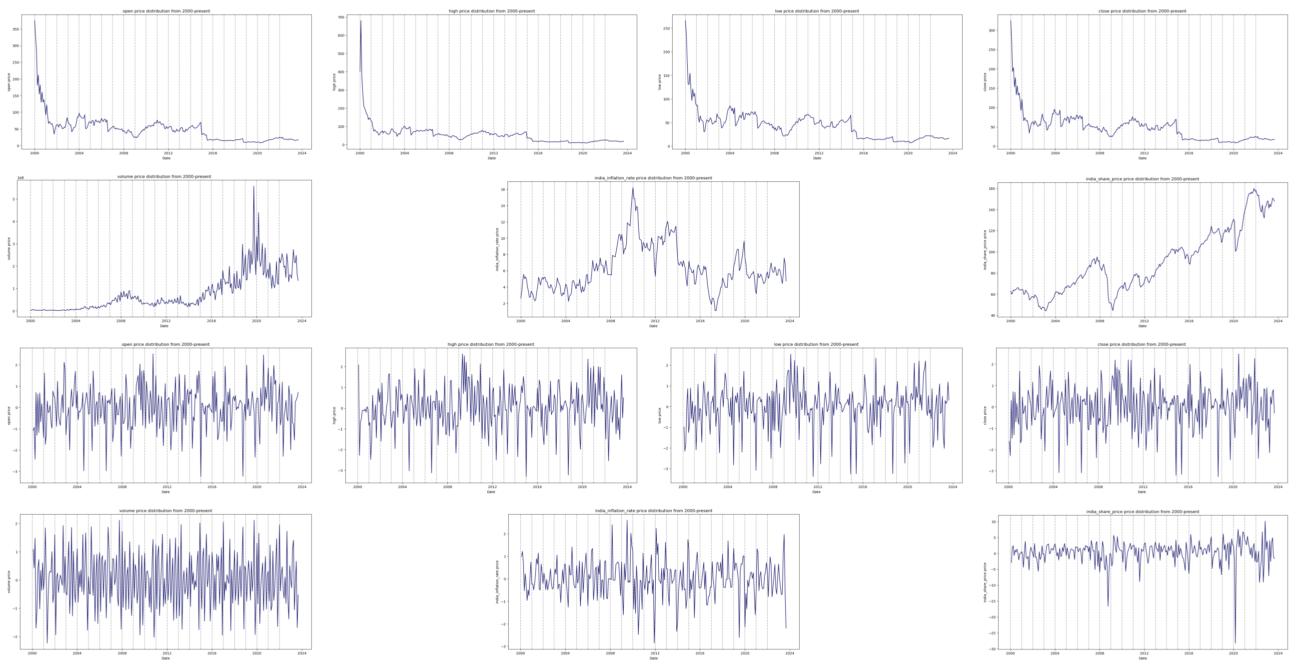

Figure 5.69: Analysis of INFY

Below is the chart of Actual data and Predicted Data:

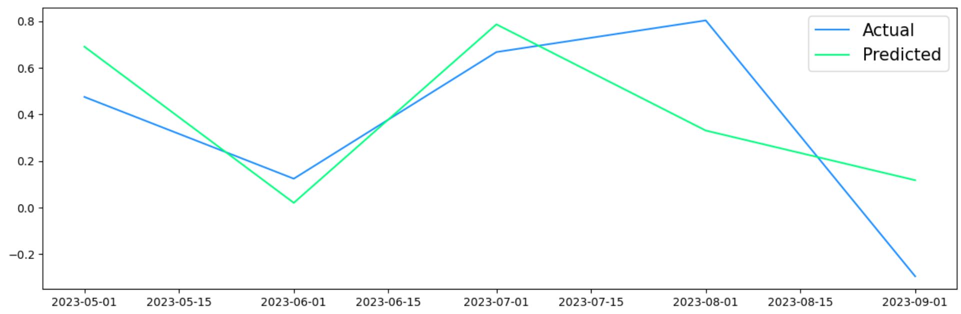

Figure 5.70: Predicted Model for INFY

5.4.3.5 ITC

Similarly from the above explanation we have further taken ITC stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

