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**AI-Powered Inflation Forecasting and Economic Decision Support System**

**Taji Mozafari Razieh**

**Dissertation submitted to International Business School  for the partial fulfilment of the requirement for the degree of  MASTER OF SCIENCE IN IT FOR BUSINESS DATA ANALYTICS**

**DECLARATION**

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Tajimozafari Razieh

**LETTER OF CONFIRMATION AND CONSENT**

19 December 2025

Dear Mr. Jones,

I am a student on the Master of Science in IT for Business Data Analytics programme at International Business School, Budapest and The University of Buckingham. As part of my course, I am completing a Business Data Analytics Project entitled: **AI-Powered Inflation Forecasting and Economic Decision Support System**.

The study aims to evaluate the effectiveness of machine learning models in forecasting US inflation trends and to develop a conceptual Decision Support System (DSS). This system is designed to translate complex economic forecasts into actionable strategic insights, helping business organizations mitigate risks associated with inflationary shocks and supply chain volatility.

Prior to completing the study, I am seeking formal confirmation to utilize the data frameworks and organizational context relevant to this project. While the primary dataset is derived from the Federal Reserve Economic Data (FRED), the study also involves the design of a dashboard tailored for business stakeholders. I would appreciate your consent to approach members of your team who deal with strategic planning or financial forecasting to gain insights into how such a dashboard could best support executive decision-making. I hope to engage with approximately six participants through short, self-administered surveys or brief interviews.

I can assure you that I will make every effort to ensure that any feedback or internal data provided is handled in strict confidence and in observance of required security guidelines. I will also take care that the research does not disrupt the working environment in any way. The findings will be used solely for my Business Data Analytics Project, which will only be accessible by evaluators affiliated with International Business School and The University of Buckingham.

Your permission to conduct this study and engage with your organization for this academic purpose will be greatly appreciated.

Yours sincerely,

Tajimozafari Razieh MSc IT for Business Data Analytics Student

I confirm that I have freely agreed to the use of data provided by my organisation by Jane Jack Doe for the Business Data Analytics Project described above.  I have been briefed on what this involves and I agree to the use of the findings as described above.

Signature:

|  |  |
| --- | --- |
| Name: | Mr Jack Jones |
| Position: | Senior Data Specialist |
| Company: | Dondow Ltd. |
| Date: | December 19th 2025 |

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# Executive Summary

## Overview of the Problem

Inflation forecasting is crucial in ensuring that the economy remains stable and enable businesses to plan.

After 2020, the economy has been very unpredictable due to the issues of Covid-19, supply chain issues, and global conflicts.

Old methods that use straight-line models, like ARIMA barely have had a hard time giving accurate predictions.

These models cannot capture the way that many different economic factors mix together - such as changes in energy prices and changes in monetary policy.

This puts a high level of uncertainty on the hands of decision makers.

This project is looking for a better, more flexible forecasting system able to handle these changes.

## Methodology :

The project built an AI pressure system called, which looks at inflation in the United States.

It followed the CRISP - DM framework (a proven step - by - step process for data mining projects).

Data Integration:

A large data set was constructed by bringing together the monthly data for 2000-2024 on six key indicators:

Consumer Price Index (CPI), Federal Funds Rate, M2 Money supply, WTI Crude Oil Prices, PPI and Unemployment Rate.

Modeling Strategy :

Three different types of models were made, and tuned:

- SARIMA: A basic statistical model using an auto selected algorithm to capture the seasonality and trends.

- Prophet: A relatively recent regression algorithm by Meta, configured with shifted inputs so that future data will not have an impact on predictions for the past.

- Random Forest: A machine learning model which is able to learn non-linear patterns. It was enhanced with lagged features (e.g. t-1, t-3) so the model can understand the effect of values on the future.

Validation

All models were tested on another set of data for 2022-2024 which was a year of high volatility and using Root Mean Squared Error (RMSE) as a scoring mechanism.

Key Findings

From the developed models, the comparison revealed that the Random Forest model had superior results compared to the other models with the lowest RMSE value of 0.2708.

The model of SARIMA had an RMSE of 0.6028, and the model of Prophet had a RMSE of 0.6544.

This proves that non,-linear methods of machine learning, given proper lagged features work much better for today's economy than the straight, linear statistical models.

Feature-importance analysis also revealed that past oil prices and PPI were the best predictors of the inflation's cost-push theory in the period under analysis.

Implications for Business

The results are of significance for both data analysts and business leaders.

For analysts the crucial point here is that building good features is going to be more important than choosing a super-complex model: data alone is not enough without converting it into a format that is aware of time.

For managers, the great accuracy of the ML model is a real advantage.

By implementing these forecasts into a Decision Support Dashboard, leaders can move from being a reactive manager and start proactively managing the risk.

They are also able to run "What-If" scenarios such as what if the cost of oil increases by 10%, taking raw predictions and turning them into clear-cut decisions that are useful for setting prices and managing inventory on markets with uncertainties.

# Chapter 1: Introduction

## 1.1 Introduction and the Context of the Project

Inflation refers to a situation in which prices of goods and services incraese over time at a steady pace. It is one of the most important economic indicators. It affects how well the economy is doing and also has an impact on how much peoplecan purchase and how expensive life is and how much company spend to operate. Central banks such as the US Federal Reserve try and maintain a smooth inflation, typically 2% to enable stable growth. When the rate of inflation is stable, businesses can more confidently plan investments, set prices, and enter into contracts with their business partners. (Mishkin, 2017)

But after 2020 the world economy has changed a lot. The suden ups and downs made by the extent of the pandemic of Covid-19, wars such as the war with Ukraine, or the policy reactions are not seen since the 1970s. Global supply chains previously crafted to deliver promptly were disrupted with lockdowns and sudden demand leading to massive increases in the price index producers pay. Energy markets also changed a lot Crude oil prices even went negative in 2020 and went to highs years after that. On the demand side, big stimulus packages and near 0 interest rates inflates supply of money in a big way and hence more spending while supplies are limited. (Ball et al., 2022; Bernanke & Blanchard, 2023)

Now, with such a volatile ecinomy, prediction of inflation is no longer a routine activity, but a necessity. Old assumptions about the economy (or that it is stable) no longer function. Companies are stuck without being able to predict cost or demand.Misjudging inflation can lead to loss in profits, incorrect pricing and unplannned spending. So we need models that are dynamic, and make use of data-e.g., that change rapidly with the situation.

## 1.2 Business and Technical Significance

The imporrtance of this project is at the intersection of the fields of macro economic theory, complex data analytics providing a lot of value to both the business and technical data science community.

Business Significance: For corporate decision your decision makers inflation is an external risk factor tobe taken care of. Accurete forecasting is the foundation of agility in the finanncial world.

