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

- **Stock Market behavior**

  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[1], 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. This argument is consistent with the finding from Investopedia 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)[2], who suggested that there was a negative correlation between inflation and stock returns. This theory, sometimes referred to as the "stagflation phenomenon," contends that expectations of future actual activity determine both inflation rates and stock values. Investopedia[3] 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, which is according to a study by Alexakis et al. (1996)[4], 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.

Further 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.[5] (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 several distinct worldwide stock market sectors. Herrero's study[6], emerging economies were particularly hard hit by the COVID-19 pandemic's third wave. 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 by [7], 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.

Raja Ram's[8] analysis reflects significantly what impacted both the Indian and international stock markets. The pandemic caused the world financial market to collapse, which sharply fluctuated the Indian stock market. 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. The 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)[9]. This indicates a large decline in the stock market as the BSE Sensex's value dropped by 13.2% in a single day. Investigation on how the pandemic affected the various segments of the Chinese stock market was done by Al-Awadhi et al. in (2020)[10]. They discovered that while the information technology and pharmaceutical industries performed comparably better, big market capitalization stocks suffered. And the 2020 study "Spillover of COVID-19: Impact on the Global Economy" by Peterson K. Ozili and Thankom Arun[11] sought to examine how the COVID-19 pandemic affected the economies of the four continents: Asia, Europe, Africa, and North America. 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. Which also caused a decline in business revenue and productivity as well as expenses and cash flow issues. The analysis also showed how the epidemic caused a decline in global equities, bonds, and oil shares. 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[12] 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.

- **Relationship between Risk and Return**
  when it comes to investing in the stock market, understanding how different factors like inflation, exchange rates, and news can affect returns is crucial for making informed decisions about where to put your money. 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 because equities are typically seen 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.[13] in 2020 examined the nonlinear behavior of the US and Chinese financial markets. The researchers like Jorge Caiado[14] imposed 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. Asymmetric power from the model permits distinct volatility patterns for positive and negative shocks. The study shows from 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 a negligible effect on the Nasdaq composite index. 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. 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. As a result, investors have left the market, which has caused the value of the equities to drop. Cepoi[15] 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.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. This is due to the fact that negative or unfavorable news, like a rise in COVID-19 cases or fatalities, can lower investor confidence and, as a result, lower stock market returns. Furthermore research revealed that there was an uneven dependence 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 the reason for this. Osagie et al.[16] proposed legislative changes to strengthen the financial system. They recommended creating a stable political environment to reduce market volatility and uncertainty, providing incentives to local businesses for economic growth, and promoting economic diversification by spreading investments across different industries and regions. These measures aim to enhance investor confidence and market performance during challenging times like a pandemic. 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 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), 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. A drop in oil prices can have a big effect on the economy of the country indicated in the statement because of its heavy dependence on oil revenue. This might result in less consumer spending, poorer government revenue, and possibly even greater unemployment rates.

The pandemic was brought to light, which caused unheard-of market swings that had an impact on the oil and growing countries like India. In order to make wise investing decisions, it also highlights how crucial it is to comprehend how inflation, stock market behavior, and outside variables like news interact. In addition, scholars have proposed strategies to fortify financial institutions in trying times, including fostering political stability, encouraging economic diversity, and enacting flexible exchange rate policies. The body of research thus emphasizes the necessity of proactive approaches to reduce risks and improve market resilience against unforeseen shocks like pandemics.

CHAPTER 3

Data

The study aims to find the impact of inflation in stock markets based on selected 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 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 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 3.2: S&P500 Stocks weightage.

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:

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 3.3: Shanghai Composite Index Stocks.

CHAPTER 4

Methodology

The methodology section of the project aims to outline the approach used to analyse the impact of inflation and GDP on stock prices. The analysis involves examining the relationship between these economic indicators and stock market performance, with the goal of understanding the extent to which changes in inflation and GDP affect stock prices. The following were the steps taken to analyse and achieve this objective:

- **Data Pre-Processing:** Raw data is usually erroneous and misses out some crucial factors. In this case, when analysing correlation between 3 different types of data, being the index, inflation and GDP, number scales do not match up, leading to higher complexity in analysis. To solve this, the data is scaled into matching ranges using a list of techniques like Standard Scaling, Normalizing, Power Transformations and Log Transformation, which are detailed further below.

- **Statistical Tests:** Statistical techniques such as correlation analysis, regression analysis, and time-series modelling are employed to examine the relationship between inflation, GDP, and stock prices. Correlation analysis determines the strength and direction of the linear relationship between variables, while regression analysis quantifies the impact of inflation and GDP on stock prices. Time-series models, such as VAR (Vector Autoregression), may also be utilised to capture the dynamic interactions between these variables over time.

- **Hypothesis Testing:** Along with the statistical tests, some more tests are more focused proving the outcome of the hypothesis. These are tests such as the Augmented Dickey-Fuller test, the F-test and the Granger Causality Test. The outcome of these tests is to provide a probability approximation of how the data fares against a given scenario, which in this case is the correlation. VAR is also utilised to capture an understanding of correlation between these features.

4.1 Data Indicators

- **Index Price**

  Purpose: The index price represents the aggregated value of a specific set of stocks, providing a broad measure of market performance for a particular sector or economy.

  Formula: Let P denote the index price, which is typically calculated as the weighted average of the prices of constituent stocks. If p_i represents the price of stock i and w_i represents its weight in the index, the index price P is given by:

  $$P = \sum_i p_i \times w_i$$

- **Stock Price**

  Purpose: The stock price refers to the current market value of a single share of a company's stock, which is determined by the supply and demand dynamics in the market.

  Formula: Let S represent the stock price, which is determined by various factors including company performance, market sentiment, and macroeconomic conditions. There is no specific formula for calculating stock prices as they are determined by market forces.

- **Volume**

  Purpose: Volume refers to the total number of shares traded during a specific period, indicating the level of market activity for a particular stock or index.

  Formula: Let V denote the volume, which is simply the total number of shares traded during a given period. It can be calculated by summing the individual trade volumes over the period.

$$V = \sum_i v_i$$

- **Price-Volume**

  Purpose: The price-volume product (PV) is a key technical analysis metric that reflects the total transaction value in a security. High PV indicates strong market activity and potential momentum shifts.

  Formula: The price-volume product is calculated by directly multiplying the current market price of a security with its trading volume during a given time interval. Let (P) represent the price and (V) represent the volume.

$$PV = P \cdot V$$

- **Inflation**

  Purpose: Inflation measures the rate of increase in the general price level of goods and services in an economy over a certain period, indicating the erosion of purchasing power.

  Formula: Let I denote the inflation rate, which is typically calculated as the percentage change in a price index (such as the Consumer Price Index) over a specified time period. The formula for calculating inflation rate I is:

$$I = \frac{(P_t - P_{t-1})}{P_{t-1}} \times 100\%$$

- **Share Price**

  Purpose: Share price refers to the price at which a single share of a company's stock is bought or sold in the market.

  Formula: Share price SP is determined by market forces and reflects the perceived value of the company by investors. There is no specific formula for calculating share prices as they are determined by supply and demand dynamics in the market.

- **Gross Domestic Product (GDP)**

Purpose: GDP is a measure of the total value of all goods and services produced within a country's borders over a specific period, indicating the overall economic performance of a nation.

Formula: Let Y denote GDP, which can be calculated using three different approaches: the production approach, the income approach, and the expenditure approach. The expenditure approach is often used and is calculated as the sum of consumption (C), investment (I), government spending (G), and net exports (NX):

$$Y = C + I + G + NX$$

4.2 Mathematical and Statistical Concepts

1. **MinMaxScaler**

   Purpose: MinMaxScaler is a scaling technique used to transform features by scaling them to a specified range, typically between 0 and 1.

   Formula: Let X be the feature to be scaled. The scaled feature X_{scaled} is calculated as:

   $$X_{\text{scaled}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$

   where X_{min} and X_{max} are the minimum and maximum values of X respectively.

2. **PowerTransformer**

   Purpose: PowerTransformer is used to transform features by applying a power transformation to stabilize variance and make the data more Gaussian-like.

   Formula: Let X be the feature to be transformed. The transformed feature X_{trans} is calculated as:

   $$X_{\text{trans}} = \begin{cases} \log(X) & \text{if method is 'log'} \\ \sqrt{X} & \text{if method is 'yeo-johnson'} \\ \text{Other transformations} & \text{if method is 'other'} \end{cases}$$

3. **Pearson Correlation Coefficient**

   Purpose: Pearson correlation coefficient measures the linear relationship between two variables.

   Formula: Let X and Y be the two variables. The Pearson correlation coefficient ρ is calculated as:

$$\rho = \frac{\text{cov}(X,Y)}{\sigma_X \cdot \sigma_Y}$$

   where $\text{cov}(X,Y)$ is the covariance between X and Y, and σ_X and σ_Y are the standard deviations of X and Y respectively.

4. **Augmented Dickey-Fuller Test (ADF Test)**

   Purpose: Augmented Dickey-Fuller test is used to determine if a time series is stationary or not.

   Formula: The null hypothesis H_0 of the ADF test is that the time series has a unit root, indicating it is non-stationary. The test statistic is compared to critical values to determine if H_0 can be rejected.

5. **Granger Causality Test**

   Purpose: Granger causality test is used to determine if one time series can predict another time series.

   Formula: The test involves fitting a VAR model to the data and comparing the F-statistic for the addition of lagged values of one series to the model with and without those lagged values.

6. **Seasonal Decomposition**

   Purpose: Seasonal decomposition is used to decompose a time series into trend, seasonal, and residual components.

   Formula: Seasonal decomposition involves separating the observed series Y_t into three components: trend (T_t), seasonal (S_t), and residual (R_t). The additive decomposition model is defined as:

$$Y_t = T_t + S_t + R_t$$

7. **Polynomial Regression**

   Purpose: Polynomial regression is used to model non-linear relationships between a dependent variable and independent variables. It captures trends that simple linear regression might miss.

   Formula: Polynomial regression extends the linear regression model by including higher-order terms of the independent variable. A general polynomial regression equation of degree 'd' is given by:

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + ... + \beta_d X^d + \varepsilon$$

   Where:

   (Y) is the dependent variable

   (X) is the independent variable

   $(\beta_0, \beta_1, ...\beta_d)$ are the regression coefficients

   (ε) is the error term

4.3 Country-wise Analysis

To begin understanding the impact of inflation on stock markets and indices, a country-wise approach is adopted. Inflation directly influences purchasing power, which in turn can impact consumer spending and business investment decisions. Changes in inflation rates often lead to adjustments in banking interest rates, influencing the cost of borrowing and saving. These factors can drive investors to adjust their buying and selling patterns in the stock market.
Theoretically, a correlation exists between inflation and stock market performance. To investigate this relationship empirically, this analysis applies various statistical tests and data transformation techniques. Additionally, the use of lag analysis aims to identify potential delayed effects of inflation on stock prices.

CHAPTER 5

Discussions and Results

5.1 India

5.1.1 General Overview

India, a country of vast size and rich cultural heritage, is experiencing a period of significant economic expansion. With a rapidly growing middle class and increasing foreign investment, the overall outlook on India's economic future is generally positive. However, challenges remain, including persistent poverty, inequality, and concerns about corruption within governmental structures. India's enduring traditions are a source of national pride, though modernization efforts sometimes create tension with the preservation of long-held values.

The Nifty 50 index, a benchmark for the Indian stock market, reflects the performance of 50 leading companies across diverse sectors. Its relationship with Indian inflation is complex and multifaceted. Inflation can influence interest rates set by the Reserve Bank of India (RBI), potentially impacting stock valuations. Additionally, inflation might increase input costs for companies, affecting corporate profitability within the Nifty 50. Different sectors may react differently to inflationary pressures, with some exhibiting greater resilience than others. Understanding these dynamics, along with how inflation shapes investor sentiment and the broader global economic context, is crucial for analyzing the Nifty 50 and navigating the Indian market.

Understanding how inflation interacts with the Nifty 50 can shed light on the resilience of India's leading companies and the broader market's sensitivity to price fluctuations. This analysis can equip investors with a clearer perspective for navigating the Indian market's growth potential amidst inflationary pressures.

5.1.2 Basic Correlation Analysis

To begin analysis of the Indian market, an analysis of the raw data is performed to get a basic understanding of correlations. This step will analyse data in its raw form without any standardization or re-scaling. This ensures an understanding of the differences between data with and without various transformations, removal of trends and making the data stationary.

- **Market Influence of NIFTY 50:** The NIFTY 50 index closing price exhibits strong positive correlations with volume, price-volume, and India's share price. This suggests that:

  * Individual stock prices tend to follow the broader market trend represented by the NIFTY 50 index.

  * Trading activity and the total value of market transactions are closely linked to the NIFTY 50's performance.

- **Inflation's Limited Impact:** India's inflation rate shows surprisingly weak correlations with the NIFTY 50 index, individual stock prices, volume, and India's share price. This implies that inflation might not be a primary short-term driver of price fluctuations in the Indian market within the time-frame of your analysis.

	NIFTY 50 Close	Volume	Price-Vol	Inflation (India)	Share Price (India)
NIFTY 50 Close	1.00	0.62	0.82	0.03	0.97
Volume	0.62	1.00	0.92	0.09	0.67
Price-Vol	0.82	0.92	1.00	-0.05	0.84
Inflation (India)	0.03	0.09	-0.05	1.00	-0.11
Share Price (India)	0.97	0.67	0.84	-0.11	1.00

Table 5.1: Correlation Matrix of Raw Data for Nifty 50

5.1.3 Stationarity Tests

Stationarity tests are used to determine whether a time series exhibits constant statistical properties (e.g., mean, variance) over time. This analysis uses stationarity tests, such as the Augmented Dickey-Fuller (ADF) test, to assess if the NIFTY 50 close prices contain trends, seasonality, or other non-constant patterns. Understanding stationarity is crucial as it guides the potential need for transformations (such as differencing) and helps select appropriate time-series forecasting models.

5.1.3.1 Testing Raw Data

On the raw dataset, tests are performed on the two columns of significance, NIFTY 50 Close Prices and Inflation Rates. When understanding correlation in a time series based dataset, it is important that both the variables, dependant and independent, are stationary. In case of non-stationarity, the variables may display the same trends and seasonality but have different residual patterns, which may not correlate, or vice versa.

- **Interpretation:** Test statistic value is greater than all critical values and the p-value is very high suggesting that the null hypothesis (data is non-stationary) cannot be rejected.
- **Non-Stationarity:** Both datasets exhibit non-stationary behavior. The positive test statistics exceed all critical values, and the high p-values further support this conclusion.
- **Implications:** The data likely contains trends, seasonality, or other forms of non-stationarity. To achieve stationarity, pre-processing techniques such as differencing might be necessary before applying many standard time-series models.

