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An Analysis of Drivers of the Federal Funds Rate

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Abstract. The Federal Funds Rate (FFR) is a tool used by the Federal Reserve to set monetary policy on borrowing costs for consumers and businesses. The Fed's primary motivation with the FFR is to control macroeconomic factors such as inflation and unemployment. Over time, policy stances for the Fed have varied in response to events such as the Great Recession, and more recently the COVID-19 pandemic. In light of the Fed's actions following these events, there is intensified debate over which macroeconomic factors should be prioritized, and what magnitude of change is sufficient to warrant action. Additionally, when action is taken (e.g., an increase in FFR), it is important to understand whether such action is consistent with historical trends based on the data, or whether the change resulted from a shift in policy stance. This research provides quantitative analysis and insight into the factors that drive the Fed to act. It also compares various time series modeling techniques to identify the most effective method and combination of variables for predicting the FFR.

1 Introduction

The Federal Funds Rate (FFR) is a tool used by the Federal Reserve (Fed) to set borrowing costs for consumers and businesses. It plays a significant role in shaping the US economy and sets the tone for growth across all sectors. Generally, when the FFR is lowered, economic growth accelerates through increased investment and spending. Conversely, raising the FFR tends to slow economic growth (e.g., decrease in spending) to bring down inflation. These changes have implications for consumer households and businesses regarding spending, investing, and financial planning.

Fluctuations in the FFR have been dramatic since the COVID-19 pandemic. From February to April 2020, the FFR dropped from 1.58% to 0.05% (Statista, 2024). This decline is representative of the Fed's action to stimulate the economy in response to the economic fallout of the pandemic. Soon after, inflationary pressures took hold with sudden spikes in prices of food, energy, and new and used automobiles (Bernanke, et. al 2023). More recently, the Fed has been forced to move in the opposite direction to slow spending with an FFR of 5.33% in February 2024 (Statista, 2024).

Considering that the implications of changes in the FFR are significant and wide-ranging, it is important to understand the economic indicators or drivers that influence the Federal Reserve to act and examine the effects of rate changes on the economy.

Monetary policy driven by the Taylor Rule[1] lends insight into the drivers of rate changes and the Fed's goal of economic stabilization from a formulaic perspective (Hamilton, et al., 2000). The Fed's dual mandate of employment and price stability explains reasons for the Fed to act. Bernanke (1992) maintains that the Fed's policy should be focused on targets such as unemployment and inflation. These two targets will be analyzed in the current study as key drivers of change in the FFR.

Inflation is perhaps the metric of the highest importance for the Fed. Its target has remained steady at around 2% for the past decade (Croushore, et al., 2019). In response to the sudden increase in unemployment brought on from the COVID-19 pandemic, a sudden policy change was made evident in 2020 when Fed Chair Jerome Powell announced a loosened target allowing the inflation rate to rise moderately above 2%. What followed was a sudden rise in prices as measured by the Consumer Price Index (CPI) with an inflation rate of 1.2% in 2020 and climbing to a peak of 9.1% in 2022 (Statista, 2024). As noted, the FFR has increased significantly over the past 2 years, a signal of the Fed's response to controlling inflation. The recent upswings and pressures on household expenses have gained much attention in the media.

The unemployment rate represents the health of the labor market and is a critical measure of the overall economy. Historically, high unemployment leads the Fed to lower the FFR. When interest rates are low, businesses have more access to capital, allowing them to grow and expand. As a result, they expand and hire more people. The COVID-19 pandemic led to a high unemployment rate of 8.1% in 2020. This was followed by a strong economic rebound in the labor force with record-low unemployment levels down to 3.6% in 2023 (Statista, 2024). Over the past two decades, increases in unemployment tended to be sharp and dramatic, while decreases were observed to occur more gradually. The Great Recession is particularly telling with the unemployment rate growing from 4.6% in 2007 to 9.3% in 2009. The Fed was swift to act as demonstrated by the FFR being held at nearly 0% from 2009 through 2016. Throughout this period, the unemployment rate gradually decreased to close to its pre-crash level of 4.7% by the end of 2016 (Statista, 2024).

Consistent with economic theory regarding inflation and unemployment, research indicates that the FFR's predictive significance for the economy is superior to other monetary indicators (Bernanke, et al., 1992). The unique impacts of FFR on spending across industries as part of macroeconomic models (e.g., home buying) are important factors that influence the overall economy. For unemployment, a more granular approach to understanding the FFR's impacts demonstrates variations of time and magnitude across sectors (Williams, R. et al., 2004).