\* Risk Management: By antiicipating cost rises (such as oil or raw materials), companies can manage their risks in terms of rising costs by entering into a futures contract or by stockpilinng inventory.

\* Pricing Strategy: Knowing how much time it takes under the prodicer prices to reach the consumer pricese, it helps businesses to set prices before time taking changes in marginn without disturbing the customers.

\* Strategic Planninng: Good forecasts allow firms to better budget in the areas of wages, investments, and debt. The Decision Support System that i build will give managers clear scenarios against which they can test strategies against potential economic shocks. (Power, 2002)

Technical Significasnce: Taking the data science approach, predicting infllation is a complicated multivariatte time series problem. It poses a challenge to analysts to model non linear interactions bettween variables suchas monetary policy, labor markets and energy costes over time.

\* Model Benchmarking: In this study, the classical statistical models such as ARIMA are comparred with the newer models such as Prophet and machine learning models such as Random Forest.

\* Feature Engineering: Through the project, I realized the important of using lag features for time series forecasting. The power of a model, often is in the transformations of data to capture "when" and not just the algorithem itself. (Kuhn & Johnson, 2013)

## 1.3 Problem statement and Objectives

Problem Statement: Many businesses require the ability to forecast inflation, but the tools that they use today are inadequate for the economy of today. Old statistical methods, like ARIMA, make an assumption that the future is the same as the past which is, often, wrong. These methods have a hard time accommodating the impacts of events such as oil prices shocks on inflation, and they are most problematic when markets are volatile. New Machine Learning (ML) methods often work like "black boxes" so those who run the business can't understand why they make certain predictions. There is not one system that employs the power of ML but also provides clearly and easy to use results for non-technical managers.

Objectives: The principal objectives of this project is to create a powerful AI machine that can forecast inflation more than the old ways. It will also place those results on a business dashboard that can be used by managers. The specifiic goals are:

1. Data Integration Create a single huge U.S. macroeconomice dataset. Collect, clean and consolidate data of six key indicators (CPI, Federal Funds Rate, M2 Money Supply, WTI Oil Prices, PPI and Unemployment Rate) every months from January 2000 to Dec 2024.

2. Model Development: Developed, trained and tuned three types of models:

- SARIMA for the baselines of the classic statistics.

- Additive model prophet of modern day.

- Random Forest with Lagged Feautres for Non Non Non linear ML.

3. Comparative Evaluation: Test Models on strict hold out set 2022 -2024 measurement of accuracy using Root Maen Squarred Error RMSE Choose the premium volatile market approaach.

4. Decision Support Design: Design the organization of an Intereactive Decision Support System (DSS) which displays forecasts and allows menuing user to experiment with alternate scenarios, the integrations of technical analysis with business decision.

## 1.4 Scope and Contributions to be Made

Scope of the Study:

\* Geographic Focus: The study focuses only on the economy in the U.S. All of the selected indicatores are applicable to the US market.

\* Temporal Focus: The data is monthly and January 2000 to December 2024. Training uses 2000 - 2021, which test focuses on the high infelation period 2022 - 2024, in order to challenge the modelse.

\* Methodological Focus: Methodical framework of the project based on CRISP - DM for clearly and step by step processes from data prep to model launching.

Expected Contributions: This dissertation will demonstrate that ML models, even if linear such as Random Forests with good feature engineering, can predict inflation better than older linear models in chaotic times in the marketse. By identifying the way inflation is affected by supply side factores such as oil and PPI with some time delay, the study provides helpful information regarding modern inflation. The design of the dashboard will also provide organizations with a plan ready for the use of datadriven risk tools.

# Chapter 2: Literature Review

Inflation forecasting remains a great challenge in the macro economics. It is important for the stability of financial markets and for the planninng of business. This chapter examines the primary theories to explain the movements in inflation, and takes a look at the evolution of forecasting, from model econometrics to machine learning machines. It has a strong focus on work regarding the United States, on the use of outside economic signals and the comparisson of statisticale models with algorithmice ones. It illustrates where, particularly since 2020, research is lackinng and uses that as a justification for a new AI based forecasting system.

## 2.1 Theoretical background on Inflation

To make a good forecast you first had to know what causes inflation. Most papers combinned these causes into three categories: monetary factors, demand pull and cost push factorrs. These groups help make the decisions regarding the variables to use in the model.

### 2.1.1 The Quantity theory of Money (Monetary Factors)

Classical theory (in particular, the Quantity Theory of Money espoussed by monetarests) states that there is a link between the amount of money and the prices levels in the long run. Mishkin (2017) famously stated that, "inflation is always and everywhere a monetary phenommenon." The thinking here is that if the money supply (M2) will incraese at a faster rate than real output, prices will incraese. This rule is very relevent after Covid 19 and the approache taken by central banks, such as the Fed, to expand their balance sheets to prevent a recession. Money combiness have been shown by Stock and Watson (2003) to be good leading indicatorse of future inflation, so should be included into models. Bernanke and Blanchard (2023) have noted that the relationship is now more complex as the limits on supply are also relevant, and therefore the multtiple variables need to be considered in combination.

### 2.1.2 Cost Push Inflation and Supply Shocks

While monetary policy affects demand, more and more economists believe that inflation is coming from supply problems. This is referred to as cost pushing inflation. It occurs when the cost of producing the goods increases and producers charge the costs to consumers. Hamilton (2009) discusses how the oil shocks can be the source of this type of inflation as it increases the cost of transportation and production globally. The Producer Price Index (PPI) is an advance indicator. Taylor (2000) points out that an increase in factory gate prices tends to appaer in the Consumer Price Index (CPI) a little later. This implies that past values of PPI and the oil prices are predictive of CPI.

### 2.1.3 The Dynamics of the Labor Market (Phillips Curve)

The Phillips Curve depicts an historical trade off between unemployment and inflation. Blanchard (2016) updated the curve for modern economies and found that it still held water, but the relationship is less strong. When unemployment decraeses, wages incraese and that can lead to an incraese in prices. So unemployment rate is a still an important hint to what are going to see in inflation in the future, but maybe its powere is less today than supply side factors (Ball et al. 2022).

## 2.2 Review of Forecasting Methodologies

Economic forecasting has transitioned from basic structural models to time series methods of single time variables and has now shifted towards non linear machine learning algorithems.

### 2.2.1 Classical Statistical Models: Models - ARIMA and SARIMA

The Box Jenkins method has been the standard for single variance time series forecasting for a long time. The ARIMA model states that values in the future depened upon future values as well as past forecast errors. Whereas when there are seasons in the data, as seen with inflation, the seasonal version SARIMA is used.

- Strengths: These models are good at captuuring straight line trend and regular seasonal trends. They are easy to understand and require lesser data compared to deep learning. Hyndman and Athanasopoulos (2018) say that they should serve as good baselines againsts any kind of forecast.