5.1.3.2 Post-Differencing Stationarity Analysis

After applying first-order differencing to both the NIFTY 50 close price and inflation series, Augmented Dickey-Fuller (ADF) tests are re-conducted to assess stationarity. The results are as follows:

Dataset	**NIFTY 50 Close**	**Inflation**
Test Statistic	1.8445	-1.8479
P-value	0.9984	0.3570
Lags Used	12	12
Observations	272	272
Critical Values		
Significance Level	1%: -3.4546	5%: -2.8722
	10%: -2.5725	

Table 5.2: ADF Test Results for NIFTY 50 Close Prices and Inflation

Dataset	**NIFTY 50 Close**	**Inflation**
Test Statistic	-5.3596	-7.0393
P-value	4.1166e-06	5.9032e-10
Lags Used	11	11
Observations	272	271
Critical Values		
Significance Level	1%: -3.4546	5%: -2.8723
	10%: -2.5725	

Table 5.3: ADF Test Results for Differenced Datasets

- **Interpretation:** The test statistic values for both variables are lower than the critical values, which signify that the null hypothesis can be rejected if p-value is lower than 5%. The p-values achieved are significantly lower than 0.05 or 5%, therefore confirming that the null hypothesis is rejected, or that the variables are now stationary.

- **Stationarity Achieved:** The ADF tests now yield highly negative test statistics, which fall below all critical values. Moreover, the extremely low p-values (close to zero) strongly suggest that we can reject the null hypothesis of a unit root in both datasets.

5.1.4 Correlation Analysis with Data Transformations

Following the analysis of raw data, a correlation study is conducted on standardized data. Standardization helps compare variables on a similar scale and might uncover relationships masked by differing scales in the raw data. Further, this data is transformed using some power transforms, namely Yeo-Johnson, Box-Cox and Log Transforms.

5.1.4.1 Standardized Data

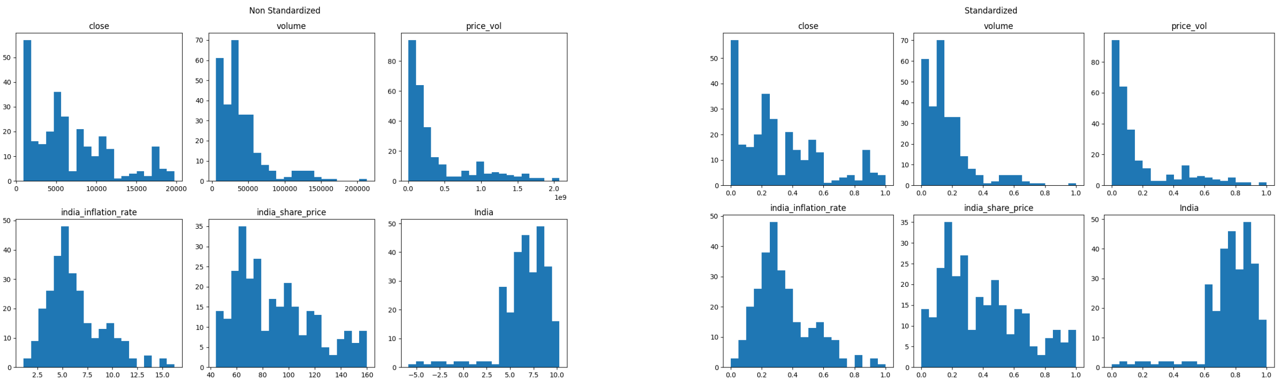

Figure 5.1: India: Difference between Non Standardized and Standardized Data

	NIFTY 50 Close	Volume	Price-Vol	Inflation (India)	Share Price (India)
NIFTY 50 Close	1.0000	0.6226	0.8244	0.0330	0.9701
Volume	0.6226	1.0000	0.9170	0.0850	0.6690
Price-Vol	0.8244	0.9170	1.0000	-0.0532	0.8391
Inflation (India)	0.0330	0.0850	-0.0532	1.0000	-0.1090
Share Price (India)	0.9701	0.6690	0.8391	-0.1090	1.0000

Table 5.4: Correlation Matrix for Standardized Data

- **Key Changes:** Compared to the raw data correlations, standardization slightly weakens some existing correlations (e.g., between NIFTY 50 close and share price). Notably, the correlation between inflation and other variables remains minimal, suggesting their relationships might not be inherently linear.
- **Implications:** The differences resulting from standardization highlight variables whose relationships are sensitive to differences in scale or measurement units.

The continued weak correlations involving inflation imply that exploring non-linear relationships might be necessary to uncover a stronger connection.

5.1.4.2 Yeo-Johnson Transformation

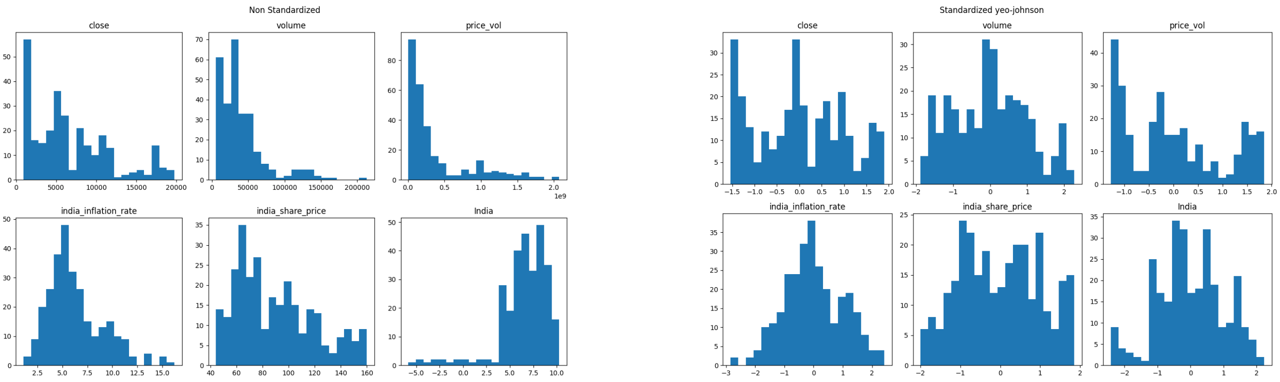

Figure 5.2: India: Difference between Non Standardized and Y-J Transformed Data

	NIFTY 50 Close	Volume	Price-Vol	Inflation (India)	Share Price (India)
NIFTY 50 Close	1.0000	0.8147	0.9476	0.1519	0.9405
Volume	0.8147	1.0000	0.9279	0.2427	0.6882
Price-Vol	0.9476	0.9279	1.0000	0.1234	0.8705
Inflation (India)	0.1519	0.2427	0.1234	1.0000	-0.0129
Share Price (India)	0.9405	0.6882	0.8705	-0.0129	1.0000

Table 5.5: Correlation Matrix for Yeo-Johnson Transformed Data

- **Improved Inflation Impact:** The Yeo-Johnson transform significantly increases the correlation between inflation and several variables, particularly NIFTY 50 close (from 0.0330 in raw data to 0.1519) and volume. This indicates that the Yeo-Johnson transform better captures potential non-linear relationships between inflation and these market indicators.

- **Other Correlations:** The Yeo-Johnson transform also moderately strengthens some other correlations within the dataset.

- **Implications:** The results suggest that underlying non-linearities might exist in the data. The Yeo-Johnson transform might be a suitable pre-processing step before further analysis, particularly when investigating the impact of inflation.

5.1.4.3 Box-Cox Transformation

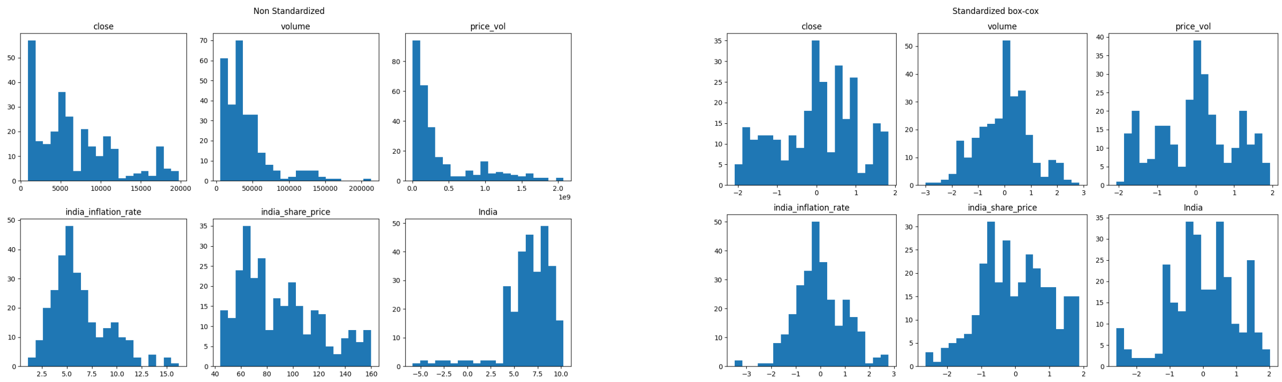

Figure 5.3: India: Difference between Non Standardized and B-C transformed Data

	NIFTY 50 Close	Volume	Price-Vol	Inflation (India)	Share Price (India)
NIFTY 50 Close	1.0000	0.8030	0.9529	0.1841	0.9232
Volume	0.8030	1.0000	0.9422	0.2351	0.6630
Price-Vol	0.9529	0.9422	1.0000	0.2084	0.8490
Inflation (India)	0.1841	0.2351	0.2084	1.0000	-0.0249
Share Price (India)	0.9232	0.6630	0.8490	-0.0249	1.0000

Table 5.6: Correlation Matrix for Box-Cox Transformed Data

- **Reduced Inflation Correlations:** The Box-Cox transform weakens the correlation between inflation and certain variables (e.g., share price), meanwhile the correlation between NIFTY and inflation slightly increases.
- **Implications:** The Box-Cox transform, designed for strictly positive data, might introduce distortions, making it less reliable for this particular dataset. It emphasizes the importance of choosing transformations that align with the characteristics of the data.

5.1.4.4 Logarithmic Transformation

- **Mixed Results:** The log transform has a varied effect on correlations. It strengthens some correlations involving inflation (e.g., with NIFTY 50 close), while weakening others.

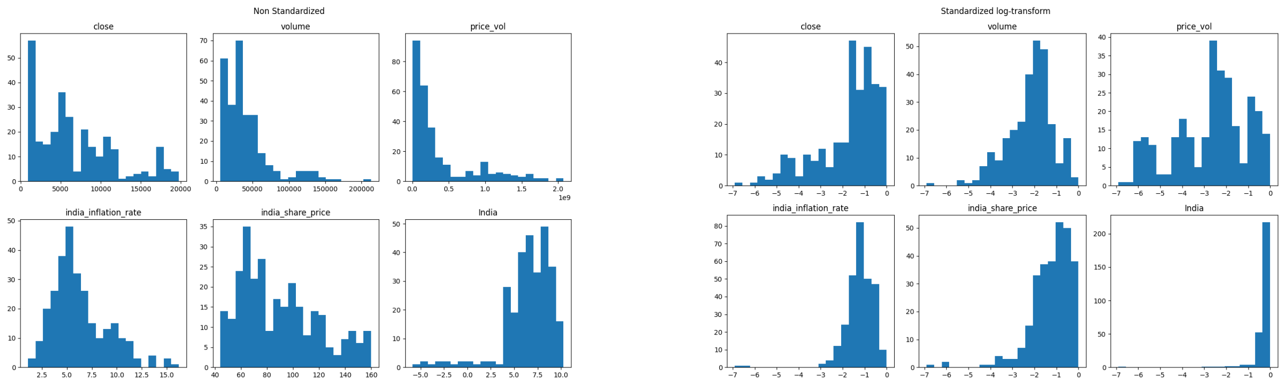

Figure 5.4: India: Difference between Non Standardized and Log-Transformed Data

	NIFTY 50 Close	Volume	Price-Vol	Inflation (India)	Share Price (India)
NIFTY 50 Close	1.0000	0.8046	0.9411	0.2114	0.8108
Volume	0.8046	1.0000	0.9387	0.1983	0.5621
Price-Vol	0.9411	0.9387	1.0000	0.1957	0.7369
Inflation (India)	0.2114	0.1983	0.1957	1.0000	0.0254
Share Price (India)	0.8108	0.5621	0.7369	0.0254	1.0000

Table 5.7: Correlation Matrix for Log Transformed Data

- **Implications:** The log transform might be beneficial for emphasizing specific relationships, particularly for variables suspected to have exponential tendencies. However, a lack of any serious improvements suggests the lack of any exponential correlations.

5.1.4.5 Overall Insights

The application of transformations significantly alters the correlation landscape within the Indian market data. Crucially, these changes highlight the following:

- **The Presence of Non-linearities:** The Yeo-Johnson transformation, in particular, strengthens the correlations between inflation and other variables, implying that non-linear relationships might be a crucial factor in understanding inflation's influence on the market.

- **Transformation Sensitivity:** The data appears sensitive to the choice of transformation. This underscores the importance of selecting transformations that align with the data's underlying structure.

- **Contextualizing Inflation's Impact:** While the raw and standardized correlations showed minimal impact from inflation, the transformations reveal a more nuanced picture. Inflation's influence might be better understood by incorporating non-linear models or focusing on specific market indicators.

5.1.5 Study of Leading Inflation:

To study the impact of inflation on the stock market, it may be very important to consider inflation as a leading variable, which suggests, the changes in inflation today will not be seen in the stock market today, but rather at a later date. To do this, we look into the statistics of how a leading inflation value modifies the understanding of these results.

5.1.5.1 Standardization on Leading Inflation

By manual testing, it was found that the inflation leading by 1 time point produces the best results. This is also backed by the fact that the impact of inflation on the market must be immediate rather than very prolonged. Since time points are monthly, it makes our analysis effectively look at the impact of inflation after one month on the stock market. Further, GDP is an annual data point and is hence not shifted since its monthly values are estimated (by linear approximation) and a shift will not make a major change.