Time-series methods are widely used in economic forecasting and present an attractive option for examining past patterns of the relationship between inflation, unemployment, and changes in FFR. This includes an analysis of certain drivers as triggers of change and their magnitude. Hamilton (2000) focuses on questions related to when and how the Fed decides to change the FFR. This study compares the autoregressive conditional duration (ACD) model and the autoregressive conditional

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[1] The Taylor Rule was proposed in 1992 by American economist John B. Taylor. The formula suggests that the Fed should adjust short-term interest rates in response to inflation and GDP.

hazard (ACH) model. Hamilton's ACH framework performed well in forecasting the probability of changes in the FFR target, specifically in the short term. By accurately predicting FFR targets, businesses can make more informed and strategic decisions to assist in their financial planning.

Based on the initial data exploration across a variety of metrics, new and emerging patterns are evident starting in 2020. For instance, producer price inflation, which measures the change in the price level for product manufacturers and service suppliers, shows a downward trend following a spike in 2021. However, consumer inflation, both overall and core (excluding volatile food and energy prices), remains at its highest level since the 1980s. Both metrics at their recent peak likely contributed to the Fed's recent action to increase the FFR. In contrast, overall commodity prices have increased, and food prices have gone up substantially in recent times. Also, iron prices have spiked along with an overall increase in coal prices. In response to such significant increases in inflation, the Fed has been especially active recently in bringing down inflation with a soft landing that avoids recession.

Based on the data, the unemployment rate remains low compared to COVID-era peaks, suggesting a strong labor market and recovery from the pandemic recession. However, with the recent tech layoffs and continued global tension, it would be helpful to understand the overall impact of these factors and any additional complexity they add to the overall picture. Though we do not investigate trends by sector in the current research, an exploration of data related to unemployment trends and payrolls by sector could provide valuable insights into the relationship between FFR and the unemployment rate.

This research aims to build on existing research findings and seeks to understand the short-term and long-term drivers of changes in the FFR. In this research, quantitative models are built to help predict changes in FFR. By further analyzing the drivers of changes in the FFR and the impact of economic indicators on Fed policy decisions, we can better understand and forecast unemployment rates, inflation, economic growth, and more.

2 Literature Review

A review of publications related to modeling the causes and effects of rate changes provides a basis for the analysis. In terms of variables, the analysis scope is centered around macroeconomic factors. Existing models developed in this context are reviewed before developing new time series and logistic regression with new and evolving datasets. This review will help provide context for the current research.

2.1 Drivers of FFR

Economic stabilization is central to the motivation of the Fed to raise or lower FFR as described by the Taylor rule (Hamilton, et al., 2002). Key aspects of the Taylor rule include inflation and output gap (the difference between the actual and potential level of gross domestic product). Additionally, the Federal Reserve's dual mandate, established by Congress in the 1970s, calls for a focus on maximum employment and price stability. Bernanke (1992) has maintained that the Fed's policy should be focused on targets such as unemployment and inflation.

Since 2012, the Fed's average annual inflation rate target has been 2% (Croushore, et al., 2019). According to Croushore's research, in the 2000s, the Fed switched from the consumer price index (CPI) to the personal consumption expenditures (PCE) price index as its main variable measuring inflation. The PCE Price Index tracks consumer spending and prices through business receipts used to calculate the gross domestic product (GDP). More recently in 2020, Jerome Powell announced that the Fed would loosen its policy to control inflation above 2% by allowing the FFR to rise moderately.

The output gap represents the level at which real GDP is above (positive output gap) or below (negative output gap) potential (St-Amant, et al., 1997). This metric is difficult to measure due to the challenge of estimating potential GDP. The Congressional Budget Office (CBO) defines potential GDP as the level of GDP reached when the economy is at full employment (Arnold, et al, 2004). While opinions on the usefulness of calculating potential GDP vary among economists, the CBO contends that it is a useful tool for managing short-term fiscal and monetary policy as well as serving as a basis for predicting 10-year GDP. Nominal GDP is an alternative to the proposed output gap in response to the 2008 financial crisis (Fackler, et al., 2020). The nominal GDP approach looks at GDP without adjusting for inflation.

2.2 Impacts of FFR

Research suggests that macroeconomic variables are highly impacted by changes in the FFR (Bernanke, et al., 1992). From Bernanke's study, a comparison between FFR and 4 other monetary indicators (M1, M2, treasury bill rate, bond rate) suggests the FFR's predictive significance to be superior among the indicators concerning industrial production, capacity utilization, employment, unemployment rate, housing starts, personal income, retail sales, consumption, and durable goods orders. The subject of inflation and employment/unemployment-related factors is consistent in the research studied for both drivers and impacts of FFR.

Bernanke's (1992) research demonstrates increases in the FFR are shown to have minimal effects on unemployment during the first two or three quarters of the first year of a rate change; however, increases are observed in the fourth quarter with peak unemployment occurring at the two-year mark. Bernanke and Gertler (1995) contend that declines in corporate cash flows and profits occur more quickly than cost reductions, leading to a corporate cash squeeze. This effect varies and depends on a firm's access to credit. Research conducted by Gertler and Gilchrist (1994) reinforces these findings with insight that large firms respond to tightening in monetary policy by increasing short-term borrowing and are less likely to make short-term cuts to production and employment.