- Limitations: ARIMA is linear and needs to consider a single variable at a time. It often cannot do anything with complex, non linear interactions between a lot of other variables. It also assumes that the data is stable (stationary), which often is not the case during times of crisis. Makridakis et al. (2018) conclude that statistical models are quite good on staedy data but fail to capture sudden changes in the economy such as those of 2008 or 2020.

2.2.2 Component-Based Models: Facebook Prophet

Due to the limitations of ARIMA, in particular with missing data and multiple seasons, Meta (Facebook) developed Prophet.

- Methodology: Prophet is an additive regression model that separatse a series into trend, seasonal and holiday componentse. It is good with outliers and making it easier to add additional variables.

- Relevance: Prophet is quite popular when it comes to business analytics as it works right away. However, according to studies, it may not be the best for complex macroeconomic data. Its simple additive structure can have trouble with highly volatile, nonlinear relationships wherever they don't fit in with the normal trend patterns.

### 2.2.3 Advanced Data Analytics: Learning from the Random Forest: Machine Learning

The greatest change in forecasting study is that the people are now practicing Machine Learning (ML) methods. Unlike the traditional statistical models that rely on some mathematical rule sets, ML algorithems look for patterns that lie right from the data.

\* Random Forests: Breiman (2001) has invented Random Forestes by creating a bunch of decision trees alltogether. It is great for economic forecasting because it does not require assuming anything about the way the data is distributed (it is non parametric) and can pick up trickey, non linear relationships between variables (the effect, say, of high oil prices and low interest rates combined on the economy).

\* Empirical Evidence: One of the key practical studies found in the literature was carrieed out by Medeiros et al. (2019) on forecasting US Inflation using ML methods versus the classic ones. They demonstrated that Randome Forests typically did better compared to AR and ARIMA models speciffrically when the data set had plenty of outside variables. Chakraborty and Joseph 2017 found similar results and stated that ML models operated by central banks were better at identifying non linear changes in the economy.

\* The "Lag" Technique (Feature Engineering): There is a key spect of difference in ML Forecasting, I need to create special features. Kuhn and Johnson (2013) note that regular regression models do not necessarily know anything about "time." To make them good to forecast, I need to transform the data using "Lag Features" (for example, using values from $t-1$, $t-3$, $t-12$ as predicters). This allows the model to learn how past events affect future events, thus giving the model a sort of "memory" like ARIMA, but with a non linear power.

## 2.3 Determination of Research Gaps

Even though there is lot of work on inflation forecasting, there are some important gaps which this project will try to fill:

1. Post-2020 Volatility: Most classical research (such as Stock & Watson, 2003; Medeiros, 2019), for example, takes information from before the pandemic of 2020. The economy after 2020 had new problems like supply chains being broke and such huge spending by the government, which creates "a structure break" in the way economy works (Ng, 2021). I need to see whether models developed on old, stable data, may still work in this new and massivelly unstable period (2022-2024).

2. Comparative Analysis of Prophet in Macroeconnomics Although ARIMA and ML are so frequently compared, there have been few studies in which Prophet is tested at the same level as classic models for macro data. Prophet is big in business and not big in academic macroeconomics. This study thus will facilitate the gap by comparing it directly with SARIMA and Random Forest.

3. The "Decision Support" Gap Most econometric papers only address a reduction in error numbers (RMSE, for example). There is not much research linking accuracy of forecasting with utility in business. Power (2002) and Turban et al. (2014) hold that all the accuracy of a model is not at all useful to managers if they cannot understand or use it for planning scenarios. This project will not only forecast but also design a Decision Support System (Dashboard) that will transform the technnical predictions into useful business information, according to the visualization ideas of Few (2006).

## 2.4 Summary

The information in the literatture provides that though the traditional models, like the SARIMA, offer a good base, the increasing complexity of the inflation factors of the economy makes Machine Learning methods, like the Random Forest, more appaeling, provided that I properly build features with the right features. This project will employ these advanced techniques for the difficult post-2020 US economy and go further, to practical business decision support.

# Chapter 3: Methodology

## 3.1 Research Design: The CRISP-DM Model

This dissertation employs the Cross Industry Standard Process for Data Mining (CRISP DM) as the major method. CRISP DM is an approach that is structured and repaetable to make data projects reliable and repaetable. Since this study involves the comparison of complex forecasting models with respect to a real business problem, the emphasis on "Business Understanding" and "Evaluation" by CRISP DM is very useful.

There are six steps in the methodology:

1. Business Understanding I define why is it necessary to make an accurate estimate (prediction) of the inflation in order to minimize financial risk in the unstable economy after 2020 in the business.

2. Data Understanding I collect the macroeconomic indicetors and apply the Exploratory Data Analysis (EDA) to identify trends, saesonalities and relationships.

3. Data Preparation: I clean, combine, and transform the raw data in preparation to use it by statistical and machine learning models. Feature Engineering is also part of this step.

4. Modeling: I construct, fit and train 3 models(SARIMA Statistical, Prophet Additive, Random Forest Machine Learning).

5. Evaluation: i carefully compare the models using other errorr measures such as RMSE and MAE on a test set to determine the optimal method of forecasting.

6. Deployment: in this case design the conceptual Decision Support System (DSS) dashboard in which business users are able to use the findings.

## 3.2 Data Collection

### 3.2.1 Chosen data and selection criteria

The primary dataset is taken from the dataset called 'Inflation Forecasting Dataset' on Kaggle which pulls official data from Federal Reserve Bank of St. Louis (FRED) (Federal Reserve Bank of St. Louis, 2024). FRED is known for the reliability of US economic time series data.

I selected this data set for the following three reasons:

- Relevance: It includes vital macroeconomic indicators which are said by the literature to have driven inflation including monetary policy, factors driving costs and changes in the labor market.

- Time Span: The data span 24 years from January 2000 to December 2024 i.e. 300 monthly points. This period encompassess numerous economic phases an economic bubble of dot coms, the 2008 economic crisis, steady growth of the 2010s, and the volatile post 2020 economic pandemic-so the models could be tested against large changes in the economy.

- Frequency: Monthly data is a good middle ground, there is enough data to help train a machine learning algorithem, but there is less noise, which is good for medium term planning.

### 3.2.2 Variable Description

The target variable in the set has five predictors. Our choice of them is based on economic theory:

- Consumer Price Index (CPI) / Inflation Rate (Target): The year on year change in CPI which is the key metric the Fed uses to measure inflation.

- Federal Funds Rate: Is the nightly interest rate between banks that the Fed uses to control inflation.

- Money Supply M2: A broad measure of money in circulation, quickere growth of M2 is likely to predict long term inflation.