	NIFTY 50 Close	Volume	Price-Vol	Inflation (India)	Share Price (India)
NIFTY 50 Close	1.0000	0.6322	0.8252	0.0007	0.9596
Volume	0.6322	1.0000	0.9201	0.1014	0.6037
Price-Vol	0.8252	0.9201	1.0000	-0.0370	0.8114
Inflation (India)	0.0007	0.1014	-0.0370	1.0000	-0.1152
Share Price (India)	0.9596	0.6037	0.8114	-0.1152	1.0000

Table 5.8: Correlation Matrix for Standardized Data (Inflation Led)

Inflation's Lagged Impact: The correlations between inflation and other variables are generally very weak in the standardized data. This suggests that inflation, when

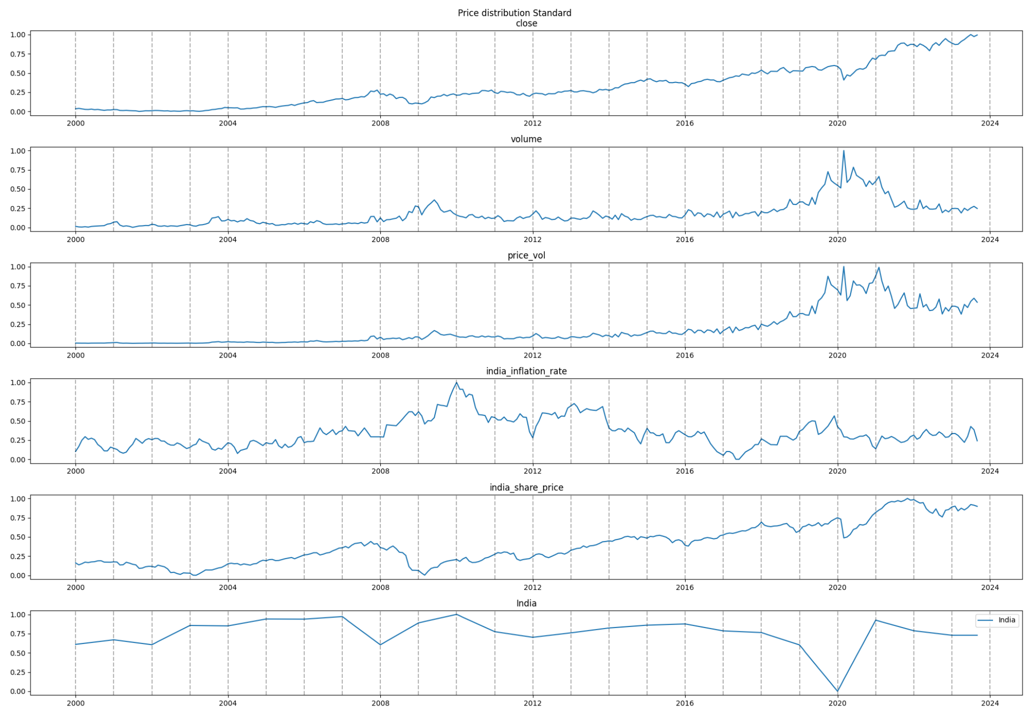

Figure 5.5: India: Standardized Data.

leading by one period, might not have a strong immediate linear impact on the analyzed market indicators.

5.1.5.2 Yeo-Johnson on Leading Inflation

	NIFTY 50 Close	Volume	Price-Vol	Inflation (India)	Share Price (India)
NIFTY 50 Close	1.0000	0.8154	0.9476	0.1492	0.9399
Volume	0.8154	1.0000	0.9285	0.2447	0.6873
Price-Vol	0.9476	0.9285	1.0000	0.1243	0.8693
Inflation (India)	0.1492	0.2447	0.1243	1.0000	-0.0163
Share Price (India)	0.9399	0.6873	0.8693	-0.0163	1.0000

Table 5.9: Correlation Matrix for Yeo-Johnson Transformed Data (Inflation Led)

- **Impact:** The Yeo-Johnson transformation moderately strengthens the correlation between leading inflation and some market variables, particularly the NIFTY 50 close. This change highlights a potential non-linear relationship that was less apparent in the raw or standardized data.

- **Implication:** The findings suggest that leading inflation might have a more complex, non-linear influence on the Indian market. Further investigation us-

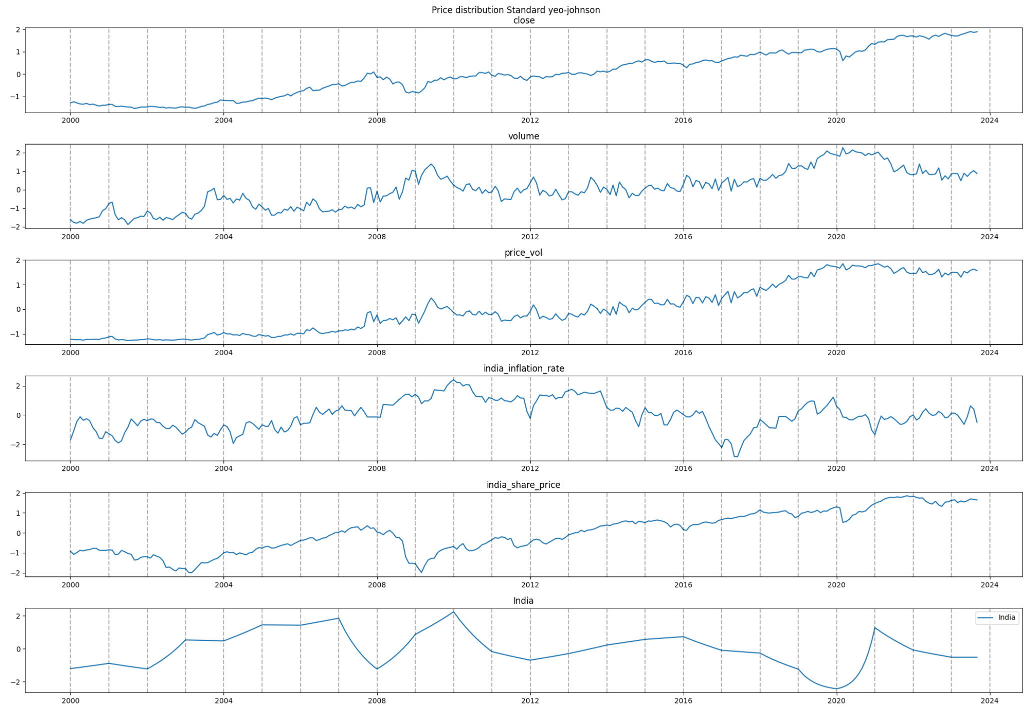

Figure 5.6: India: Yeo-Johnson Transformed Data.

ing non-linear models or more sophisticated time-series techniques could be beneficial.

5.1.5.3 Box-Cox on Leading Inflation

	NIFTY 50 Close	Volume	Price-Vol	Inflation (India)	Share Price (India)
NIFTY 50 Close	1.0000	0.8038	0.9529	0.1825	0.9226
Volume	0.8038	1.0000	0.9427	0.2341	0.6624
Price-Vol	0.9529	0.9427	1.0000	0.2080	0.8478
Inflation (India)	0.1825	0.2341	0.2080	1.0000	-0.0287
Share Price (India)	0.9226	0.6624	0.8478	-0.0287	1.0000

Table 5.10: Correlation Matrix for Box-Cox Transformed Data (Inflation Led)

- **Impact:** The Box-Cox transform also strengthens the correlation between leading inflation and the NIFTY 50 close, although the effect may be slightly less pronounced than that of the Yeo-Johnson transform.
- **Implication:** This finding aligns with the Yeo-Johnson results, further supporting the idea that non-linear relationships exist between leading inflation and market variables.

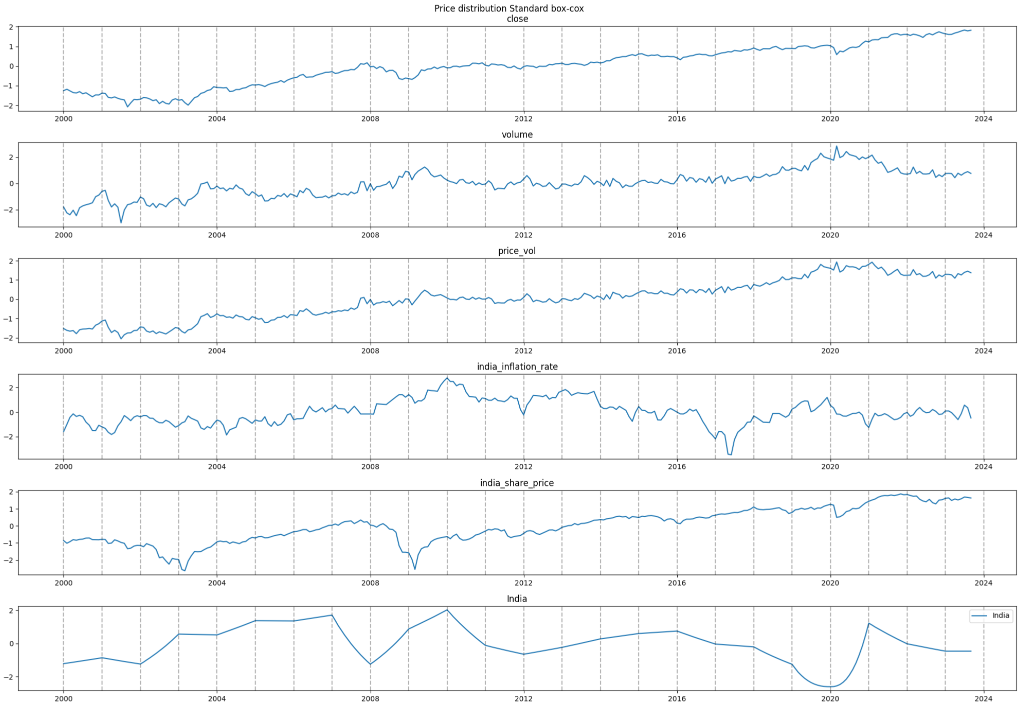

Figure 5.7: India: Box-Cox Transformed Data.

5.1.5.4 Log-Transform on Leading Inflation

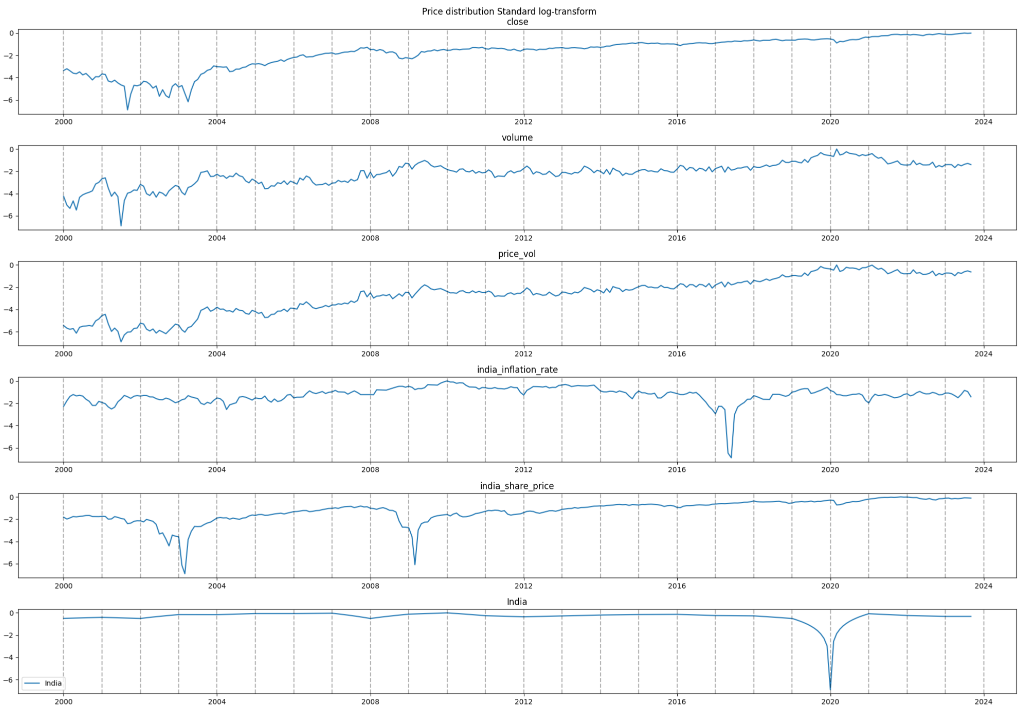

Figure 5.8: India: Log Transformed Data.

- **Impact:** The log transform has a minor impact on the correlations involving leading inflation. The slight increases observed suggest a potential weak exponential

	NIFTY 50 Close	Volume	Price-Vol	Inflation (India)	Share Price (India)
NIFTY 50 Close	1.0000	0.8043	0.9408	0.2106	0.8099
Volume	0.8043	1.0000	0.9389	0.1903	0.5609
Price-Vol	0.9408	0.9389	1.0000	0.1923	0.7356
Inflation (India)	0.2106	0.1903	0.1923	1.0000	0.0185
Share Price (India)	0.8099	0.5609	0.7356	0.0185	1.0000

Table 5.11: Correlation Matrix for Log Transformed Data (Inflation Led)

component in the relationship.

- **Implication:** While the primary influence of leading inflation might not be strictly exponential, exploring models that incorporate some logarithmic aspects could be worthwhile.

5.1.5.5 Overall Analysis

- **Strong Evidence of Non-linearity:** The consistent improvement in correlations after the Yeo-Johnson and Box-Cox transformations provides strong evidence that leading inflation has a non-linear influence on the Indian market.
- **Next steps:** With the evidence of non-linearity, Polynomial regression can be a good method to approach the data being modelled further to understand the correlation further.

5.1.6 Inter-predictability Test- Granger Causality Test

The Granger Causality test is performed next. The aim of this test is to confirm that one variable can be used to predict the other variable. We conduct these tests on transformed and raw datasets to further understand their correlation.
If Granger Causality is proven, a linear relationship is usually seen. Since the correlation tests were somewhat inconclusive, the Granger causality test is used to gain better understanding of the relationship between inflation and NIFTY 50 close prices. The optimal lag length was determined to be 2 based on information criteria and domain knowledge. Here are the results:

- **F-tests (ssr based and parameter):**

  - F-statistic: 1.1030
  - p-value: 0.3333
  - Degrees of freedom (denominator): 278
  - Degrees of freedom (numerator): 2

- **Chi-Squared Tests (ssr based and likelihood ratio):**
  - Chi-squared statistic: 2.2456 (ssr based), 2.2368 (likelihood ratio)
  - p-value: 0.3254 (ssr based), 0.3268 (likelihood ratio)
  - Degrees of freedom: 2

- **Interpretation:** The consistently high p-values across all tests (F-tests and Chi-squared tests) suggest that the null hypothesis of no Granger causality cannot be rejected. This implies that, after the Box-Cox transformation, past values of the independent variable are not statistically significant predictors of the current values of the dependent variable.

- The test value with a lag of 2 was the highest in all data transformations. With the highest p-value achieved of 35%. The values at a lag of 1 and 3 both were significantly higher (>70%), which shows that there is a sudden increase in causality at the chosen lag value.

- **Implications:** The results suggest that the predictive relationship between the variables after the Box-Cox transformation might be weak or absent at the tested lag structure, but the sudden drop in p-values shows that the lag structure chosen identifies a sudden increase in causality.

5.1.7 Non-Linear Regression

Previous sections explored the relationship between inflation and the NIFTY 50 close values, including transformations and tests for Granger causality. Linear models often provide a foundation for understanding such relationships. However, economic and financial data can exhibit complex, non-linear patterns that linear models might not fully capture.

This section introduces non-linear regression analysis to investigate potential non-linear relationships between inflation and the NIFTY 50 close prices. Non-linear models can accommodate a wider range of functional forms (e.g., quadratic, exponential, logarithmic), potentially enhancing our ability to model and forecast the impact of inflation on the NIFTY 50 close prices. The following are the steps taken and the analysis on the model.

5.1.7.1 Yeo-Johnson Transformation

To address potential non-linearities in the relationship between inflation (leading) and the target variable, the Yeo-Johnson transformation was applied to the data. This transformation helps normalize data and can improve the fit of regression models.