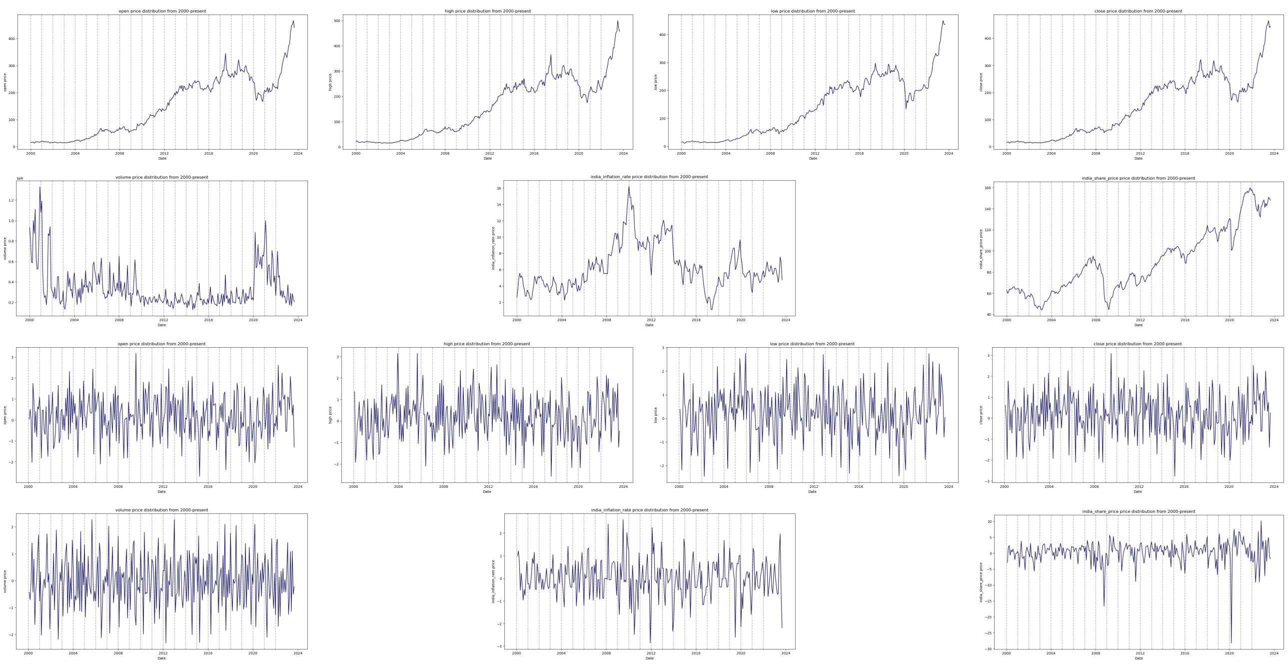

Figure 5.71: Analysis of ITC

Below is the chart of Actual data and Predicted Data:

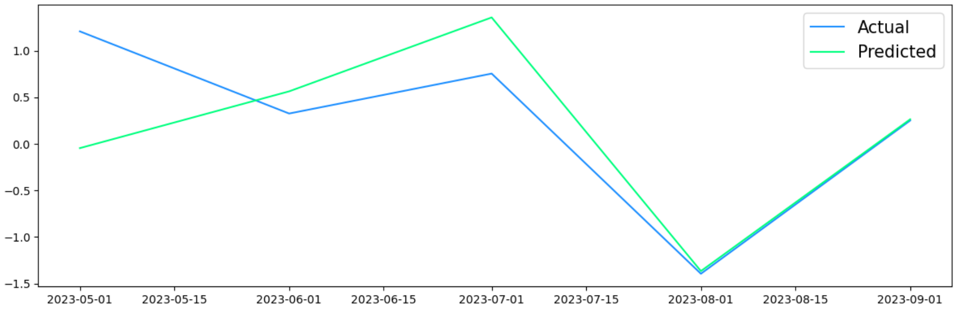

Figure 5.72: Predicted Model for ITC

5.4.3.6 LT

Similarly from the above explanation we have further taken LT stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