- WTI Crude Oil Price: The standard price for crude oil Energy price and costs for many industries can cause an increase in the price of consumers.

- Producer Price Index (PPI): Change in prices, on average, producers receive for their goods and this is an early warning indicator for consumer inflation.

- Unemployment Rate: Reflectes pressure for demand pull inflation, as explained by Phillips Curve.

## 3.3 Process Data Preprocessing and Transformation

Raw economic data however, is often not ready for modeling. I used Python and the Pandas library for cleaning the data to a large extent so as to make the data high quality and ready for models.

### 3.3.1. Cleaning and integrating data is the task performed in

The initial data was contained in six different CSV files. I wrote a custom python pipeline to combine them:

1. Date Standardization: All the date columns were converted to datetime objects to be used as a common index.

2. Merging: The data frame of 6 were mergged in 1 master data frame with the inner join on the date index. This is done to keep only those months where all six variables are present. mismattched

3. Handling Missing Values Year over year inflation generates missing values for the first 12 months. I removed these rows so as to not dissrupt the completeness of the dataset for training.

### 3.3.2 Feature Engineering (Preventing Data Leakage)

Time series forecasting has the risk of using futare data unintentionally, which I refer to as data leakage. Is handled with two approaches on our part:

1. Lag Features for Machine Learning For models such as Random Forest I included lag columns for each feature, for t - 1, t - 3, t - 6, t - 12. This allows the model to train for any delayed effects without the possibility of bringing in future data that slipped in during the process.

2. Shifted Regressors for Prophet: Prophet is not able to use the value from the month t because this value would not be known while making the predictions for month t. I used past information only and to maintain the realism of the forecast, I moved all the external regressors back in time by 1 month (t-1).

### 3.3.3 Statistical Validation(Stationarity)

Time series models such as ARIMA require that the data be stationery that the average and spraed of the data do not change over time. To check this I ran Augmented Dickey Fuller (ADF) Test on inflation series.

\* Method: If the p value from the test was higher than 0.05 then null hypothesis was kept i.e., series is not stationary.

\* Result: Result of the first test was that the series was not stationary. I therefore differenced the data once (d = 1) during the ARIMA modeling in order to level the mean and to make this model reliable (Hyndman and Athanasopoulos, 2018).

## 3.4 Modeling Strategy

### 3.4.1 Train‑Test Split

To simulate the real world, and not cheating this way, I separate the data according to time, instead of randomly order.

\* Training Set (2000 - 2021): used to teach the models about the patterns for the past.

\* Testing Set (2022 - 2024): A 36-month block that will only be kept separate to be used during final evaluation. This split was chosen to see how well the models deal with the post COVID high inflation period, which is the result of a sharpe change, from a stable 2010s experrience.

### 3.4.2 Selection of Algorithm and Its Implementation

I compared three different styles of models:

1. SARIMA ( Seasonal Auto Regressive Integrated Moving Average)\*\*:

\* Type:Classic statistical model.

\* Implementation: auto\_arima function of pmdarima library is used to find the best parameters (p, d, q) and seasonal ones (P, D, Q)12 automaticelly by minimizing AIC. This eliminattes human biological prejudice and selects the easiest good model.

2. \*\*Facebook Prophet\*\*

\* Type: Modern Type, namely additive regression model.

\* Implementation: Prophet breaks the series into trend, seasonality and holiday parts. I introduced some additional variables such as Oil and M2 as linear variables using add regressor. The shiftted values were used to avoid data laekage.

3. \*\*Random Forest Regressor\*\*

\* Type: Ensemble machine learning model.

\* Implementation Trained on the engineered delayhed dataset.

\* Optimization: I optimized the number of trees and depth using grid search but TimeSeriesSplit (five expanding windows) instead of the regular k fold cross validation to ensure that trainning data were from the past and validation from the future to avoid the risk of leakage and overfitting (Bergstra and Bengio, 2012).

## 3.5 Evaluation Metrics

In order to objectively measure success, I computed two metrics of errorr on the test set:

1. \*\*Root Mean Squared Error (RMSE)\*\*

($RMSE= \sqrt{\frac{1}{n}\sum\_{i=1}{n}(y\_i - y\_i}\hat(y\_))$

RMSE was chosen because it also penalizes the large mistakes more and this is important in inflation forecasting which a big mistake is costlier than a small mistake.

2. \*\*Mean Absolute Error (MAE)\*\*

$MAE = \frac{1}{n}\sum\_{i=1}^{n}|y\_i - \hat{y}\_i|$

MAE is a good tool providing average errorr in percentage points, and is therefore easy to understand by non technical people.

The model which has least RMSE value on the unseen test data set will be considered the best one.

# Chapter 4: EDA

## 4.1 Exploratory data analysis (EDA)

Before we began with the predictive modelling I performed a holistic Exploratory Data Analysis (EDA) of the combined data. This step is essential to understand the form of the time series, detect any strange patternes or any major changes, and inspect if the data conform to assummptions for fitting models such as ARIMA. The data consists of 300 monthly observations from January 2000 to December 2024 and includes six important macroeconomic indicators namely, Consumer Price Index (Inflation), Federal Funds Rate, M2 Money Supply, WTI Crude Oil Price, Producer Price Index (PPI), and Unemployment Rate.

### 4.1.1 Trends Analysis and Structural Breaks

The first part of the analysis was a visual examination of the time series plots for inflation and major predictors of inflation. Seeing the plots helps us to spot long term trends and "structural breaks" times when the economy does things very differently.

The data revaels three different time periods in the economy:

1. Pre Crisis Stabilitty 2000 - 2007 Inflation moved moderately in the direction of normal business cycles.

2. Financial Crisis Shock (2008-2009): Towards the end of 2008 a sharp downfall is visible. This break is associated with the collapse of the housing market and the global recession: there is a sharp reduction in demand. This is a crucial period for models to be trained on in terms of learning how the economy works during a deep downturn.

3. Post Pandemicsurge (2020-2024): The biggest feature is a jump starting early 2021 and peaking mid 2024. Inflation rose to levels not experienced in forty years. This volatility was driven by supply chain disruption as a result of the lockdown caused by Covid 19, surprised consumer demand and the strong economic stimuluse.

This is a visual check of the fact that if we used a simple linaer model to model these this would not be accurate, as the extremes would not be modeled. The volatility "clustering" experienced after 2020 justifies the use of complex Machine Learning algorithms (such as Random Forest) that are able to take into account non linear changes to a greater extent than simple linaer preeddictions.

Exogenous Variables Analysis: Similar structural breaks occurred in the predictor variables. The M2 Money Supply plot provides a huge jump in 2020, which reflects the massive injjection of liquidity by the Fed. Meanwhile, WTI Crude Oil Prices were known to be highly volatile as the price of oil dropped significantly in 2020 only to surge to multi year highs in 2022 as a result of geopolitical tenssions. The correspondence between these spikes and inflation has a high predictive potential.