5.1.7.2 Normalization

Following the Yeo-Johnson transformation, a MinMaxScaler was used to normalize the data. Normalization ensures that features have a similar range, which can aid in the convergence and performance of certain models.

5.1.7.3 Polynomial Regression Results

After pre-processing the data, a polynomial regression model of degree 3 was applied. The model achieved the following performance metrics:

- **Mean Squared Error (MSE):** 0.0389
- **Mean Absolute Error (MAE):** 0.1507

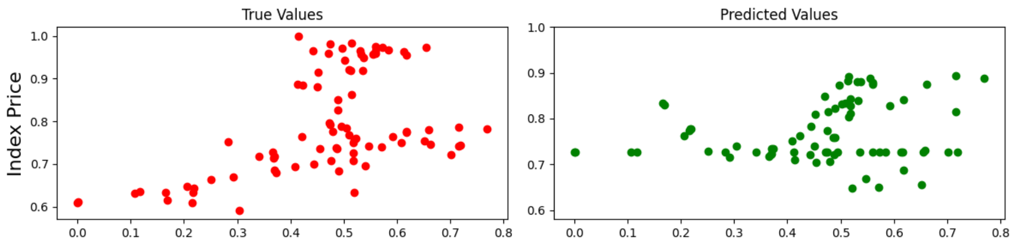

Figure 5.9: India: True vs Predicted Values.

5.1.7.4 Interpretation

- **MSE:** The MSE measures the average squared difference between the predicted values and the true values. A lower MSE indicates a better fit of the model to the data.

- **MAE:** The MAE measures the average absolute difference between the predictions and true values. It provides insight into the average magnitude of the model's errors.

5.1.7.5 Results

The model shows a significant output in terms of predictive ability. The MSE and MAE scores show a very high reliability on the model, specially when looking at results from previous tests. An MAE of 0.15 in Normalized data (which ranges between 0 and 1) paired with the mean squared error of 0.04 shows a very minimal difference between true and predicted values.
The overall analysis of the given statistical methods and the regression model provide evidence that there is an underlying correlation, which can further be explored with a more detailed dataset, with either more observations(maybe looking into daily values) or more variables(other factors that may indicate purchasing power such as national bank interest rates) which may help a secondary correlation that may exist as understood theoretically.

5.2 USA

5.2.1 General Overview

The United States, a global economic powerhouse, boasts a long history of innovation, a strong entrepreneurial spirit, and a market-driven economy. With its well-developed infrastructure, skilled workforce, and diverse industries, the USA presents ample opportunities for investment. However, it also faces challenges such as income inequality, rising healthcare costs, and political polarization that can influence economic policy. The USA's commitment to free-market principles drives its dynamic economy, though navigating regulatory frameworks can be complex at times.

The S&P 500 index, a widely followed benchmark for the US stock market, tracks the performance of 500 large-cap companies across various sectors. Its movements are influenced by macroeconomic indicators, investor confidence, and corporate earnings. Understanding the relationship between the S&P 500 and key economic factors like inflation, interest rates, and economic growth is essential for investors seeking to capitalize on the US market's potential while managing associated risks.

By analyzing inflation's interplay with the S&P 500, we can gain valuable insights into how the US market navigates periods of rising prices, potentially revealing investment opportunities and mitigating risks within this dynamic financial landscape.

5.2.2 Basic Correlation Analysis

The analysis starts with an analysis of the raw data for the S&P 500 index and other factors like volume, price-volume pair, inflation and GDP. This provides a baseline for understanding the analysis of the correlation between the index and inflation rates.

- **Positive Correlation:** A strong positive correlation exists between 'close' and 'price_vol' (0.9225), indicating a tendency for these variables to move in the same direction.

- **Moderate Positive Correlation:** The 'us_share_price' shows moderate positive correlations with 'close', 'volume', and 'price_vol'.

	S&P Price	volume	price_vol	us_inflation_rate	us_share_price	GDP
S&P Price	1.0000	0.3604	0.9225	0.4179	0.5226	0.1407
volume	0.3604	1.0000	0.6425	-0.0152	0.5789	-0.4377
price_vol	0.9225	0.6425	1.0000	0.3696	0.5936	-0.0095
us_inflation_rate	0.4179	-0.0152	0.3696	1.0000	0.0787	0.1357
us_share_price	0.5226	0.5789	0.5936	0.0787	1.0000	-0.2137
GDP	0.1407	-0.4377	-0.0095	0.1357	-0.2137	1.0000

Table 5.12: Correlation Matrix for US Economic Indicators

- **Weak Correlation:** The 'us_inflation_rate' exhibits relatively weak correlations with most other variables.

5.2.3 Stationarity Tests

Stationarity is a key assumption in many time series models. A stationary time series has statistical properties that remain constant over time. To analyze the presence of stationarity in our data, we employ the Augmented Dickey-Fuller (ADF) test.

5.2.3.1 Testing Raw Data

For time series analysis, it's crucial to ensure stationarity in both dependent and independent variables. Non-stationarity can lead to unreliable correlation assessments due to shared trends or seasonality that might mask true relationships within the data. We perform Augmented Dickey-Fuller (ADF) tests on the raw NIFTY 50 Close Prices and Inflation Rates.

Dataset	**S&P 500 Price**	**Inflation**
Test Statistic	1.8445	-1.8479
P-value	0.9984	0.3570
Lags Used	12	12
Observations	272	272
Critical Values		
Significance Level	1%: -3.4546	5%: -2.8722
	10%: -2.5725	

Table 5.13: ADF Test Results for S&P 500 Price and Inflation

- **Interpretation** High p-values for both datasets indicate that we cannot reject the null hypothesis of a unit root (non-stationarity).
- **Non-Stationarity:** Both the S&P 500 Price and US Inflation exhibit non-stationary behavior.
- **Presence of Non-Constant Patterns:** This non-stationarity likely stems from trends, seasonality, or other non-constant patterns within the data.
- **Implications:** Pre-processing techniques, such as differencing, might be necessary to achieve stationarity before proceeding with time-series modeling.

5.2.3.2 Post-Differencing Stationarity Analysis

After applying first-order differencing to the S&P 500 Price and US Inflation datasets, the Augmented Dickey-Fuller (ADF) tests are re-conducted to assess if stationarity has been achieved.

Dataset	**S&P 500 Prices**	Inflation
Test Statistic	-6.1374	-8.1333
P-value	8.12e-08	1.08e-12
Lags Used	15	13
Observations	264	266
Critical Values		
Significance Level	1%: -3.4549	5%: -2.8724
	10%: -2.5725	

Table 5.14: ADF Test Results for Differenced S&P 500 Prices

- **Interpretation:** The extremely low p-value (much smaller than 0.05) and highly negative test statistic (significantly exceeding critical values) provide strong evidence to reject the null hypothesis of a unit root (non-stationarity) in the differenced S&P 500 Prices dataset.
- **Stationarity Achieved:** First-order differencing appears to have successfully induced stationarity in the differenced S&P 500 Prices dataset.

5.2.4 Correlation Analysis with Data Transformations

As in the case of the previous country, the next step undertaken are data transformations using standardization and power transforms like Yeo-Johnson, Box-Cox and Log Transforms.

5.2.4.1 Standardized Data

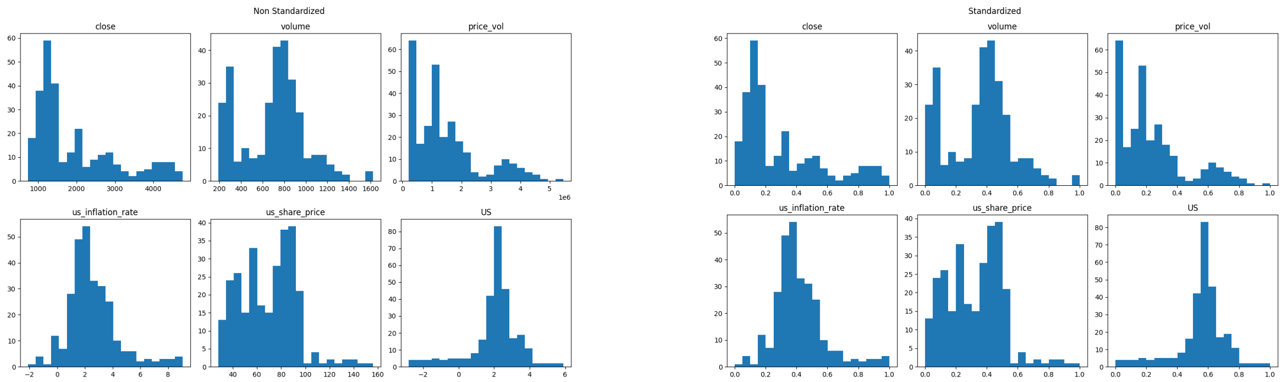

Figure 5.10: USA: Difference between Non Standardized and Standardized Data

	S&P 500 Price	volume	price_vol	us_inflation_rate	us_share_price	GDP
S&P 500 Price	1.0000	0.3604	0.9225	0.4179	0.5226	0.1407
volume	0.3604	1.0000	0.6425	-0.0152	0.5789	-0.4377
price_vol	0.9225	0.6425	1.0000	0.3696	0.5936	-0.0095
us_inflation_rate	0.4179	-0.0152	0.3696	1.0000	0.0787	0.1357
us_share_price	0.5226	0.5789	0.5936	0.0787	1.0000	-0.2137
GDP	0.1407	-0.4377	-0.0095	0.1357	-0.2137	1.0000

Table 5.15: Correlation Matrix for Standardized US Economic Indicators

- **Scaling Effects:** Standardization removes the influence of differing scales among variables. Correlations might appear stronger or weaker as they're now based on relative deviations from the mean.

- **Correlation Preservation:** The general patterns of positive and negative correlations seem to be largely preserved compared to the raw data analysis.

- **Implications:** Standardization makes correlations more directly comparable across variables that originally had vastly different scales. This can aid in identifying potentially more important relationships that would have been masked by scale differences in the raw data.

5.2.4.2 Data Transform using Yeo-Johnson

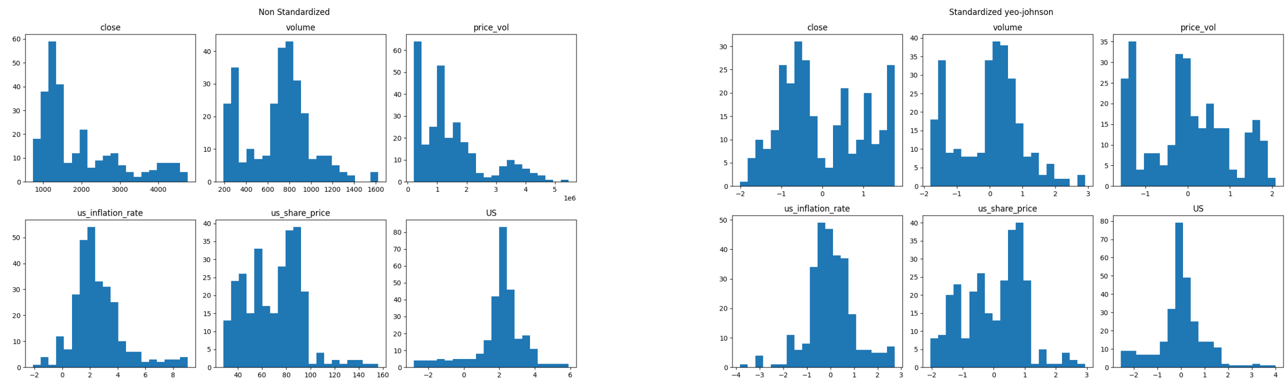

Figure 5.11: USA: Difference between Non Standardized and Y-J Transformed Data

	S&P 500 Price	volume	price_vol	us_inflation_rate	us_share_price	GDP
S&P 500 Price	1.0000	0.3641	0.8687	0.2569	0.5980	0.1349
volume	0.3641	1.0000	0.7636	-0.1082	0.6297	-0.3790
price_vol	0.8687	0.7636	1.0000	0.1479	0.7272	-0.0832
us_inflation_rate	0.2569	-0.1082	0.1479	1.0000	0.0038	0.1716
us_share_price	0.5980	0.6297	0.7272	0.0038	1.0000	-0.2376
GDP	0.1349	-0.3790	-0.0832	0.1716	-0.2376	1.0000

Table 5.16: Correlation Matrix: Yeo-Johnson Transformed US Data

- **Non-Linear Relationships:** The Yeo-Johnson transformation attempts to address non-linearities. This can lead to changes in correlation strengths compared to both raw and standardized data.

- **Potential Outlier Impact:** If outliers were significantly influencing correlations, the Yeo-Johnson transformation might mitigate their effect, leading to altered correlations.

- **Implications:** Changes in correlation strengths after the Yeo-Johnson transformation might suggest that non-linear models could be more suitable than linear models for capturing certain relationships within the US economic data.

5.2.4.3 Data Transform using Box-Cox

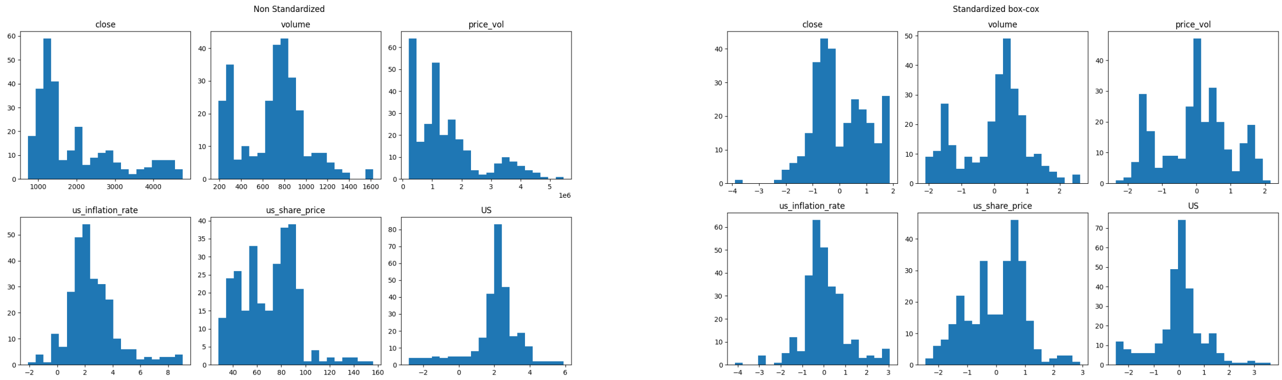

Figure 5.12: USA: Difference between Non Standardized and B-C Transformed Data

	S&P 500 Price	volume	price_vol	us_inflation_rate	us_share_price	GDP
S&P 500 Price	1.0000	0.3498	0.8199	0.3149	0.5783	0.1649
volume	0.3498	1.0000	0.8110	-0.0815	0.6413	-0.3813
price_vol	0.8199	0.8110	1.0000	0.1627	0.7241	-0.1120
us_inflation_rate	0.3149	-0.0815	0.1627	1.0000	0.0151	0.1642
us_share_price	0.5783	0.6413	0.7241	0.0151	1.0000	-0.2584
GDP	0.1649	-0.3813	-0.1120	0.1642	-0.2584	1.0000

Table 5.17: Correlation Matrix: Box-Cox Transformed US Data

- **Non-linearity:** The Box-Cox transformation aims to make relationships more linear. Changes in correlation strengths suggest potential non-linearities in the original data and the transformation's impact on them.
- **Model Selection:** If correlations are significantly altered, non-linear models might be more appropriate for capturing certain relationships within the US economic data.
- **Outlier Sensitivity:** The Box-Cox transformation can reduce the influence of outliers. Correlation differences, compared to the raw data, might indicate the presence of outliers and how the transformation addresses their impact.