2.3 Industry Sectors

Though this research doesn't analyze how changes in the FFR impact sectors, it is important because the effect of FFR changes does appear to vary for business types. The majority of outside research is focused on macroeconomic factors in aggregate, and insight is lacking on the impact of FFR at a more granular level, such as by sector

(Williams, R. et al., 2004). Williams' study revealed the impact of FFR at a disaggregated level varied by magnitude and time for unemployment in diverse sectors from manufacturing to services, and in occupations from laborer to manager. The most significant impacts from changes in FFR were in the construction and durable manufacturing sectors, which were impacted as much as two times more than in the service sector.

Understanding that Fed rate changes don't immediately spread through the economy and that the impact evolves and is influenced by external factors such as global events and technology changes suggests differential influence on industries. As illustrated by Bernanke and Blinder's (1992) study looking at industry-specific sensitivities, FFR rate increases (when borrowing gets expensive) strongly impact home buying activity (Housing and construction industry), financial sectors (higher rates benefit banks with greater margins between lending and deposit rates), automotive sales and production, and consumer discretionary spending (high-end retail, travel). Inversely, when energy prices, raw material prices, and unemployment statistics show a sharp increase (Bernanke & Blinder 1992), the Fed may intervene by changing the FFR rates to stabilize the economy.

2.4 Modeling FFR

Time-series modeling is widely used in economics and presents the most viable option for this analysis. Forecasts employing time series are often used in setting monetary and fiscal policies (e.g., FFR), state and local budgeting, financial management, and financial engineering (Stock et al., 2002). As the specific modeling techniques are considered, there are two key factors the model should be able to predict within the context of drivers: (1) an increase/decrease in the FFR and 2) short-term and long-term confidence intervals associated with rate changes.

At a high level, driver modeling should confirm that high inflation leads to an increase in the FFR to cool prices and bring down inflation. Given recent policy changes such as Powell's loosening of the FFR policy on interest rates, recent data could reveal a shift in the relationship between inflation and FFR changes. More specifically, findings could indicate that the lag between inflation and FFR changes has become longer (e.g., the Fed is slower to respond to inflation with FFR increases). In the context of unemployment, it should be confirmed that rising unemployment rates lead to a decline in the FFR. Recent events such as the Great Recession and COVID-19 can provide valuable context for any recent shifts in the Fed's response to macroeconomic changes. For instance, modeling could be used to determine whether the Fed is taking more immediate action with FFR changes in response to rising unemployment. Under these scenarios, tools such as cross-correlation functions are of key interest to detect lagged relationships in multivariate time series analysis.

While not covered in this research, a more comprehensive view of the relationship between FFR and inflation should involve a deep dive into the components of PCE. For example, factors such as housing are known to play a significant role in the inflation trend in recent years. A historic housing supply shortage has kept home prices and rents high, making it harder for the Fed to curb inflation. Homeowners with low mortgage rates put in place during the pandemic are reluctant to sell their homes, leading to a supply shortage keeping prices high. In terms of unemployment, determining which sectors represent the highest proportions of the labor force should provide more insight into unemployment impacts and the varying sensitivities between industries.

The first step in evaluating a time series realization is determining the stationarity of the dataset using the mean, variance, and covariance. While identifying which models to consider, univariate autoregressive integrated moving average (ARIMA), seasonal model (using factor tables), multivariate regression with lagged variables, vector autoregressive (VAR), or Multilayered Perceptron (MLP) (Zhang, Yong, et 2017) seem a good start.

Using ARIMA(p,d,q) to fit the data implies building AR, MA, and ARMA with different orders, and d as the difference term and p and q as the delay parameter (Li, Zhenwei, 2020). As modeling these data sets involves simultaneously modeling several time series, using Vector AR models is sensible because there is no distinction between dependent and independent variables. We thereby can establish a more robust model with interrelationships between variables impacting the forecasted values. For prediction models the key performance measure is precision. Each of these model's performance can be evaluated using root mean square error (RMSE) or average square error (ASE).

3 Methods

3.1 Data Collection

The key data sets used in this research are varied and publicly available online. The Federal Reserve Bank of St. Louis (FRED) is the primary FFR metric source. The Bureau of Economic Analysis (BEA) is the primary PCE metric source. Unemployment data is sourced through the Bureau of Labor Statistics (BLS). Data sets are downloaded in either CSV format or extracted using API endpoints using the API key. During the initial analysis, it was discovered that the date ranges and frequency were not uniform across all sources. Hence, the time series was aggregated to have uniform date ranges in alignment with the months beginning in February 1959 and ending in November 2023.