### 4.1.2 Statistical Diagnostics: Testing for Stationarity

While the visual check is suggestive of the non almost stationary, we must rely on formal tests. I performed the Augmented Dickey Fuller (ADF) test for the inflation series to determine whether there is a unit root in the series. This is required for the ARIMA modeling which assumes that the mean and variance remain constant over time.

Hypothesis:

H0 (null): The time series is non stationary.

Notes: - H1 (alternative): The time series will be stationary.

Test Results:

- ADF Statistic: -2.84

- p-value: 0.052

- Critical Values: 1% (-3.45), 5% (-2.87), 10% (-2.57)

Interpretattion: Since p -- values are slightly more than 0.05, we cannot reject the null hypothesis at the 5% level. This confirms that the series of raw inflation is non Stationary.

Implication for Modeling This result implies that we need differencing in order to stabillize the mean. I transform the data by subtracting one observation from the previous observation (y t - y t - 1). The auto arima algorithem has been configured to automatically discover the optimal differencing order, which for the process was d=1 (first order differencing).

### 4.1.3 Time Series Decomposition

In order to extract the underlying signal from noise, the inflation series was decomposed into Trend, Seasonality and Residduals by using an additive model.

1. Trend Component: The trend line eliminates the short term noise and indicates the general tendency of the economy. It shows a steady increase of prices in 2021 (apart from monthly fluctuations).

2. Seasonal Component: There is a strong 12 month seasonal component of decomposition. Inflation jumps in some months typically when people spend more on holidays in Q4, and energy consummption in summertime and wintertime , but falls in others.

3. Residual Component: The residual component or the errorrf (after I removed the trend and season) high variability especially in 2008 and 2022. This means while seasonality is responsible for the change in normal, the abnormal shocks (like the pandemic) are caused by outside factors that are not captured by the factor of time.

Insight: It is the strong seasonality that means that a standard ARIMA model is not enough. To account for these yearly cycles irequire the Seasonal ARIMA (SARIMA) model and a seasonal period of m=12.

### 4.1.4 Correlation Analysis and Feature Selection

I measured the linear correlational relationships between inflation and five external factors using a Pearson correlation matrrix and a haetmap. This step is helpful for selecting the most useful variables for the model.

Statistical Summary:

\* Producer Price Index (PPI): Is correlated with the strongest positive relationship (r approx. 0.65) to consumer inflation. This provides support for the Cost Push Theory and suggests that higher factory gate prices are generally transferred to consumers. PPI is, therefore, a good leading indicator.

\* WTI Crude Oil Prices: Strong (+0.55 moderate) positive relationship. Because oil is required for transport and manufacturing, changes in the price of oil diffussed through the economy. The correlation confirms that oil price swings are largely the cause of headline inflation.

\* M2 Money Supply: Has a Positive Relationship, in Line with Quantity Theory of Money It implies that the money injections by the central bank contribute to the increase in prices over time.

\* Unemployment Rate: Shows a weak negative relationship (r= approx. -0.20). This fits in with the Phillips Curve idea that the lower the amount of unemployment, the more inflation there is, but the relationship is much waeker than the supply side factors. It means that the inflation of the day is more influenced by supply forces such as oil and PPI rather than by the condition of the labor market.

### 4.1.5 Autocorrelation Analysis (ACF/PACF)

We investigated the effect of past values of inflation on future values through ACF and PACF plots. These plots provide the memory of the series.

\* ACF Plot: The fall off is slow, hence not a stationnary series. Big jumps at Lag 12 confirm high levels of yearly seasonality that I observed earlier in the decomposition.

\* PACF Plot: Partial correlation is decreased sharply after 1st lag. This implies that an AR(1) model (only including the previous month's inflation) is a good fit model for predicting the current month before introducing other variables.

### 4.1.6 Summary of EDA Findings

The Exploratory Data Analysis provides good basis for modeling. It shows that the inflation in US is complex, non stationary and is driven by both high internal seasonality and major external shocks from PPI and Oil. The results from the tests are that I require differensing (delta =1) and a 12 month seasonal component (m=12) in the ARIMA model. The high correlations with external variables support the construction of a Machine Learning model connsisting of lagged oil and PPI values, which should give a better prediction of accuracy.

# Chapter 5: Implementation of Algorithms and Models

## 5.1 General Overview of Technical Architecture

This chapter describes how the forecasting system was construucted, working all the way from the ideas in the Methodology chapter to the actual code. The project was written with python and run using Google Colab. Google Colab was chosen since it already has the necessary data science libraries and already has free GPU power for the training of the model. The code was written in a modular, functional style so it could be repeated and scaled up as easy as possible to follow possible good software engineerinng practices.

The technical workflow of this had three parts:

1. Data Pipeline Engineering Data pipeline engineers are responsibble for reading raw CSV files, cleaning and transforming these data into a single time series format.

2. Algorithm Development: Set up and train three types of forecasting models SARIMA (statistical), Prophet (additive), and Random Forest (machine learning).

3. Optimization and Evaluation Systematically optimize the model settings and evaluate the performance on a separate hold out set.

## 5.2 Algorithm and the Development of a Model

The comparisson of the research involves three very different forecasting methods. Each model is representing a different way of thinking about time series data: classic stats, modern component based forecasting, and machine learning.

### 5.2.1 Model 1: Seasonal Auto Regressive Integrated Moving Average (SARIMA)

Description and Tooling: SARIMA is the usual statistical standard expected of a single variable time series forecast. This looks at the trend, seasonality, and how the values move together over time, of the data without making use of any outside variables. This provides a good standard by which to view how much additional information can be provided by other variables (such as oil prices).

Implemenntation Jusstification: I have used the auto arima function of pmdarima library. Unlike selecting ARIMA parameters manually based on plots, instead of selecting model parameters (p, d, q, P, D, Q) by hand, auto arima selects the best values for the parameters. This eliminates human bias and the baseline is made as strong as possible.

\*\[Stationarity Handling: The algorithm tests for stationarity using the Augmented Dickey Fuller test and determines the number of times (d) to differ the series to obtain stationarrity. This is very important as inflation data varies over long periods of time.

\* Seasonality: As the data is monthly based, the seasonal period m is taken as 12. The model looks for seasonal terms of AR and MA (P, Q), to captture yearly cycles such as holiday bumps in prices.

\* Optimization Criterion: The model searches step by step in order to get the lowest Akaike Information Criterion (AIC). AIC provides a balannce between model fit and complexity to help in deciding the best balance of model accuracy and simplicity.

Diagnostics: After the above training, I plot probing diagnostics to check if the residual (errors) are normally distributed and if the residual are uncorrelated, which is required for a valid statistical model.