5.2.4.4 Data Transform using Log Transforms

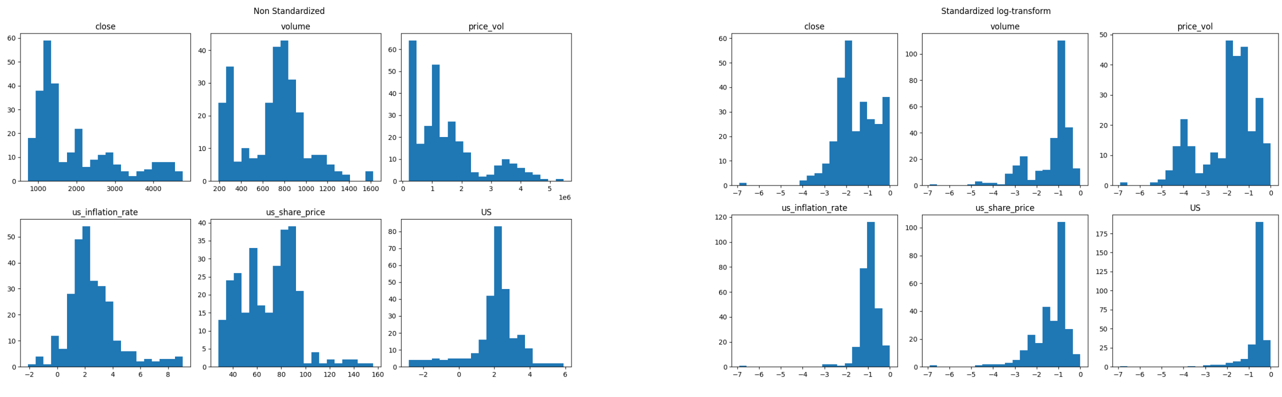

Figure 5.13: USA: Difference between Non Standardized and Log-transformed Data

	S&P 500 Price	volume	price_vol	us_inflation_rate	us_share_price	GDP
S&P 500 Price	1.0000	0.3498	0.8199	0.3149	0.5783	0.1649
volume	0.3498	1.0000	0.8110	-0.0815	0.6413	-0.3813
price_vol	0.8199	0.8110	1.0000	0.1627	0.7241	-0.1120
us_inflation_rate	0.3149	-0.0815	0.1627	1.0000	0.0151	0.1642
us_share_price	0.5783	0.6413	0.7241	0.0151	1.0000	-0.2584
GDP	0.1649	-0.3813	-0.1120	0.1642	-0.2584	1.0000

Table 5.18: Correlation Matrix: Box-Cox Transformed US Data

- **Mitigating Skewness and Scale:** The log transformation can normalize skewed data and equalize the impact of variables with vastly different scales. Changed correlations highlight the potential influence of these factors in the original dataset.

- **Percentage Changes:** With log-transformed data, correlations are often interpreted in terms of percentage changes. This provides a different perspective on the strength and nature of relationships.

- **Implications:** If the log transformation leads to more meaningful correlations, it could improve the fit and assumptions of certain regression models, particularly those sensitive to skewness and outliers.

5.2.4.5 Overall Insights (USA)

The application of various transformations reveals important characteristics of the US economic data and how they influence our understanding of correlations:

- **Non-linearity and Scale:** Changes in correlations after Box-Cox and logarithmic transformations suggest that non-linear relationships and differences in scale might have been present in the original data. This highlights the potential for more complex relationships than those captured by simple linear analysis.
- **Transformation Impact:** The choice of transformation significantly alters correlation patterns. This emphasizes the need to carefully consider which transformations best represent the underlying economic phenomena and relationships of interest.
- **Influence of Inflation:** While raw or standardized data might downplay inflation's impact, transformed correlations suggest a potentially stronger, and possibly non-linear, influence of inflation on certain aspects of the US market.

5.2.5 Study of Leading Inflation

Inflation is always perceived to have an impact on economical factors. This usually means that inflation will have a delayed impact on those factors. To study this, the inflation feature is made to 'lead' the other data by being shifted to a previous time point, to help in better analysing the results. In the case of the US market, the highest impact is seen with a 6 time point leading Inflation value. This can be justified by the fact that the US market is a more matured one, with a more stable economy, hence having the inflation to leave a long term impact, in both good and bad scenario.

5.2.5.1 Standardisation on Leading Inflation

- **Positive Correlation:** Strong positive correlation between S&P 500 Price and "price_vol" (0.929), indicating a close association between these variables.
- **Moderate Positive Correlation:** Moderate positive correlation between S&P 500 Price and "us_inflation_rate" (0.497), suggesting a potential relationship between inflation and the variable "close".

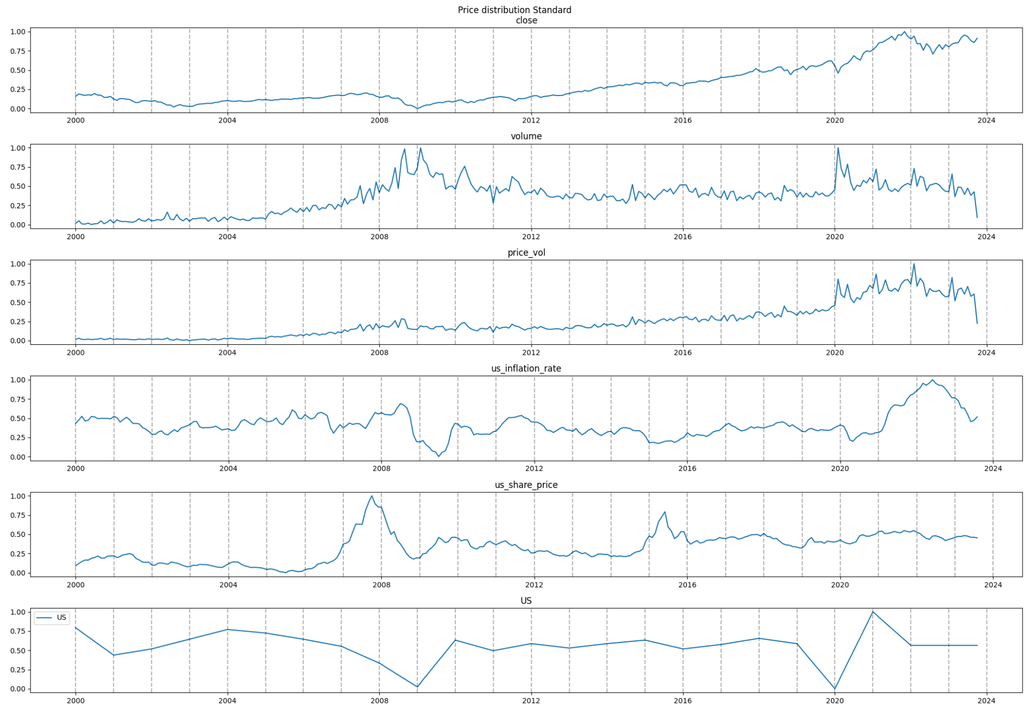

Figure 5.14: USA: Standardized Data.

	S&P 500 Price	volume	price_vol	us_inflation_rate	us_share_price	GDP
S&P 500 Price	1.000	0.380	0.929	0.497	0.521	0.146
volume	0.380	1.00	0.652	-0.053	0.578	-0.440
price_vol	0.929	0.652	1.000	0.428	0.591	-0.012
us_inflation_rate	0.497	-0.053	0.428	1.000	0.234	0.413
us_share_price	0.521	0.578	0.591	0.234	1.000	-0.215
GDP	0.146	-0.440	-0.012	0.413	-0.215	1.000

Table 5.19: USA: Correlation Matrix: Standardized Data with Leading Inflation.

- **Insights with Inflation Lead:** The inflation leading data further increases correlation of inflation with all the other variables, hence showing inflation leading the market indicators does have an impact on knowledge gain.

5.2.5.2 Yeo-Johnson Transformed Data with Leading Inflation

- **Improved Correlation:** Correlation, again, has improved by using a leading inflation value, indicating that the leading inflation is providing a high information gain value.

- **Non-Linearity:** Since the Yeo-Johnson transform brings a change to the correlation values of inflation, it shows there is a significant non-linear component to

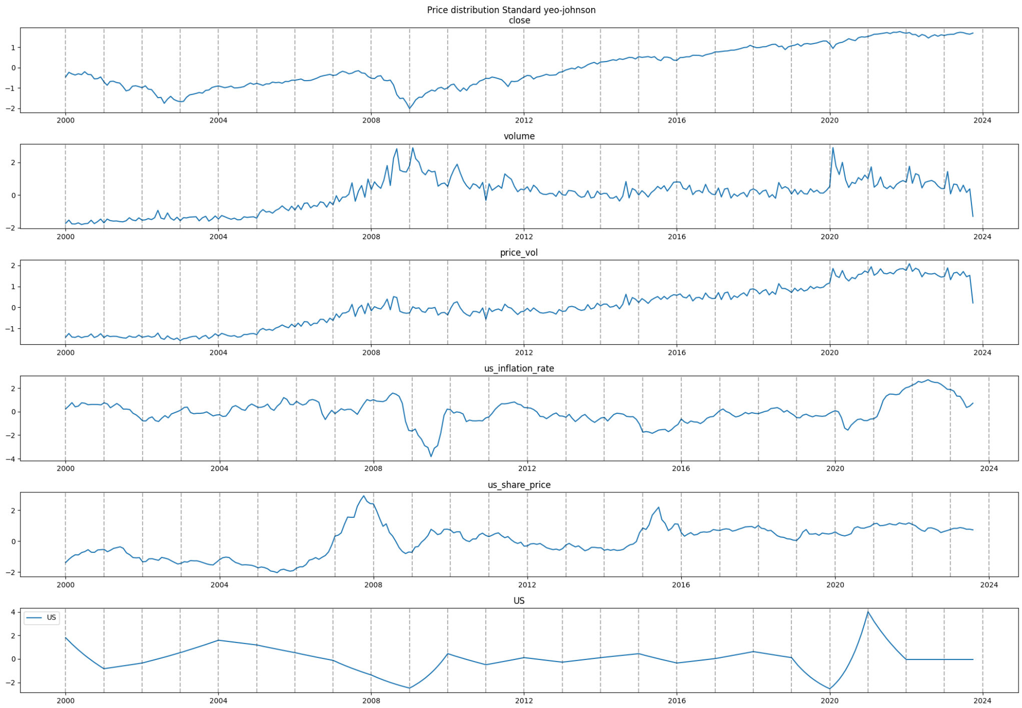

Figure 5.15: USA: Y-J Transformed Data.

	S&P 500 Price	volume	price_vol	us_inflation_rate	us_share_price	GDP
S&P 500 Price	1.000	0.373	0.862	0.313	0.596	0.140
volume	0.373	1.00	0.777	-0.147	0.632	-0.380
price_vol	0.862	0.777	1.000	0.163	0.729	-0.087
us_inflation_rate	0.313	-0.147	0.163	1.000	0.156	0.459
us_share_price	0.596	0.632	0.729	0.156	1.000	-0.239
GDP	0.140	-0.380	-0.087	0.459	-0.239	1.000

Table 5.20: Correlation Matrix: Yeo-Johnson Transformed Data with Leading Inflation.

the correlation.

5.2.5.3 USA: Box-Cox Transformed Data with Leading Inflation

- **Non-linearity:** Changes in correlation strengths compared to the standardized and Yeo-Johnson data suggest potential non-linearities in the original data. The Box-Cox transformation attempts to address these non-linearities, and its effect is evident in the altered correlations.

- **Model Selection:** If the Box-Cox transformation significantly alters correlations, it highlights the importance of considering non-linear models for capturing

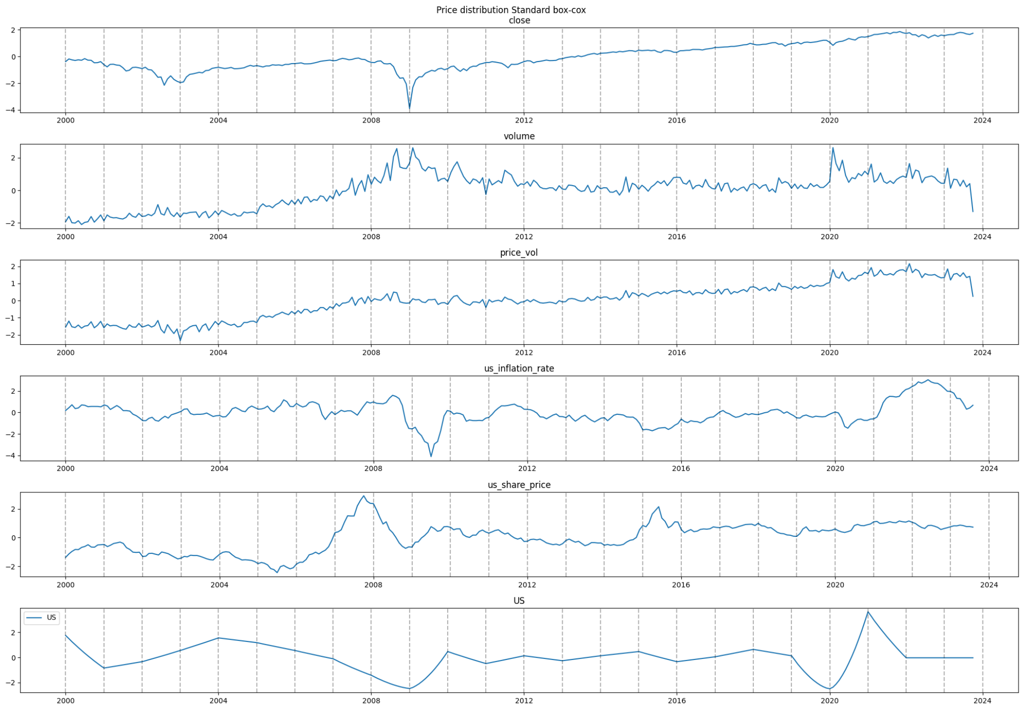

Figure 5.16: B-C Transformed Data.