The FFR data is the federal funds effective rate in percentage format, monthly, and not seasonally adjusted. The observation date for this data begins in July 1954 and continues through November 2023. This data set is accessible for download in CSV format on the FRED website. As evidenced by the plot below, FFR rates were high in the 1980s, especially at the beginning of the decade in response to the Great Inflation event brought on in part by an energy crisis caused by the Arab oil embargo in the 1970s. In the years following the Great Inflation event, FFR rates were as high as 19.1% representing a value greater than 3 standard scores from the mean for the observed time of the data. The lowest years of FFR rates occurred more recently following the onset of COVID-19 in 2021, with rates as low as 0.05%, and a standard score of -1.3.

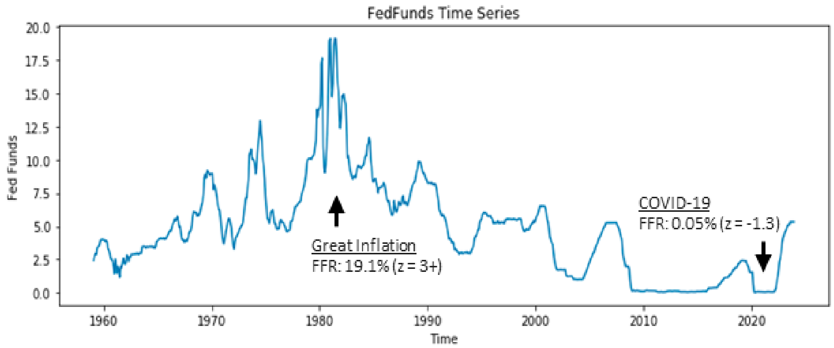

Figure 1: Federal Funds Rate from February 1959 to November 2023 (Month)

The PCE data is represented as the PCE Price Index. The observation date for this data begins in January 1959 and runs through November 2023. This data set is accessible for download in CSV format on the BEA website. One of the earliest high periods of the PCE Price Index occurred in the 1970s, specifically in February 1974 with a value of 1.2 and a standard score of 3.7. Additional peaks in the early 1980s aligned with the highest observed years of FFR. More recently in June 2022, the PCE Price Index reached 0.9 representing a standard score of 2.5.

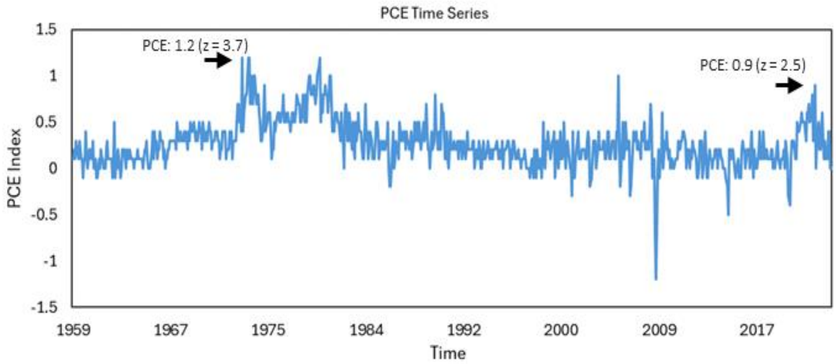

Figure 2: PCE Price Index from February 1959 to November 2023 (by Month)

The unemployment data is represented as the unemployment rate in percentage format, monthly, and seasonally adjusted. The observation date for this data begins in January 1948 and runs through November 2023. This data is accessible for download in CSV format on the BLS website. The early 1980s marked one of the highest periods of unemployment with rates hovering over 10%. This increase was preceded by a significant spike in the 4th quarter of 1976 when unemployment climbed to 10.8% representing a standard score of 3.0. From 2009 to 2011, the unemployment rate reached additional monthly highs ranging from 8% to 10%. More recently in 2020, the unemployment rate climbed again to an all-time high of 14.8% (z = 5.3) as observed from the analysis period.

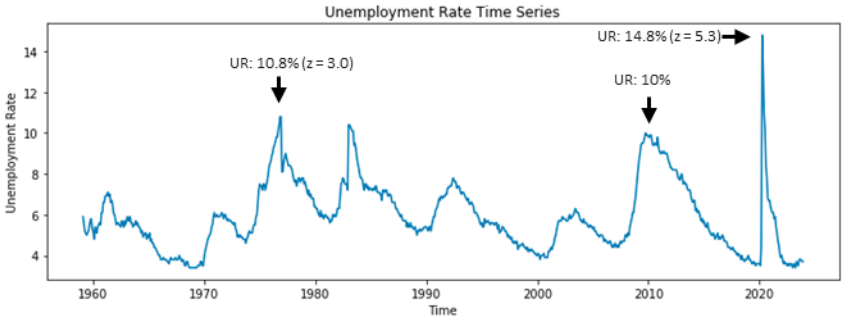

Figure 3: Unemployment Rate from February 1959 to November 2023 (by Month)

3.2 Model Preparation

Initially, the monthly data sets are investigated for any correlations (or lagged correlations) to understand how changes in each economic factor affect the federal funds rate and vice versa. Through exploratory data analysis, periods of high/low rates are identified along with insights into seasonality associated with federal funds rate changes. Additionally, outliers are investigated for linkage to key economic events or data issues stemming from erroneous measurements.