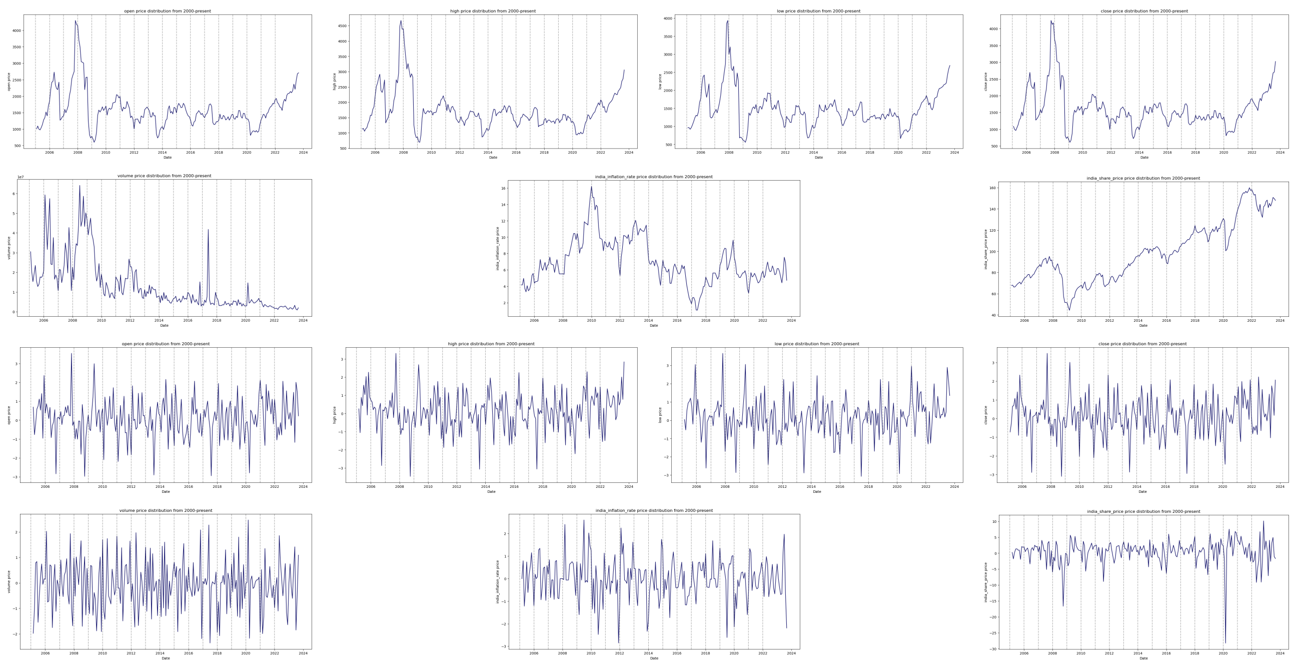

Figure 5.73: Analysis of LT

Below is the chart of Actual data and Predicted Data:

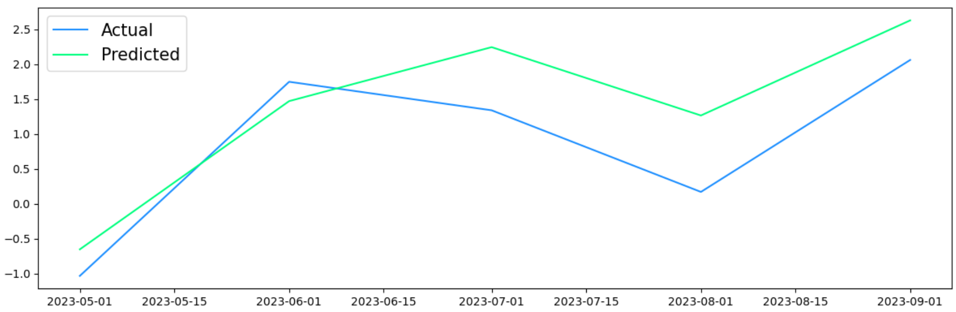

Figure 5.74: Predicted Model for LT

5.4.3.7 RELIANCE

Similarly from the above explanation we have further taken RELIANCE stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