	S&P 500 Price	volume	price_vol	us_inflation_rate	us_share_price	GDP
S&P 500 Price	1.000	0.360	0.815	0.402	0.575	0.171
volume	0.360	1.00	0.822	-0.112	0.642	-0.383
price_vol	0.815	0.822	1.000	0.186	0.723	-0.115
us_inflation_rate	0.402	-0.112	0.186	1.000	0.157	0.446
us_share_price	0.575	0.642	0.723	0.157	1.000	-0.260
GDP	0.171	-0.383	-0.115	0.446	-0.260	1.000

Table 5.21: USA: Correlation Matrix: Box-Cox Transformed Data with Leading Inflation.

certain relationships within this US economic data.

5.2.5.4 Log-Transformed Data with Leading Inflation

- **Reduced Inflation Impact:** Correlations between S&P 500 Price and "us_inflation_rate" have further diminished (0.464). The log transformation seems to weaken the linear relationship between these variables.

- **Nature of Transformation:** Log transformations can be particularly useful when dealing with data that has skewed distributions or exhibits exponential relationships. Since a drop in correlation is seen, it is same to assume there is a

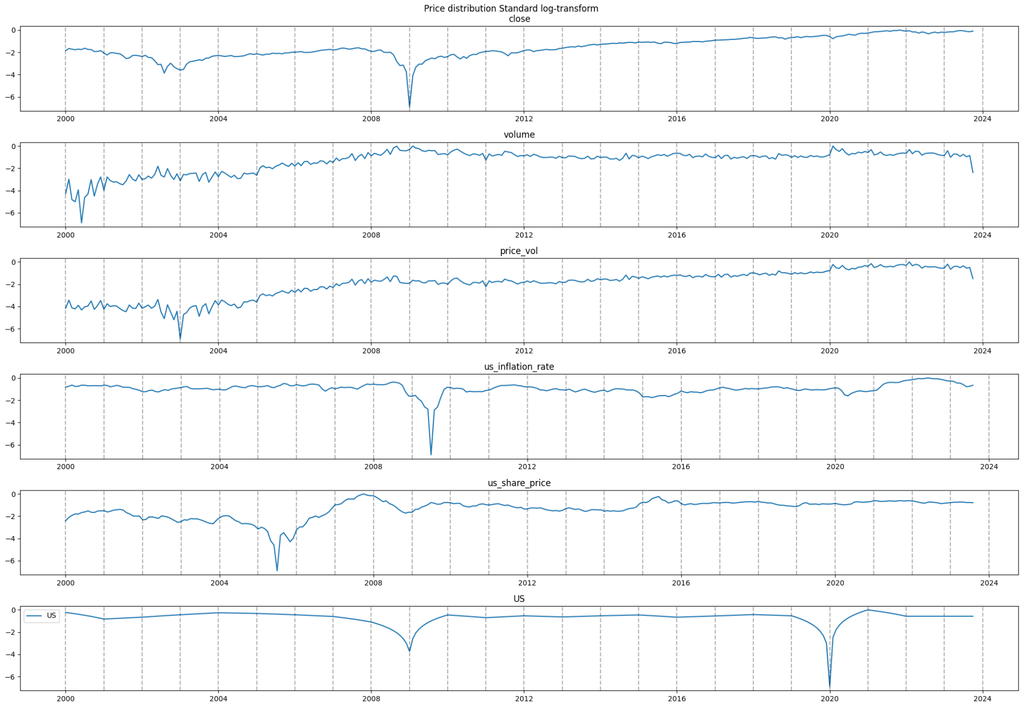

Figure 5.17: USA: Log Transformed Data.

	S&P 500 Price	volume	price_vol	us_inflation_rate	us_share_price	GDP
S&P 500 Price	1.000	0.352	0.720	0.464	0.492	0.179
volume	0.352	1.00	0.858	-0.150	0.528	-0.255
price_vol	0.720	0.858	1.000	0.026	0.649	-0.168
us_inflation_rate	0.464	-0.150	0.026	1.000	0.004	0.518
us_share_price	0.492	0.528	0.649	0.004	1.000	-0.168
GDP	0.179	-0.255	-0.168	0.518	-0.168	1.000

Table 5.22: USA: USA: Correlation Matrix: Log-Transformed Data with Leading Inflation.

lack of an exponential component to the correlation.

5.2.5.5 Overall Analysis

- **Impact of Inflation:** A consistent, though moderate, positive correlation emerged between the S&P 500 Price and "us_inflation_rate". This suggests a potential association, with inflation tending to move in tandem with the "close" variable. The strength of this correlation varied slightly depending on the data transformation applied.

- **Strong Non-Linearity:** When assessing results from all tests, it is very evident that inflation-stock correlation is highly altered with Yeo-Johnson and Box-Cox transformations, which prove there is some non-linear correlation between inflation and stock values.

5.2.6 Granger Causality Test (Inflation -> US Share Prices)

The Granger Causality test is performed next. The aim of this test is to prove causality between two variables. That is, if one variable directly causes the other, hence providing an idea of the correlation between the variables. This test is used to understand the impact of Inflation on the S&P 500 index.
A linearly correlated dataset will show Granger causality while a non-linearly correlated dataset may show causality. The relationship between inflation and US share prices is analysed, building upon any insights from the correlation analysis. The optimal lag length was determined to be 4 based on information criteria and domain knowledge. Here are the results:

- **F-tests (ssr based and parameter):**
  - F-statistic: 1.7676
  - p-value: 0.1536
  - Degrees of freedom (denominator) [samples]: 274
  - Degrees of freedom (numerator) [number of lags]: 4
- **Chi-Squared Tests (ssr based and likelihood ratio):**
  - Chi-squared statistic: 5.4382 (ssr based), 5.3862 (likelihood ratio)
  - p-value: 0.1424 (ssr based), 0.1456 (likelihood ratio)
  - Degrees of freedom [number of lags]: 4

Interpretation: While the p-values from the Granger causality tests are above the typical significance threshold of 0.05, they are relatively low compared to what might be expected if there were truly no predictive relationship. This suggests a potential weak or nuanced predictive relationship between past inflation values and current US share prices.

Implications: Rather than assuming no relationship, the Granger test results hint at a potentially subtle connection between inflation and US share prices. The results encourage further exploration to fully understand the nature and dynamics of the relationship.

5.2.7 Non-Linear Regression

With evidence from both normal and leading inflation data, it is seen that a non-linear relationship is more than likely. This is further proved with a high causality score, which confirms a correlation between the two variables. To further prove the variables being correlated, a non linear regression model is adopted.

5.2.7.1 Box-Cox Transformation

The Box-Cox transformation was applied to the USA dataset to address potential non-linearity and improve the fit of the polynomial regression model. It aims to make the distribution of the dependent variable more normally distributed.

5.2.7.2 Normalization

Following the Box-Cox transformation, data normalization was performed. This involved standardization or scaling techniques to bring variables onto a common scale. The purpose of normalization is to prevent features with larger magnitudes from dominating the model.

5.2.7.3 Polynomial Regression Results

Polynomial regression models of varying degrees were fitted to the transformed and normalized data. The optimal model was selected based on performance metrics and domain knowledge. The results for the chosen model are as below:

- **Mean squared error:** 0.0151
- **Mean absolute error:** 0.0982
- **Model Performance:** The mean squared error (MSE) and mean absolute error (MAE) provide insights into the model's accuracy. Very low MAE and MSE scores show the high prediction accuracy of the model, with MAE at about 10%.

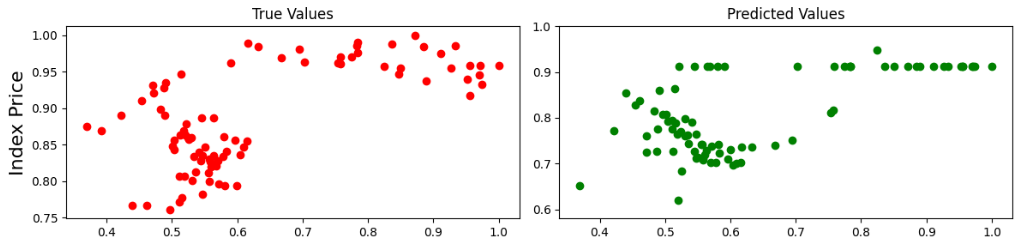

Figure 5.18: USA: True vs Predicted Values.

5.2.8 Results and Discussions

The analysis of the relationship between the S&P 500 and US inflation unveiled several significant findings.

- A moderate positive correlation was observed between the S&P 500 and inflation, implying that the stock market has a tendency to move in conjunction with rising prices.
- Data transformations suggest the presence of a non-linear element within this relationship.
- Furthermore, leading inflation indicators demonstrated stronger correlations, indicating a potential lagged impact of inflation on the stock market.
- The Granger Causality tests suggested a subtle predictive relationship between historical inflation and stock prices.
- Finally, non-linear regression models achieved a superior fit, lending further credence to the non-linear association between inflation and the S&P 500.

The overall idea from this analysis is that there is a moderate level of correlation between the inflation and S&P Index in the USA. There seems to be a possibility of higher correlation, which can be achieved by looking into some other secondary factors that may affect both inflation and the stock markets, where it is individual perception, news stories or other financial factors such as interest rates.

5.3 China

5.3.1 General Overview: The Chinese Market and Inflation

China, the world's second-largest economy, has experienced remarkable growth in recent decades. Its transition from a centrally planned to a more market-oriented system has spurred economic development and improved living standards. State-owned enterprises still play a significant role, with the government exerting influence on economic policy and strategic sectors.

The Shanghai Composite Index, a key benchmark for the Chinese stock market, tracks the performance of all stocks listed on the Shanghai Stock Exchange. It provides a broad overview of the Chinese market's performance. Understanding the index's characteristics is essential for investors:

- **Regulatory Landscape:** Strict capital controls and a less predictable regulatory environment can present challenges for foreign investors.
- **Government Influence:** The Chinese government retains considerable influence over the economy and the stock market through policy interventions.
- **Market Structure:** A large proportion of retail investors and potential for speculative behavior can increase the volatility of the Shanghai Composite Index.

Inflation, the rate of price increases, impacts the Chinese economy and its financial markets. Understanding the dynamics is crucial for making informed investment decisions about the Shanghai Composite Index. Here's how inflation interacts with it:

- **Impact on Real Returns:** Inflation can erode the returns from investments. Investors must factor in inflation when evaluating real returns in the Chinese market.
- **Central Bank Policies:** The People's Bank of China adjusts monetary policies, including interest rates, to manage inflation. These policy actions can influence the stock market.

- **Company Costs and Valuation:** Inflation affects companies' input costs and profitability. These changes can have an impact on stock valuations and market performance.

By carefully monitoring inflation indicators and their potential implications for companies represented in the Shanghai Composite Index, investors can make better-informed decisions and navigate potential risks within this complex financial landscape.

5.3.2 Basic Correlation Analysis

The correlation matrix below reveals potential relationships between the Shanghai Composite Index (close), trading volume, price-volume ratio, China's inflation rate, share prices, and overall GDP indicator (China).

	Shanghai Composite	volume	price_vol	china_inflation_rate	china_share_price	GDP
Shanghai Composite	1.000	0.649	0.681	0.250	0.606	-0.386
volume	0.649	1.000	0.982	-0.090	0.779	-0.630
price_vol	0.681	0.982	1.000	-0.086	0.727	-0.568
china_inflation_rate	0.250	-0.090	-0.086	1.000	-0.001	0.040
china_share_price	0.606	0.779	0.727	-0.001	1.000	-0.760
GDP	-0.386	-0.630	-0.568	0.040	-0.760	1.000

Table 5.23: China: Correlation Matrix: Raw Data.

- **Scaling Effects:** Standardization brings variables onto a comparable scale. This can potentially reveal or strengthen weaker correlations that might have been obscured by differences in the original magnitudes of variables. Conversely, it can also diminish the appearance of strong correlations driven primarily by large differences in scale.

- **Preservation of Patterns:** Analyze whether the general pattern of positive and negative correlations in your standardized data broadly aligns with your earlier analysis of the untransformed data.

- **Implications:** Standardization facilitates the comparison of correlation strengths across different variables. In the context of the Chinese market, this might help you pinpoint relationships deserving of closer scrutiny, which otherwise could have been overshadowed by discrepancies in the original scales of measurement.

5.3.3 Stationarity Analysis

The Augmented Dickey-Fuller (ADF) test was applied to assess the stationarity of key variables. Stationary variables are highly advantageous to understand data patterns and hence predictability.

Variable	Shanghai Composite Index	China Inflation Rate
Test Statistic	-3.383	-3.417
p-value	0.012	0.010
Lags	7	14
Observations	278	269
	Critical Values	
Significance Level	1%: -3.455	5%: -2.872
	10%: -2.573	

Table 5.24: ADF Test Results for Shanghai Composite Price and Inflation

- **p-values and Critical Values:** We compare the calculated test statistics to the critical values at different significance levels (1%, 5%, 10%). Since the p-values for both the Shanghai Composite Index and China's inflation rate are smaller than the critical values at the 5% significance level, we reject the null hypothesis of a unit root (non-stationarity).
- **Suggests Stationarity:** The ADF results provide evidence that the analyzed variables (Shanghai Composite Index and China inflation rate) might exhibit stationarity. This is a positive indication for employing time series models that often assume stationarity.

5.3.4 Correlation Analysis with Data Transforms

5.3.4.1 Standardized Data

Standardization is a common data transformation that involves subtracting the mean and dividing by the standard deviation of each variable. This process brings variables onto a common scale, making it easier to compare their relationships.

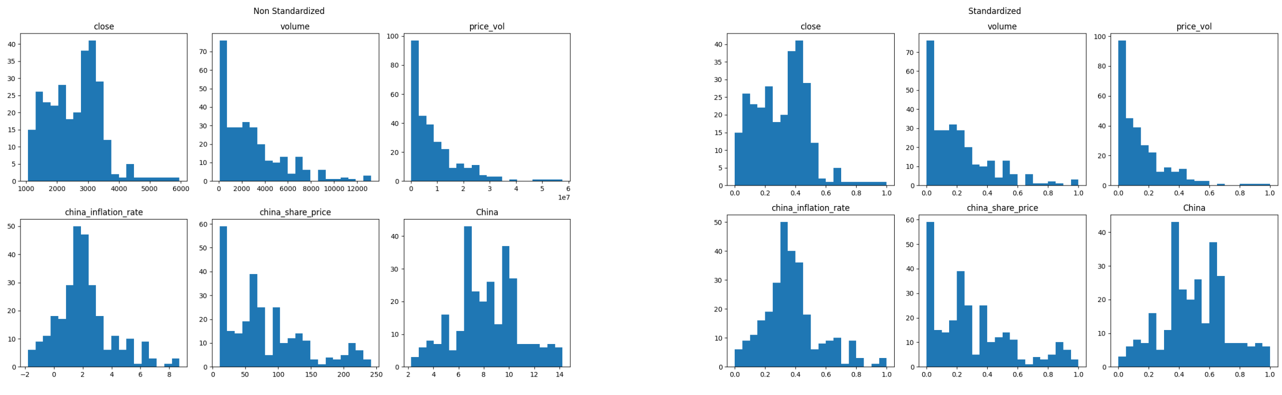

Figure 5.19: China: Difference between Non Standardized and Standardized Data

	Shanghai Composite	volume	price_vol	china_inflation_rate	china_share_price	GDP
Shanghai Composite	1.000	0.649	0.681	0.250	0.606	-0.386
volume	0.649	1.000	0.982	-0.090	0.779	-0.630
price_vol	0.681	0.982	1.000	-0.086	0.727	-0.568
china_inflation_rate	0.250	-0.090	-0.086	1.000	-0.001	0.040
china_share_price	0.606	0.779	0.727	-0.001	1.000	-0.760
GDP	-0.386	-0.630	-0.568	0.040	-0.760	1.000

Table 5.25: China: Correlation Matrix: Standardized Data.