Time-based correlations of the FFR are uncovered through analysis of autocorrelations in the data. Key factors such as stationarity and seasonality are evaluated to provide further insight into these correlations. As observed through the ACF plot, there is a steady decline in correlations with increasing (longer) lag. This relationship suggests a trend in the FFR data with values spaced more closely in time. The data indicates a non-stationary series since the ACF plot below is "decaying" or decreasing. Non-stationarity in time series represents data that is less reliable when using past observations to predict future values.

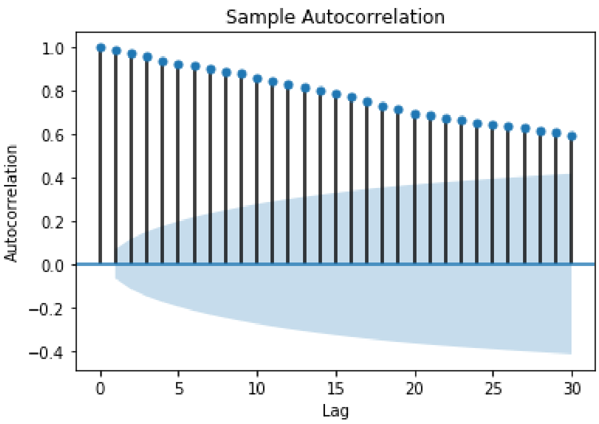

Figure 4: Visualization of ACF of FFR data

Considering the initial ACF plot (Figure 4) of the time series data on FFR indicates the data is non-stationary, a first difference transformation of the data is applied. The first difference transformation of the FFR data (Figure 5.1) is effective in making the time series stationary. The revised ACF plot (Figure 5.2) post-transformation of the data indicates a strong immediate correlation for lag 1. The p-value (p<0.001) from the ADF test on the differenced FFR time series data suggests strong evidence against the null hypothesis, suggesting stationary time series.

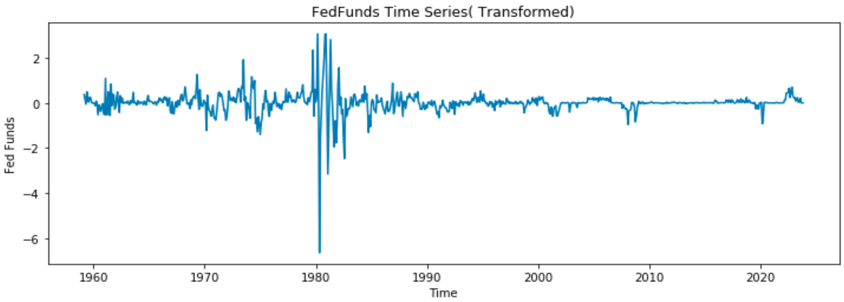

Figure 5.1: Visualization of Transformed (differenced) FFR data

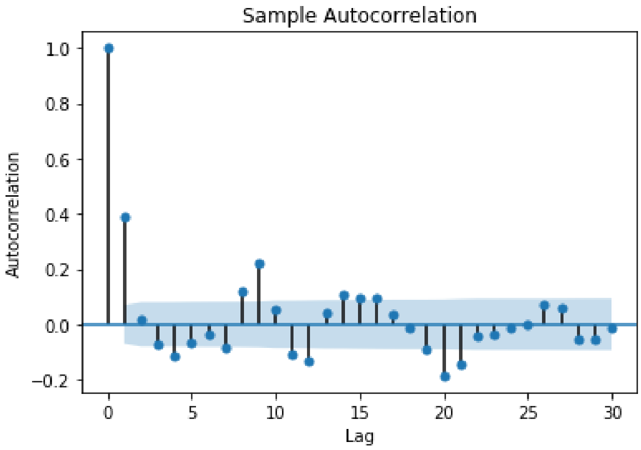

Figure 5.2: Visualization of ACF of FFR data (post-transformation)

The periodic behavior of the first differences in FFR data is revealed through spectral analysis. The spectral density plot provides insights into variance distribution across frequencies. Peaks in spectral density indicate the presence of cyclic patterns in FFR data.