### 5.2.2 Model 2: Facebook Prophet

Description and Tooling Prophet, made by the company Meta, is a modern additive regression model. It works well even if some data is missing and allows you to add some external factors in a comprehensible way. Prophet braeks the series in Trend, Seasonality, Holidays and Regressors making it more easy for business users to see what this different part do.

Implementation Justification: The model has been implemented using the prophet library. A key step was to avoid data leakage using future information that shouldn't be available in making future predictions.

\* Shifted Regressors (The Leakage Fix): For month t, I don't know the average oil price for month t yet , I know only for month t -1. So I wrote a preproccessing step that makes everything that is external go back to the previous month: Federal funds rate, M2, Oil Price, PPI, Unemployment. Prophet then goes on to predict inflation with these shiftted regressors.

\* Configuration: The model begins with interval\_width =0.95 to generate uncertainty bands to give decision makers a best case and worst case scenario.

\* Seasonality: The weekly and daily seasonality are switched off because the data is monthly; the yearly seasonality is switched on in order to capture long term cycles.

### 5.2.3 Model 3- Random Forest Regressor (Machine Learning)

Description and Tooling Random Forest is machine learning technique, it creates a lot of decision trees and an average of their predictions. It has the ability to capture complex, non linear relationships that simple linear models such as the ARIMA model may not capture.

Implementation Justiffication: Machine learning models do not typically account for time, considering each observation as somehow independent. For using Random Forest algorithm to the time series I have created a feature consideration pipeline using the pandas library.

The "Lag Feature" Strategy Basically what I did to turn this data into a supervised learning problem was to For each variable, I have made lagged variables from varying amounts of the past:

1. Lag 1 (t-1) for immediate effeects

2. Lag 3 (t‑3) for quarterly trends.

3. Lag 6 (t-6) and Lag 12 (t-12) to capture half year and yearly trends; These lags give the Random Forest a sort of memory by enabling it to learn delayed effects such as a Fed rate hike taking six months to make its effect on inflation.

\* Data Structure: The final training set contained over 30 engineered features obtained from the original 6 variables but provided the consumer data to the machine learning model for the machine to learn.

## 5.3 Optimization and Evaluation Process

Developing the models is only the first step. In order to enssure that the results were scientifically valid and statistically significant, I used a rigorous proccess of tuning and testing.

### 5.3.1 Optimization Strategy: Hyper Parameter Tuning.

For Machine Learning model, performance can dependent very much on "hyperparameters" settings which controls how the model learns (e.g. how deep decision trees can be grown. Try using the default settings and usually you will not get very good results.

\* Grid Search Cross [Validation]: For this, I have used GridSearchCV from the scikit learn module to look for the best settings. I created a list of potential values of some hyperparameters:

N estimators (Number of trees) Tested [100, 200] More trees will usually make the model more stable but it takes longer to calculate.

\* max\_depth (Tree complexity): Tested [10, 20, None]. Limiting depth prevents "overfitting" - a situation where the model learns the trainning data too well and cannot be generalized to new data (Bergstra & Bengio, 2012).

\* min\_samples\_split: Tested [2, 5].

\* Time Series Cross Validation: Normal random cross validation can't be applied for time series data because it will mean training a model on the future data. Instead I used TimeSeriesSplit which is a walk forward method. The data was divided into 5 growing windows. In each step the model trained using past data and tested on the next period. This simulates the behavior of real time forecasting and verifies that the selected hyperparameters work well in different economic times.

### 5.3.2 Evaluation Strategy: The "Fair Comparison"

In order to find the best model, I set up a strict comparison.

\* Common Test Set All three models (SARIMA, Prophet, Random Forest) were tested on same hold out set from January, 2022 to Dec, 2024. This time period was selected since it exhibits high volatility with post pandemic inflation jumps. Testing during this difficult time really gets to test the strength of the models.

\* Performance Metrics: The two standard error metrics I calculated are as:

\* Root Mean Squared Error (RMSE): The most important metric of selecting a model. RMSE: It is based on the square root of the mean of the squared differences between the predicted values and actual values. Because this is a squared error, the larger the mistakes, the higher the penalty. In the context of ecconomic forecasting, there is little implication of the scale of a mistake: a big timing error on inflation is much worse than small steady errors when it comes to business. Therefore the best model in terms of risk management is the one with the lowest RMSE (Hyndman & Athanasopoulos, 2018).

\* Mean Absolute Error (MAE): This represants a secondary view of the world as it reports the size of the average error in percentege terms. It is easier for non technical people to understand.

### 5.3.3 The Final Competition

The evaluation finished with a final "competition." The optimised versions of all the three models provided forecasts for 2022 to 2024. We graphed these forecasts against the actual inflation data to determine how well the forecast models aligned with the actual data movement (do these model forecast the crisis peak?) and I importantly examined the RMSE scores as well. This combination of visual and numerical proved to be a great way to get a complete picture of the performance of each model.

# Chapter 6: Results and Analysis

# 6.1 Introduction to Analysis

This chapter is used to share the actual the results from the modeling phase. They indicate that three different forecasting approaches SARIMA, using Prophet, and Random Forest can satisfy the severe requiremments of the volatile test period for the years from January 2022 to December 2024. The analysis has a direct look at the main research questions: how accurate are the models, how useful are external variables and what do the results mean for strategy. All the commparisons were made on the same hold out test set for fairness (Hyndman & Athanasopoulos, 2018).

## 6.2 Model Performance and Model Optimization

During evaluation I checked how well each of the tuned models could reduce the prediction error. I mostly applied the Root Mean Squared Error (RMSE).

### 6.2.1 SARIMA Model Performance

The model of choice for the classic statistical baseline is the SARIMA model. It was tuned using the auto arima algorithem which automatically determined the simplest seasonal and non on seasonal parameters which produce the lowest Akaike Information Criterion (AIC).

\* Optimization Result: The algorithem has chosen the order SARIMA(p, d, q) x (P, D, Q)12, indicating the combination of autoregressive, differencing and moving average terms that are required to fit the past value of inflation.

\* Performance: The final model gave RMSE of 0.6028 and MAE of 0.5180 on the test data.

\* Model Diagnostics: ii used diagnostic plots to verify the assumptions of the model used. The residualse appeared roughly normal and not correlated, which means that the model fit statistical the data. However, on looking closely the residualse clustered in error on the 2022 peak suggesting the model did miss some of the biggest shocks.

### 6.2.2 Prophet Model Performance

Prophet is a new additive component model. I did one important fix: We shifted the external regressores by 1 month to avoid the use of future data (Taylor & Letham, 2018).

\* Performance: The performance of our model RMSE was 0.6544 and MAE were 0.5357 for our model.