5.3.4.2 Yeo-Johnson Transformed Data

The Yeo-Johnson transformation is a power transformation that is often used to address skewness and non-normality in data, similar to the Box-Cox transformation. However, it can also handle variables with negative values. Here's the correlation matrix of the Yeo-Johnson transformed data:

	Shanghai Composite	volume	price_vol	china_inflation_rate	china_share_price	GDP
Shanghai Composite	1.000	0.759	0.827	0.223	0.715	-0.438
volume	0.759	1.000	0.987	0.029	0.900	-0.672
price_vol	0.827	0.987	1.000	0.039	0.893	-0.653
china_inflation_rate	0.223	0.029	0.039	1.000	0.147	-0.001
china_share_price	0.715	0.900	0.893	0.147	1.000	-0.743
GDP	-0.438	-0.672	-0.653	-0.001	-0.743	1.000

Table 5.26: China: Correlation Matrix: Yeo-Johnson Transformed Data.

Analysis

- **Robust Relationships:** Notice that the correlations involving "volume", "price_vol", and "china_share_price" remain consistently strong across the Yeo-Johnson

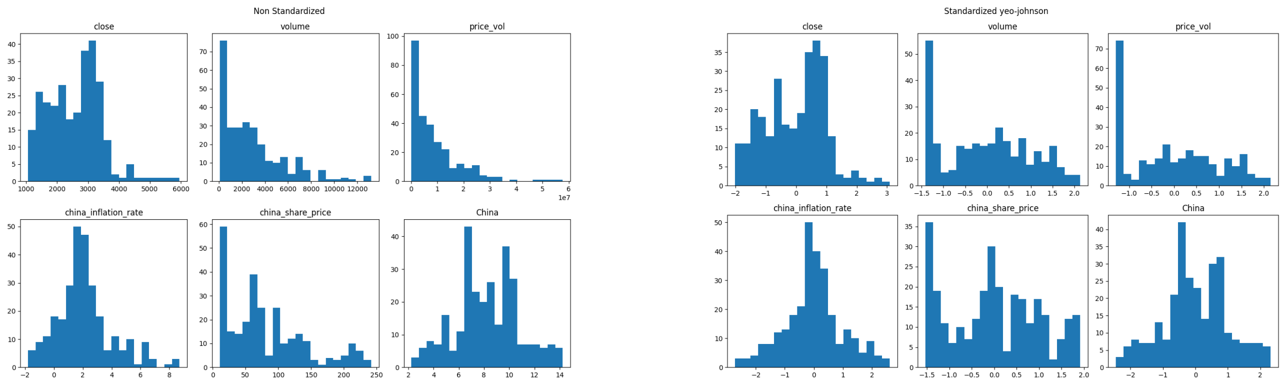

Figure 5.20: China: Difference between Non Standardized and Y-J Transformed Data

transformation. This suggests that these relationships might be less sensitive to potential non-normality or skewness in the original data.

- **Weakened Inflation Association:** The correlation between "Close" and "china_inflation_ra appears slightly weaker (0.223) compared to the standardized results.

- **Negative Correlations:** The negative correlations between "China" (GDP) and other variables persist in the transformed data.

Absolutely! Here's the consolidated LaTeX code chunk with analysis sections for both the Box-Cox and Log-Transformed data:
Code snippet

5.3.5 Correlation Analysis with Data Transforms

5.3.5.1 Box-Cox Transformed Data

The Box-Cox transformation is another technique aimed at addressing non-normality and potentially making relationships more linear. Here's the correlation matrix after applying the Box-Cox transformation:

- **Persistent Relationships:** Similar to the Yeo-Johnson results, the correlations among "volume", "price_vol", and "china_share_price" remain very strong after the Box-Cox transformation.

- **Potential Outlier Influence:** Consider whether certain extreme correlations

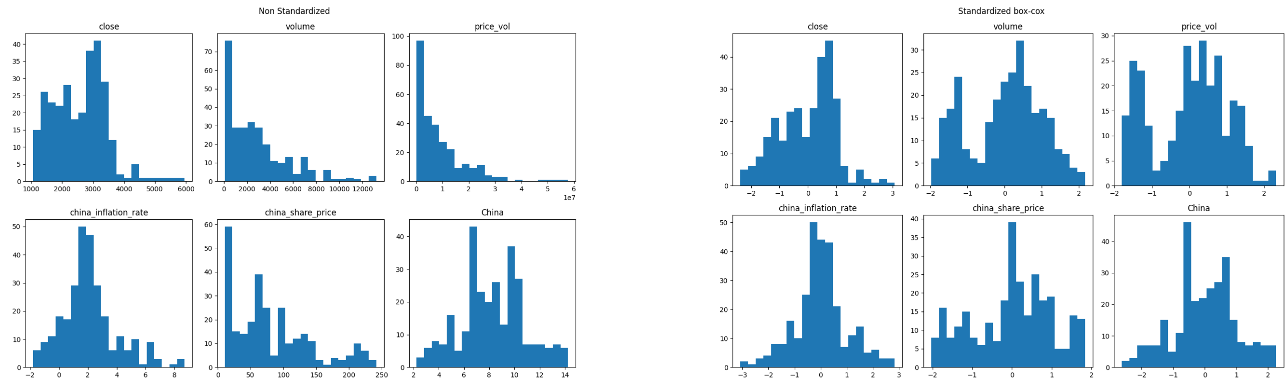

Figure 5.21: China: Difference between Non Standardized and B-C Transformed Data

	Shanghai Composite	volume	price_vol	china_inflation_rate	china_share_price	GDP
Shanghai Composite	1.000	0.766	0.843	0.220	0.712	-0.446
volume	0.766	1.000	0.991	0.098	0.911	-0.621
price_vol	0.843	0.991	1.000	0.121	0.906	-0.612
china_inflation_rate	0.220	0.098	0.121	1.000	0.192	-0.001
china_share_price	0.712	0.911	0.906	0.192	1.000	-0.690
GDP	-0.446	-0.621	-0.612	-0.001	-0.690	1.000

Table 5.27: China: Correlation Matrix: Box-Cox Transformed Data.

(approaching 1) might indicate the presence of outliers that the Box-Cox transformation is potentially amplifying.

- **Weakened Inflation Association:** The correlation between "Close" and "china_inflation_ra appears slightly weaker (0.220) compared to the standardized results. The Box-Cox transformation might be influencing this relationship.

5.3.5.2 Log-Transformed Data

The log transformation is commonly used to handle skewness and non-normality, especially for variables with exponential relationships.

- **Reduced Inflation Impact:** The log transformation markedly reduces the correlations between "Shanghai Composite" and "china_inflation_rate" (0.101). This could suggest that inflation has a non-linear relationship with stock prices, and the linear correlation framework might not fully capture it.

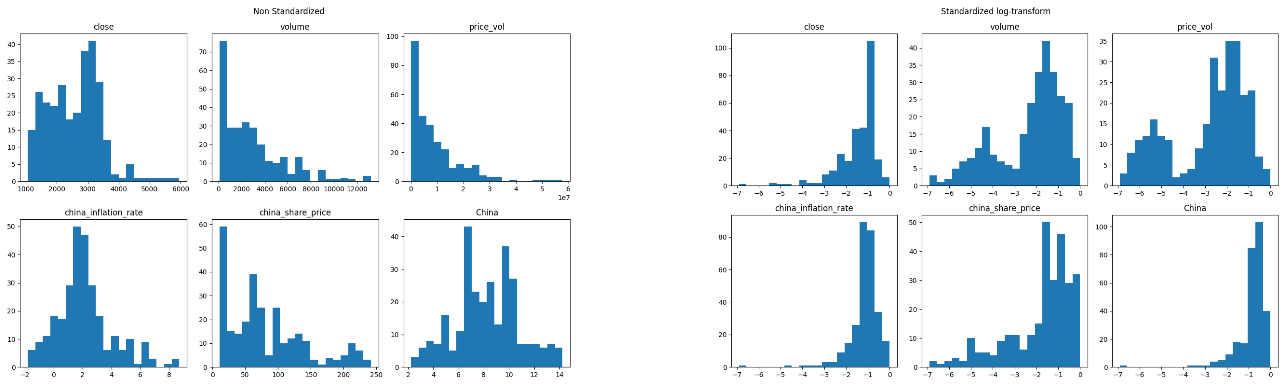

Figure 5.22: China: Difference between Non Standardized and Log Transformed Data

	Shanghai Composite	volume	price_vol	china_inflation_rate	china_share_price	GDP
Shanghai Composite	1.000	0.685	0.776	0.101	0.596	-0.371
volume	0.685	1.000	0.987	0.180	0.920	-0.460
price_vol	0.776	0.987	1.000	0.170	0.908	-0.474
china_inflation_rate	0.101	0.180	0.170	1.000	0.294	-0.115
china_share_price	0.596	0.920	0.908	0.294	1.000	-0.464
GDP	-0.371	-0.460	-0.474	-0.115	-0.464	1.000

Table 5.28: China: Correlation Matrix: Log-Transformed Data.

- **Robust Relationships Persist:** The strong associations among "volume", "price_vol", and "china_share_price" persist, even after the log transformation.
- **Moderate Correlations Emerge:** The log transformation reveals a moderate correlation between "china_share_price" and "china_inflation_rate" (0.294), which was less apparent in earlier analyses.

5.3.6 Analysis of Leading Inflation

This subsection examines the correlations between leading inflation (by 6 time points) and key variables within the Chinese market using different data transformations.

5.3.7 Standardized Data

- **Moderately Positive Correlation:** A moderate positive correlation (0.404) exists between "Shanghai Composite" and leading "china_inflation_rate". This suggests a potential lagged relationship where inflationary periods might be

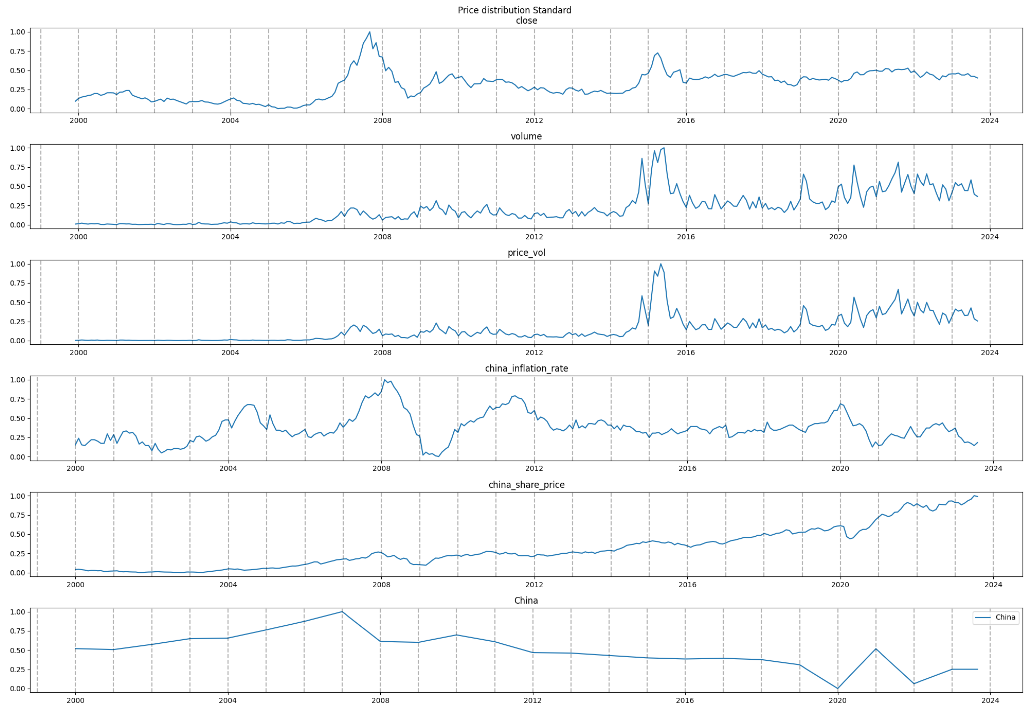

Figure 5.23: China: Standardized Data.

	Shanghai Composite	volume	price_vol	china_inflation_rate	china_share_price	GDP
Shanghai Composite	1.000	0.645	0.678	0.404	0.612	-0.376
volume	0.645	1.000	0.982	-0.050	0.777	-0.619
price_vol	0.678	0.982	1.000	-0.021	0.725	-0.556
china_inflation_rate	0.404	-0.050	-0.021	1.000	0.014	0.211
china_share_price	0.612	0.777	0.725	0.014	1.000	-0.759
GDP	-0.376	-0.619	-0.556	0.211	-0.759	1.000

Table 5.29: China: Correlation Matrix: Standardized Data, Leading Inflation.

followed by increases in stock prices.

- **Economic Interpretation:** Consider any economic theories or intuitions that might explain or contradict this observed lagged correlation pattern.

5.3.7.1 Yeo-Johnson Transformed Data

- **Similar Correlation Strength:** The correlation between "Shanghai Composite" and leading "china_inflation_rate" (0.351) remains in a similar range as the standardized results, implying some robustness to the Yeo-Johnson transformation.

- **Potential for Non-Linearity:** If the transformation aimed to address non-linearity, even the transformed correlation might not fully capture the rela-

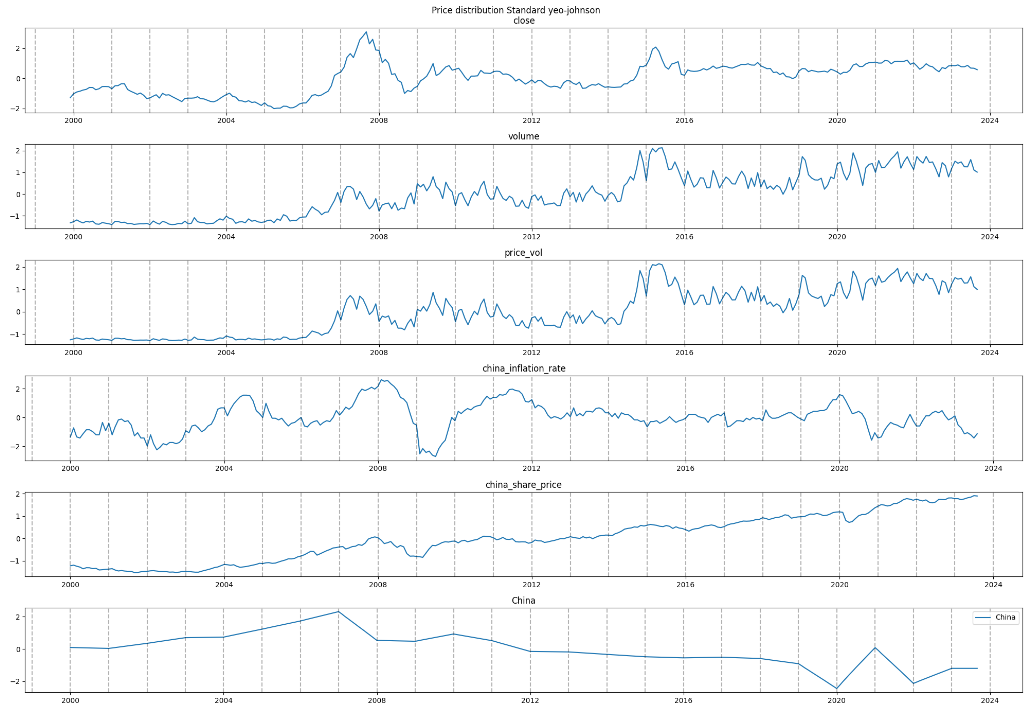

Figure 5.24: China: Y-J Transformed Data.