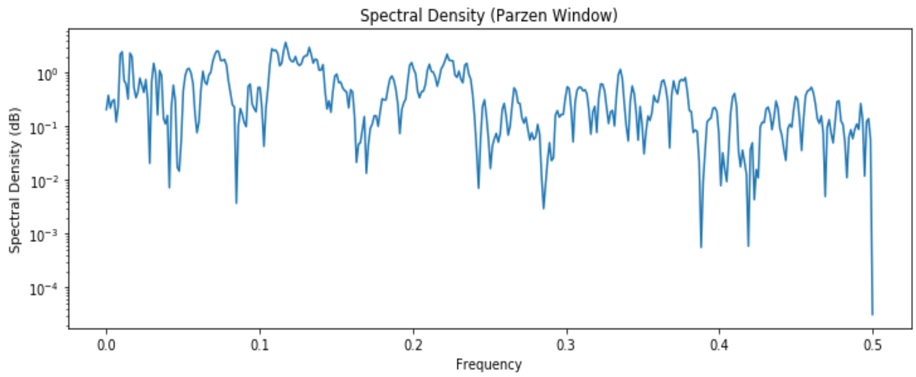

Figure 6: Visualization of Spectral Density (post-transformation)

3.3 Model Testing

A thorough examination of the drivers and impacts of the FFR calls for evaluating multiple time series-based models. Each model should provide unique insights into the FFR from different angles, whether it's through capturing historical patterns, analyzing macroeconomic relationships, forecasting future changes, or understanding the underlying market dynamics.

3.3.1 Multivariate Regression

Three multiple regression models are employed to capture the relationships and interactions between the FFR, the PCE price index, and the unemployment rate. These three models are used to perform an Ordinary Least Squares (OLS) regression analysis with the PCE price index, 'PCE', and the unemployment rate, 'UR', as independent variables. The first difference in FFR ('FEDFUNDS_DIFF') serves as the dependent variable. The first "standard" model performs an OLS regression on these variables without the transformation of independent variables. The second "trend" model is an extension of the first but incorporates a time trend variable into the model. This model attempts to capture any linear trend over time that might affect the FFR, in addition to the effects of 'PCE' and 'UR'. The third "lagged" model is performed with lagged variables used to predict the differences in the dependent variable.

For all three models, the relationship between the predictors ('PCE' and 'UR') and the dependent variable ('FEDFUNDS_DIFF') are analyzed to evaluate the parameters. Additionally, the models are tested based on goodness-of-fit and predictive performance.

3.3.2 Vector Autoregression (VAR)

As an alternative to multiple regression, the vector autoregression (VAR) model is used to capture the interdependencies of each variable with their past values. This method is widely employed in economics and finance because it more effectively models how different economic indicators influence each other. In comparison to multiple regression which involves a single equation, VAR uses multiple equations and can include multiple lags of all variables.

In this model, the past values for independent variables of 'PCE' and 'UR' are analyzed in combination with the past values for the dependent variable of 'FEDFUNDS_DIFF'. For VAR, the model is tested for performance based on the optimal lag order selection.

3.3.3 Multi-Layer Perceptron (MLP) Regressor

A more complex neural network approach known as Muti-Layer Perceptron (MLP) Regressor is more useful when modeling non-linear relationships in time series data. Given the challenging nature of forecasting economic and financial time series data, neural networks might prove to be more suitable for capturing intricate patterns in the data. As typical with neural networks, MLP consists of an input layer, one or more hidden layers with non-linear activation functions, and an output layer.

4 Results

4.1 Model Outputs

An analysis of outputs from the different models is performed to identify any relationships between variables and their respective time dependencies relevant to each independent variable within itself. This requires an evaluation of model coefficients and statistical significance of variable effects. Models are evaluated in this context to reveal unique patterns in variable relationships.

4.1.1 Multivariate Regression

The results of three models in the multivariate regression approach provide unique insights into the relationships between the variables and their time dependencies. Outputs from the "standard" OLS regression model indicate that both 'PCE' and 'UR' lack significance. With a coefficient of 0.058, 'PCE' has a positive impact on the FFR but is not statistically significant ($P>|z| = 0.439$). The coefficient for 'UR' of -0.019 is not statistically significant ($P>|z| = 0.133$). The predictive importance of past values is evident given the output of autocorrelation of the residuals extending through 5 lags ('L1 FFR'-'L5 FFR'). This implies that each residual value is influenced by the previous 5 values of the error term. While this outcome is not ideal for hypothesis testing and prediction, the results provide insight into the time dependencies of the data and implications for additional modeling approaches to account for time-trend patterns not accounted for in this model.

The "trend" model which extends from the "standard" model by incorporating a time trend variable, provides limited additional insight or benefit. The coefficients for 'PCE' and 'UR' are positive and negative, respectively, indicating that an increase in 'PCE' is associated with an increase in FFR, while an increase in 'UR' is associated with a decrease in FFR. However, these relationships are not statistically significant

(P>|z| > 0.05). What is of more interest in this model is that the significance of the lagged terms (P>|z| < 0.05) indicates that the past behavior of the Fed Funds Rate is a strong predictor of its future changes.