\* Analysis: Prophet was the worst of all 3 Models. It is designed to cope with complex issues in terms of seasonality and trends, but it employs a simple linear relationship with the external regressors that failed to captare the sharp and non linear changes after 2021. The additive aspects oversimplified combined effects of supply and monetary shocks and so could not have matched the size of the inflation spike.

### 6.2.3 Random Forest (Machine Learning) Performance

The Random Forest Regressor is an example of a non Linear machine learning competitor. I constructed a lot of features (lagged variables), and used TimeSeriesSplit cross validation.

\* Optimization Process I only used the Grid Search on the Training data of 2000-2021 using TimeSeriesSplit. It was able to find the best hyper parameters (ex: n\_estimators=200, max\_depth=20). This approach ensured that were not laeking any future data and provided the most reliable settings.

\*Performance The tuned model of Random Forest gave RMSE: 0.2708 and MAE: 0.2287.

\* Discussion: This better performance, over 50% lower errorr than the benchmark of the SARIMA, shows that non linear algorithems are more suited to high volatility forecasting. The Random Forest's many trees are able to pick up the complex, not linear relationship between the pasts and the future inflation.

## 6.3 Comparison and Discussion of Models

### 6.3.1 Final Score board and Visual Comparison

Table 6.1: Comparison of the final model performance (test 3 years: 2022-2024)

Rank(Model Name,Type) = Model Name Model Type RMSE (Lower is Better) MAE (Lower is Better)

**Table 6.1: Final Model Performance Comparison (Test Set: 2022–2024)**

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|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Rank | Model Name | Model Type | RMSE (Lower is Better) | MAE (Lower is Better) |
| 1 (Winner) | **Random Forest** | Machine Learning | **0.2708** | **0.2287** |
| 2 | SARIMA | Statistical | 0.6028 | 0.5180 |
| 3 | Prophet | Component-Based | 0.6544 | 0.5357 |

A graph of a graph showing different colored lines

AI-generated content may be incorrect. Actual vs. Forecast Comparison (2022-2024)

The models are seen to agree with the real data. ARIMA and Prophet provide a nice line but they always fail to catch the big jump in inflation in 2022. Random Forest is close to the real numbers and captures the rapid incraese, as well as the subsequant decraese. This shows that using advanced feature engineering to handle the sudden economic changes.

### 6.3.2 Importance of Features and Economic Insight

One of the most useful items from the Random Forest model is the feature importance chart. It illustrates what is really causing recent inflation.

The chart tells us that it's lagged variables that are the biggest predictors. This is equivalent to the notion that past events influence the future (Kuhn & Johnson, 2013).

1. Oil\_Price\_Lag\_3: Price of crude oil of three months is the number 1 factor. This is in support of the "cost push" theory (Hamilton, 2009). Energy price shocks appear in consumer prices about a quarter of a year later.

2. PPI\_Lag\_1: Producer Price Index of last month is also very important. It shows that factory gate inflation is followed by consuumer inflation.

3. Inflation\_Lag\_12: The inflation in the past year is still relevant, but it is not as critical as the supply side shocks.

These results are suggestive that the inflation of 2022 to 2024 was not only driven by demand. That is a point of importance to policy makers and plannerrs.

## 6.4 Why fit Objectives and Problem Statement

The results provide the answer to the main goals of the project.

\* Objective 1 (Accuracy): The study reveals that Random Forest is the optimal method. Its low RMSE proves that non linear algorithems work better in volatile markets, which answers Research Question 1.

\* Objective 2 (Exogenous Value): Random Forest used all 5 outside variables (in lagged form) and performed better than the basic ARIMA model This indicates that exogenous indicators do provide value in answering Research Question 2.

\* Problem: A reduction of the forecasting error from 0.60 to 0.27 is a clear solution for the original problem of poor traditional models. Random Forest empowered to replace old static forecasts from reliable data driven ones.

These results provide a good foundation for the last part of the project: the development of a Decision Support System that uses the Random Forest model best predictions.

# Chapter 7: Business Insights and Recommendations

This chapter is the link between the detailed analysis in Chapter 4 and the business goals in Chapter 1. It makes it possible to convert the technnical finding that the Random Forest model had the lowest RMSE of 0.2708 into actionable insights in planning, risk management and operations. It's vital to link the needs of the business to analysis to construct an actual Decision Support System (DSS).

## 7.1 Validation of Non - Linearity in Forecasting

The main technical result Random Forest did better than SARIMA and Prophet , is confirming that non linearity is better suited for today's macroeconomicee forecasting than are linear models.

\* Analytics Concept: Random Forest is feasible due to its ability to model complex relationships and relationships that are not additive, such as the relationship between Fed Funds Rate and High Oil Prices. Simple models have difficulties managing both supply shocks and demand growth simultaneously.

\* Implication for Business: For companies, the trend charts or linear budgets are not sufficient and risky. Firms have to shift from static rules to flexible AI tools that can process a lot of data inputs simultaneously. This change is not optional and is a necessary investment to remain compettitive in volatile markets.

## 7.2 The Importance of the Value Proposition of Feature Engineering

The most important reason, Random Forest outperforms other models is the aspect of Feature Engineering, i.e., creating lagged variables (t-1, t-3, t-6, t-12).

Analytics Concept: Lagging Features Convert 1 Variable series to Multi Variable learnning problem. It provides the model with "memory" to learn the time delay in economics systems. TimeSeriesSplit is used to ensure that the model is learning actual patternns and not trickes in over fitting.

\* Implication for Business: This indicates that data scientists can provide real value if they can remodel the data. The force is in the alteration of the data and not the algorithem itself. Companies should hire in people with skills in data transformation and engineering rather than just buying in more complex models.

## 7.3 Useful Insights Based on Feature Importance

The feature importance study, which identified the top predictores in the winning Random Forest model, provides direct information for business strategy.

Insight 1: Rising Supplies Side Dominance - Lagging

The two highest features were always lagged Producer Price Index (PPI) and lagged WTI Crude Oil Price, confirming that cost push inflation is both domenant after 2020.

\* Actionable Insight: The model does indicate there is a distinct three month lag between the increase in oil prices and its largest impact on overall inflation.

\* Implications for Supply Chain Management: Manager should look at PPI and Oil Price every day not only consumer demand. A great increase in Oil Price today means that by 3 months price and contract may change. Companies have the time in that period to freezee in shipping costs, renegotiate with suppliers, or to stock up internally to insure against the coming price hike.

Insight 2: Failed to get your own way? became apparent in the form of the Phillips Curve, which shows the relationship between weges and unemployment in an economy or community.

Unemployment Rate was ranked far down the list of important factors.

\* Actionable Insight: Leaders should not rely too heavily on tightness of the labour market when thinking about predicting short and medium term price changes Immediate profit risks are those that come from raw material prices and energy fluctuations, and not wagges.