	Shanghai Composite	volume	price_vol	china_inflation_rate	china_share_price	GDP
Shanghai Composite	1.000	0.761	0.831	0.351	0.719	-0.432
volume	0.761	1.000	0.987	0.080	0.900	-0.658
price_vol	0.831	0.987	1.000	0.125	0.892	-0.640
china_inflation_rate	0.351	0.080	0.125	1.000	0.150	0.163
china_share_price	0.719	0.900	0.892	0.150	1.000	-0.733
GDP	-0.432	-0.658	-0.640	0.163	-0.733	1.000

Table 5.30: China: Correlation Matrix: Yeo-Johnson Transformed Data, Leading Inflation.

tionship's complexity. Explore non-linear models if this relationship is of key interest.

5.3.8 Box-Cox Transformed Data

- **Comparable Correlation:** The correlation between "Shanghai Composite" and leading "china_inflation_rate" (0.352) is consistent with both the standardized and Yeo-Johnson results. This suggests some robustness of the observed relationship to these transformations.
- **Investigate Outliers:** The Box-Cox transformation may be sensitive to outliers. Consider outlier analysis to ensure correlations are not unduly influenced by a

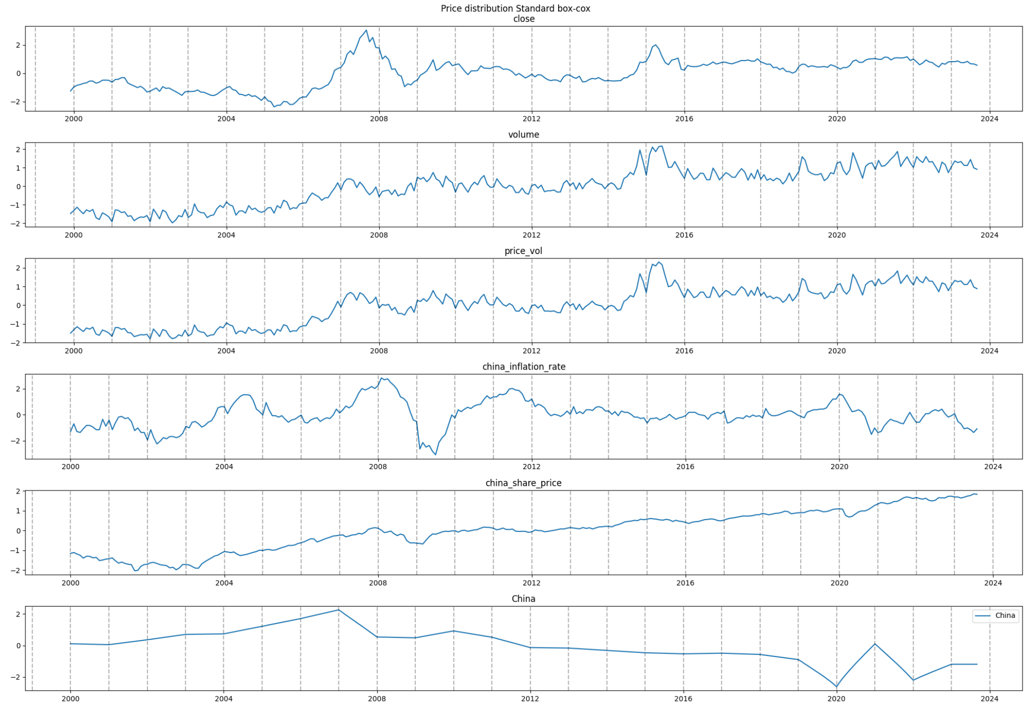

Figure 5.25: China: B-C Transformed Data.

	Shanghai Composite	volume	price_vol	china_inflation_rate	china_share_price	GDP
Shanghai Composite	1.000	0.765	0.844	0.352	0.713	-0.440
volume	0.765	1.000	0.990	0.138	0.911	-0.607
price_vol	0.844	0.990	1.000	0.186	0.906	-0.599
china_inflation_rate	0.352	0.138	0.186	1.000	0.189	0.164
china_share_price	0.713	0.911	0.906	0.189	1.000	-0.680
GDP	-0.440	-0.607	-0.599	0.164	-0.680	1.000

Table 5.31: China: Correlation Matrix: Box-Cox Transformed Data, Leading Inflation.

few extreme points.

5.3.8.1 Log-Transformed Data

	Shanghai Composite	volume	price_vol	china_inflation_rate	china_share_price	GDP
Shanghai Composite	1.000	0.682	0.774	0.192	0.591	-0.363
volume	0.682	1.000	0.986	0.196	0.918	-0.451
price_vol	0.774	0.986	1.000	0.209	0.906	-0.464
china_inflation_rate	0.192	0.196	0.209	1.000	0.288	-0.014
china_share_price	0.591	0.918	0.906	0.288	1.000	-0.454
GDP	-0.363	-0.451	-0.464	-0.014	-0.454	1.000

Table 5.32: China: Correlation Matrix: Log-Transformed Data, Leading Inflation.

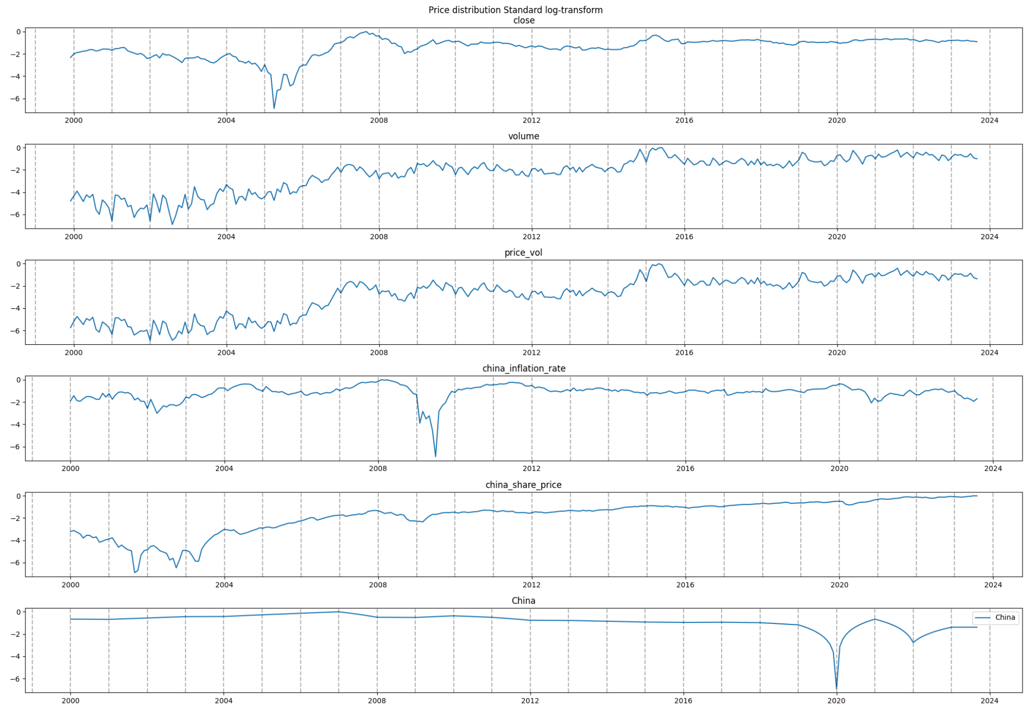

Figure 5.26: China: Log Transformed Data.

- **Weakened Correlation:** The correlation between "Shanghai Composite" and leading "china_inflation_rate" weakens considerably (0.192) compared to the other transformations. This suggests the log transformation markedly alters the relationship, potentially indicating non-linearity.

- **Log Transformation and Inflation:** The log transformation often dampens the effect of large values. Inflation might have a non-linear impact on stock prices, with larger inflationary spikes having a stronger influence. The log transformation might lessen the influence of these larger inflation periods, leading to a weaker correlation.

5.3.8.2 Overall Analysis

- **Index-Inflation Relationship:** The consistent positive correlations between the Shanghai Composite Index and leading inflation across various transformations, albeit with varying strength, suggest that past inflation may contain predictive information about future stock prices.

- **Non-Linearity Considerations:** The marked weakening of the correlation in the log-transformed case hints at a potentially non-linear relationship between inflation and stock prices. Inflation might have a disproportionate effect at certain levels or when there are large fluctuations.

5.3.9 Granger Causality Analysis

Granger causality tests were conducted to investigate whether past values of inflation help predict the current values of the Shanghai Composite Index . Here's a summary of the test results:

- F-tests (ssr based and parameter):
  - F-statistic = 2.8506
  - p-value = 0.0595
  - Degrees of freedom (denominator)[Samples] = 277
  - Degrees of freedom (numerator)[Lags] = 2
- Chi-Squared tests (ssr based and likelihood parameter):
  - Chi-squared statistic = 5.8042(ssr based), 5.7452(likelihood ratio)
  - p-value = 0.0566(ssr based), 0.0595(likelihood ratio)
  - Degrees of freedom (numerator)[Lags] = 2

Inferences

- **Marginal Significance:** While the p-values of the Granger causality tests hover around the traditional significance level of 0.05, they do not provide very strong evidence of causality. This suggests a potential weak or nuanced predictive relationship between past inflation and the Shanghai Composite Index.
- **Potential for Non-Linearity:** If the relationship between inflation and the Shanghai Composite Index is non-linear, traditional Granger causality tests might have limitations.

5.3.10 Non-Linear Regression

As seen by the results of normal and leading inflation based tests, it is seen that there is considerable correlation between the Index and Inflation values. As seen by the

Yeo-Johnson and Box-Cox transforms, it is further seen that this correlation may be of a non-linear pattern, hence promping a non-linear regression model.

5.3.11 Box-Cox Transformation

The Box-Cox transformation was applied to potentially improve the linearity of the relationship between the Shanghai Composite Index and inflation. It aims to make the data more normally distributed, which might benefit regression models.

5.3.12 Polynomial Regression Results

A polynomial regression model was fitted to the transformed data. This model allows for flexibility in capturing non-linear trends by including higher-order terms of the predictor variable (inflation). Here are the performance metrics of the chosen model:

- **Mean squared error:** 0.0044
- **Mean absolute error:** 0.0531
- **Model Performance:** The mean squared error (MSE) and mean absolute error (MAE) detail the model's accuracy. The MAE score of 5%, paired with a very low MSE shows a very capable model for predicting the Index price values using inflation rates.

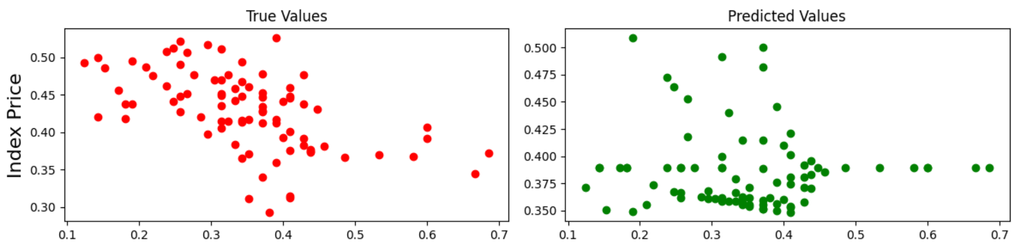

Figure 5.27: China: True vs Predicted Values.

5.3.13 Result Summary

The analysis of the Shanghai Composite Index and China's inflation rate revealed intriguing insights.

- Stationarity tests suggest that the examined variables may exhibit stationarity, making them suitable for time series modeling.
- Data transformations highlight potential non-linear relationships. Correlations between the Shanghai Composite Index and inflation tended to be positive, with leading inflation showing stronger associations. Notably, the log transformation weakened this correlation, hinting at a non-linear relationship.
- Granger causality results were marginally significant, indicating a possible subtle predictive relationship between past inflation and the Shanghai Composite Index.
- Finally, non-linear regression achieved a good fit with the data, further supporting the idea of a non-linear connection between inflation and the Shanghai Composite Index.

The Shanghai model was slightly different from the NIFTY and S%P models, in the sense of it being inherently stationary. The model also displayed a lower correlation using the pearson's correlation table, but showed a better non-linear regression output, providing evidence of the index being significantly dependant on inflation.

CHAPTER 6

Conclusions

The study of the three indexes all proved to be very similar in their behaviours. The inflation in all cases proved to moderately impact the stock market, while there being a 6 month lead for inflation in US and China and a 1 month lead in India. This could be a factor of India being a less mature economy and the sort term impact of inflation being magnified in the market.

The overall analysis suggests a room for better applicability of this model, with the use of a daily dataset, providing deeper insights into the workings of inflation and stock market indices, while also demanding the analysis of a connecting variable. The various tests done in each case signify heavily the impact of inflation on stock market indices, but also show a certain degree of uncertainty, which can be improved with the analysis of other variables that may connect the information provided by the inflation and indices.

The Fisher Hypothesis: The Fisher Hypothesis is a classical economic theory that suggests a positive correlation between expected inflation and nominal stock returns. This arises when investors demand higher returns to compensate for inflation-induced erosion of purchasing power.

The study conducted, also aligns with the understandings of the Fisher Hypothesis, where inflation has a significant positive impact in all three countries analysed. As suggested by this hypothesis, there is a strong impact of inflation induced purchasing power, which further leads to an impact on the stock market index. This suggests the study of purchasing power and interest rates, which will provide a bridge to fill in the information gap currently lying between the two analyzed variables.

In summary, this paper sets a strong precedent to conclude that there is rather significant evidence to show the impact of inflation on stock market indices and that they do positively correlate. The study puts to use a strong set of statistical tests that go on to prove the correlation between inflation and stock market indices, which is theoretically accepted in the financial industry but is not something that has been conclusively proven yet. A continued study on this topic should bring forward a more detailed understanding of the correlation and help understand an otherwise very volatile subject of time series analysis.

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