In terms of the "lagged" model, the coefficient for 'PCE' with a lag of 1 period suggests that a 1-unit increase in PCE1 is associated with an increase of 0.181 in the Fed Funds Rate. This relationship is statistically significant (P>|z| = 0.013). The coefficient for UR1 (-0.013) suggests that a 1-unit increase in UR1 (lagged UR by period 1) is associated with a decrease of 0.013 in the Fed Funds Rate. However, this relationship is not statistically significant (P>|z| = 0.300). The lagged terms of FFR are highly significant (p < 0.05) for 'L1 FFR', 'L2 FFR', and 'L4 FFR' indicating that the past behavior of the Fed Funds Rate is a strong predictor of its future changes.

All three multiple regression models indicate significant activity with 'L1 FFR', 'L2 FFR', and 'L4 FFR', while the "lagged" model shows significance with 'PCE'. While the direction of the coefficients for 'PCE' (positive) and 'UR' (negative) between models is encouraging, the lack of significance with these variables in two of the three models indicates more analysis would be needed if these variables predict FFR. The significance of the lags across models supports the potential for a lagged variable model in this context.

Multivariate Regression – 3 Models

	Standard		Trend		Lagged (1 period)	
Variable	Coef	P-Value	Coef	P-Value	Coef	P-Value
PCE	0.058	0.439	0.083	0.261	0.181	0.013
UR	-0.019	0.133	-0.019	0.135	-0.013	0.300
L1 FFR	0.457	0.000	0.435	0.000	0.463	0.000
L2 FFR	-0.169	0.000	-0.106	0.006	-0.181	0.000
L3 FFR	0.008	0.852	0.014	0.719	0.016	0.676
L4 FFR	-0.076	0.049	-0.107	0.005	-0.081	0.036
L5 FFR	0.004	0.922	-0.015	0.691	0.003	0.936

Table 1: Variable Comparison (Multivariate Regression – 3 Models)

4.1.2 Vector Autoregression (VAR)

In the VAR approach, the model with 5 lags is selected because it minimizes the AIC, indicating a good balance between model fit and complexity. The coefficients of the lagged values between 'FFR', 'PCE', and 'UR' are examined to determine the effects of past values on current values. Based on the outputs, the coefficients for the first and second lags of 'FFR' are highly significant, confirming a strong autoregressive component. The significance of the first and second lags suggests that changes in the federal funds rate tend to persist over time. In terms of 'PCE', the coefficient 0.242 represents the effect of the first lag on the current federal funds rate with statistical significance (P>|z| = 0.010). The coefficient for 'UR', though in the expected direction, (-0.033) is not statistically significant (P>|z| = 0.362).

Multivariate Regression – 3 Models vs. VAR

	Standard		Trend		Lagged (1 period)		VAR	
Variable	Coef	P-Value	Coef	P-Value	Coef	P-Value	Coef	P-Value
PCE	0.058	0.439	0.083	0.261	0.181	0.013	0.242	0.010
UR	-0.019	0.133	-0.019	0.135	-0.013	0.300	-0.033	0.362
L1 FFR	0.457	0.000	0.435	0.000	0.463	0.000	0.443	0.000
L2 FFR	-0.169	0.000	-0.106	0.006	-0.181	0.000	-0.187	0.000
L3 FFR	0.008	0.852	0.014	0.719	0.016	0.676	0.021	0.603
L4 FFR	-0.076	0.049	-0.107	0.005	-0.081	0.036	-0.106	0.008
L5 FFR	0.004	0.922	-0.015	0.691	0.003	0.936	0.003	0.933

Table 2: Variable Comparison (Multivariate Regression – 3 Models vs. VAR)

4.1.3 Multi-Layer Perceptron (MLP) Regressor

In the MLP approach, forecasting FFR solely based on time index, the Average Squared Error (ASE) of 0.024 is quite low, indicating the model's predictions are relatively close to the actual value. This suggests a moderate degree of predictability in the changes of the FFR based on time alone. Also, this implies that there may be underlying trends indicating that when the Fed increases rates in one period they are likely to increase in the next.

When additional regressors (UR, PCE) are included in the forecasting model, there is a slight increase in the ASE (0.031). This indicates that time is a more dominant factor in predicting FFR compared to the other variables. This also brings up an interesting observation. When the model is run with different periods of data, it performs differently with additional regressors. Specifically, when using data from the time period prior to the 1970s, the model with additional regressors performs better.

4.2 Prediction

Based on the ASE results of the MLP approach, 2 models (with and without regressors (PCE, UE)) are compared in terms of model fit and predictive performance. As shown in the plots, the 'Actual' data on FFR starts relatively stable, with only minor fluctuations. There is a noticeable decline followed by a significant increase towards the end of the observed period.

Per the 'Time Only' forecast plot in Figure 7, the forecast is a straight line which isn't effective at predicting the variability and trends in the FFR data. The resulting generalization could be due to skewed learning. This scenario could occur when outliers are forcing the model to converge on a solution that minimizes the influence of all data points. Based on the results of the plot, this 'Time Only' forecast model doesn't effectively capture the dynamics present in the actual data which suggests additional variables could give a more accurate prediction. In Figure 8, additional regressors are added to the model for predictions.