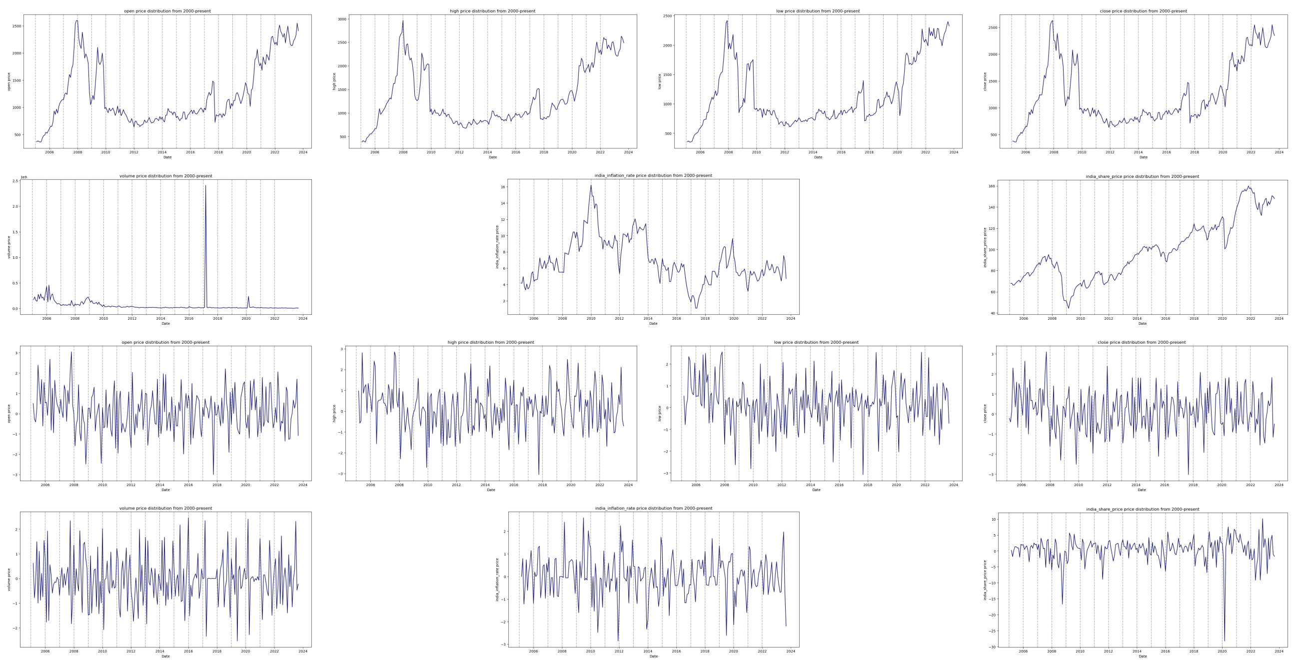

Figure 5.75: Analysis of RELIANCE

Below is the chart of Actual data and Predicted Data:

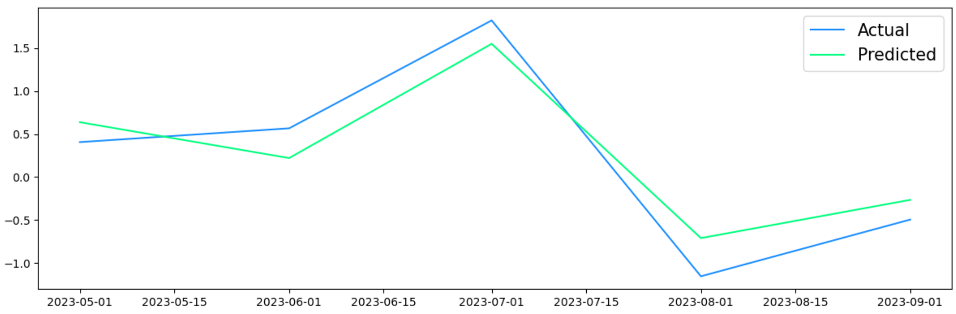

Figure 5.76: Predicted Model for RELIANCE

5.4.3.8 TCS

Similarly from the above explanation we have further taken TCS stock and done the analysis. Find the results from the below charts, the first two line of charts is the of the values from dataset and the next two line is of the normalized data.