\* Implications for Financial Planning: Although wage developments are still a key factor for HR, finance organisations should look to commodity price volatility (PPI/Oil) as their key guide for revenue forecasting and budgetting for the following year.

## 7.4 Recommendations to Stakeholders

Based on the numbars that we found, and on business lessons that we have learnt, the following ideas are proposed to people in different parts of the organisation:

### 7.4.1 Recommending Corporate Finance and Strategy Teams

1. Use AI Models in Finance Corporate finance should start using advanced machine learning models, especially Random Forest or similar tree based models for big riske calcullations. The goal is to reduce the level of forecast errorr from approximately 0.60 (using ARIMA) to approximately 0.27 (using Random Forest).

2. Switch to Flexible Budgets: Instead of year over year fixed budgets, change to a flexible, scenario based, planning system. The new Decision Support System (DSS) should test financial plans against various PPI and oil price changes and provide a range of potential results, rather than being a guess. This helps in protecting against inflation.

3. Collect Lag Information: Spend Time Tracking how long it takes for different economic indicators to show up (i.e. oil prices lag by 3 months, PPI by 1 month). This will convert lagging data into laeding indicators of use for strategy.

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### 7.4.2 Recommendations for Operational Teams and Supply Chain Teams

1. Make PPI a Key Metric/Treat issues with the Producer Price Index/PPI as one main KPI for Health of the Supply Chain. If PPI shows increases a lot in a month, immediately re-view supplier contracts and levels of stock.

2. Reduce Energy Risks: Because the oil price is a big factor, any companies that move or use a lot of energy in their operations should consider hedging (buying oil futures, for example, to lock in costs based on the Random Forest forecasts).

3. Check Inventory Levels: Take the help of very accurate Random Forest forecasts to plan the inventory. If the forecast is for a period of high inflation, it might be smart to buy more inventory this time around as storing goods might cost less than the expected price inflations.

### 7.4.3 Suggestions for Future research and Development

1. Try Deep Learning The currennt Random Forest is a good benchmarke to go by, but the future R&D should be to try and replace this with Deep Learning techniques like the LSTM network which speciallizes in laerning how to learn like patterns over time and may improve the accuracy slightly.

2. Integrate Real Time Data The last update to the DSS should be linking it to live FRED APIs such that the model can be updated to reflect the latest monthly data. This will make the prototype a fully operational risk management tool.

### 7.4.4 The Decision Support System (Dashboard) figures:

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# Chapter 8 : Conclusion

## 8.1 Summary of the Project and Important Findings

This dissertation was aimed at the construction of a strong AI system that had a predictive ability of determmining inflation in the United States. It used the monthly data from years 2000 to 2024 for six major economice indicators such as: Consumer Price Index (CPI), Federal Funds Rate, Money Supply M2, WTI Crude Oil Prices, Producer Price Index (PPI) and Unemployment Rate. Using the CRISP-DM framework, the three different forecasting techniques used were the classic statistical model of SARIMA, a modern technique of the Prophet model, and a machine learning technique of Random Forest.

The results show that the best was Random Forest. With engineered lagged features it achieved a lowest root mean square error (RMSE) of 0.2708 on the hold out test set. This is much better than SARIMA (RMSE 0.6028) and Prophet (RMSE 0.6544) which riduce the forecast errorr of more than half.

These results confirm the ability of non linear machine learning methods to capture complex patterns in the data more than linear ones. The feature importance analysis showed that former oil prices and former PPI were the most powerful predictors of future inflation, which is a result of cost push supply side forces being predominant during the study period.

## 8.2 Assignment of Relevance and Business Implications

The study is not important for academics only , there is real business value. The increased accuracy of the ML model implies that firms should be abandoning the simple trend extrapollation. They require dynamic, using many leading indicators, AI driven forecasting tools. The three month delay in raflecting the impact of oil prices does provide a very clear window for supply chain managers. By tracking today's energy markets, companies can anticipate with a high degree of certainty what inflation pressuure they will be exposed to in the next quarter in order to successfully hedge, adjust inventory, and set prices. The proposed Decision Support System Dashboard makes these analytics in a user friendly interface for planning scenarios.

## 8.3 Limitations of the Study

Several limitations can be mentioned:

- Data Frequency: The data frequency used in the analysis is monthly, normal for macroeconomice related forecasting, but may not capture short term volatility, which is important to quick trading deccisions.

- Geographic Scope: The study only covered the US economy. The relationships found , such as the importance of oil prices , may not be true in other countries with different economic structures.

- Secondary Data Reliance: The quality and history of revisions of the official FRED data used will determine the quality of the forecast.

## 8.4 Suggestions for Future Work

There are a number of ways future research can build on this work:

- Deep Learning Integration: Implementing Long Short Term Memory (LSTM) networks or Transformer models may potentially learn even more complex long term dependencies thereby decreasing the forecast error even more.

- Sentiment Analysis: Injecting "soft" data such as news sentiment or social media data on inflation expectations could help improve the accuracy of the model in predicting changes in economice behavior.

- Real time deployment: How to raelise the conceptual design without too many steps and investment in building a full web based application using tools like Streamlit or Dash would bring immediate value to users, including the ability of real time integration with live economic data feeds.

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# Appendices

1.Visuals:

A black text on a white background

AI-generated content may be incorrect.A graph of a graph showing different colored lines

AI-generated content may be incorrect.A graph with a number of drivers

AI-generated content may be incorrect.A screen shot of a graph

AI-generated content may be incorrect.A collage of graphs and diagrams

AI-generated content may be incorrect.A graph of a function

AI-generated content may be incorrect.A graph showing a number of blue lines

AI-generated content may be incorrect.

A graph with a line going up

AI-generated content may be incorrect.

A graph with a line in the middle

AI-generated content may be incorrect.   
  
A screenshot of a graph

AI-generated content may be incorrect.A screenshot of a graph

AI-generated content may be incorrect.A graph on a white background

AI-generated content may be incorrect.A graph of different colored lines

AI-generated content may be incorrect.

2. Github repository link: <https://github.com/rozi2300/Inflation-Forecasting-and-Economic-Decision-Support-System>

3. Usage of AI:A screenshot of a chat

AI-generated content may be incorrect.A screenshot of a computer

AI-generated content may be incorrect.A screenshot of a computer

AI-generated content may be incorrect.A screenshot of a chat

AI-generated content may be incorrect.A screenshot of a computer

AI-generated content may be incorrect.A screenshot of a chat

AI-generated content may be incorrect.A screenshot of a chat

AI-generated content may be incorrect.A screenshot of a paper

AI-generated content may be incorrect.A screenshot of a computer

AI-generated content may be incorrect.A screenshot of a computer

AI-generated content may be incorrect.