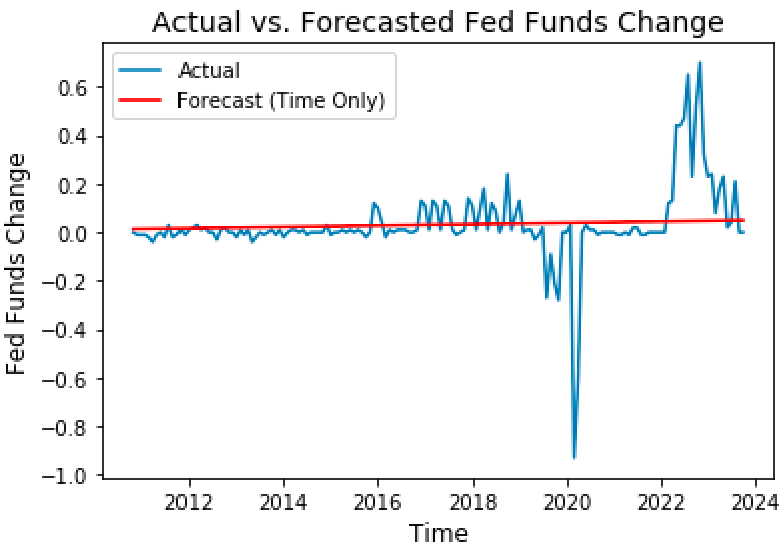

Figure 7: Visualization of Forecast vs. Actual (Time Only, no Regressors)

Per the 'With Regressors' forecast plot, the forecast shows variability that corresponds with some of the peak changes in FFR, however, the forecast falls short of capturing the extreme values identified in the observed trend analysis.

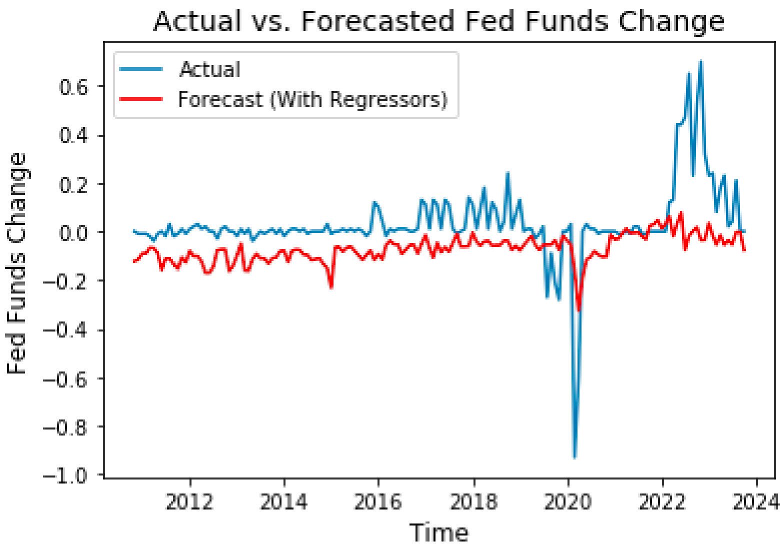

Figure 8: Visualization of Forecast vs. Actual (With Regressors)

5 Discussion

Lag results suggest that the relationship between FFR and past values in FFR is critical to understanding what triggers the Fed to act and adjust rates. PCE results demonstrate greater importance (with significance) over UR. While the Fed claims that unemployment is a critical metric in determining whether to adjust rates, the modeling doesn't support this outcome. The relationship between unemployment and FFR may be more evident when unemployment is shown as a response to changes in FFR. Additionally, unemployment could be more significant as a driver when the value increases to more extreme high levels triggering the Fed to act and lower rates. Considering the Fed's focus on 2% inflation as a target (per the Taylor Rule), the relationship between PCE and FFR isn't surprising and implies that PCE is a more reliable indicator for the Fed when making decisions on rate changes. While the UR is considered a critical economic indicator, the data suggests a lack of impact on FFR.

Key challenges in the study include limitations in the scope of the data studied. An analysis of the metrics within the context of industries could prove useful to uncover more insights and potentially surface the importance of the UR in relation to FFR. In terms of the ethical implications of this research, a greater focus on PCE over UR could be considered unbalanced and unfair in terms of the impact of unemployment on specific industries and even households which often seem to be more likely impacted. Future research may involve more data collection and analysis to consider these implications.

6 Conclusion

In conclusion, PCE is a significant predictor of FFR, while UR isn't. The time lags between variables hold importance with significance as well. The models also indicated when the Fed acts in one direction it is likely to continue to act in that direction for several periods. This has important implications in understanding how the Fed sets economic policy. Further research should include a deeper dive into unemployment and inflation by sector. Additionally, examining the macroeconomic effects of the FFR will offer greater insight into how monetary policy interacts with financial conditions in the economy.

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