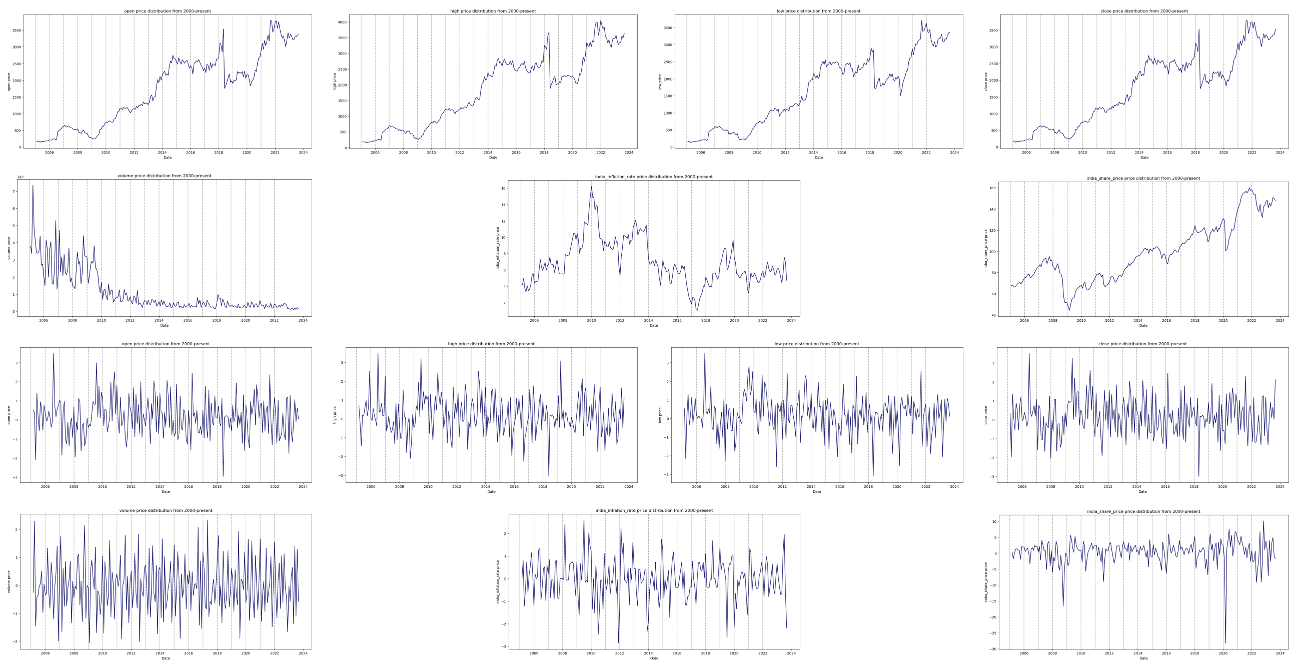

Figure 5.77: Analysis of TCS

Below is the chart of Actual data and Predicted Data:

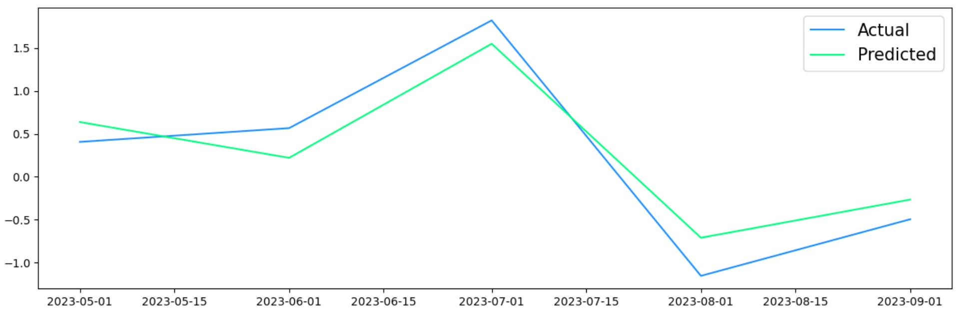

Figure 5.78: Predicted Model for TCS

5.4.3.9 Results for INDIA:

Yes, there has a been a huge impact of inflation in stock market. Through our observation from the above charts and graph we can say that the financial sectors has have a steady movement in the economy even with the higher inflation rate, this might be because it the center of rotation for the money circulation so it has not had a major setback. But corporate company has some unstable movement in the stocks, this effect is by high inflation which can squeeze corporate profits with higher input costs and effect the overall economy.

5.5 Conclusion

By knowing what inflation rate is to, training and testing data for the prediction we for analysis we have come to a decision on how and how much the inflation rate has a effect on stock market. Not only the stock but also we have compared it to other countries and their market and economy. We also know that these are just a part of consideration to determine the analysis and there are various elements which has to be taken. We have discovered patterns and trends along with variations in behaviour of stock market indices when they are changed or unique patterns formed. The we have also predicted the charts through our analysis with ARIMA model and got results where it shows that inflation do have a effect on stock market and seven out of ten prediction are found to have less than 40% Root Mean Square Error (RMSE). And this error has occurred moslty in Indian stocks, these results can be consider and taken into consideration for future analysis and valuation.

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